**Detecting Human Life during Fire**

## A PROJECT REPORT

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**Mr. GNANAKUMAR GANESAN**

***in partial fulfillment for the award of the degree of***

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**IN**

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**PRESIDENCY UNIVERSITY**

**SCHOOL OF COMPUTER SCIENCE ENGINEERING**

**CERTIFICATE**

This is to certify that the Project report **“Detecting Human Life during Fire”** being submitted by “STUDENTS NAMES” bearing roll number(s) “STUDENTS ROLL NUMBERS” in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence & Machine Learning) is a Bonafide work carried out under my supervision.

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**DECLARATION**

We hereby declare that the work, which is being presented in the project report entitled **TITLE OF THE PROJECT** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **COMPUTER SCIENCE AND ENGINEERING (Artificial Intelligence & Machine Learning**, is a record of our own investigations carried under the guidance of **Mr. GNANAKUMAR GANESAN, Assistant professor,** **School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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**ABSTRACT**

Fire emergencies are among the most critical and time-sensitive situations, posing significant challenges to timely and effective rescue operations. Identifying and locating individuals trapped in hazardous environments, particularly those obscured by smoke, fire, or debris, remains a key obstacle in disaster management. Addressing this challenge, this research introduces an advanced AI-driven deep learning model that leverages state-of-the-art technologies to enhance the precision and speed of detection and identification efforts in fire emergency scenarios. By employing video footage from CCTV cameras or drone platforms, this model provides an efficient, real-time solution for identifying people in distress and supporting rescue missions.

Central to this system is the YOLOv8 framework, a cutting-edge object detection algorithm built upon convolutional neural network (CNN) architecture. YOLOv8 offers significant advancements over its predecessors, including enhanced accuracy, faster inference times, and a more lightweight architecture, making it particularly suitable for real-time applications in complex environments. The model is capable of detecting humans with high precision even under adverse conditions such as dense smoke, poor lighting, and occlusions. Its real-time capabilities allow rescue teams to monitor live feeds and make informed decisions quickly, reducing response times and potentially saving lives in life-critical situations.

Beyond mere detection, this system incorporates an additional layer of functionality by integrating Mediapipe, an open-source framework known for its pose estimation capabilities. Mediapipe enables the system to analyze the posture of detected individuals, effectively distinguishing between those who are standing and those who are lying down. This distinction is particularly critical in prioritizing rescue efforts, as individuals lying down may require immediate medical attention or be at a greater risk of injury. By providing detailed insights into the condition and position of individuals, the model enhances situational awareness for rescue teams, allowing them to allocate resources more effectively and respond to emergencies with greater precision.

Another distinguishing feature of this system is its built-in privacy preservation mechanism. Recognizing the sensitivity of video data captured during emergencies, the model integrates a face detection and blurring module. This component ensures that individuals' identities are safeguarded, addressing ethical and legal concerns surrounding the use of surveillance data. The face-blurring mechanism is implemented without compromising the overall functionality or accuracy of the system, maintaining a balance between privacy and operational efficiency. This capability is particularly important for fostering public trust and ensuring compliance with data protection regulations, paving the way for broader adoption of the technology.

The proposed system has undergone extensive testing across a variety of environmental conditions, including varying levels of visibility, crowd density, and scene complexity. The results demonstrate its robustness and reliability in detecting individuals amidst challenging scenarios such as heavy smoke and fluctuating lighting. Furthermore, its modular design allows seamless integration with existing surveillance infrastructure or deployment on drone platforms, making it a versatile tool for disaster management.

In conclusion, this AI-driven model, with its combination of YOLOv8 for object detection, Mediapipe for posture recognition, and privacy-preserving face blurring, represents a transformative solution for addressing the challenges of fire emergencies. Its ability to deliver real-time analytics, ensure ethical compliance, and adapt to diverse conditions underscores its potential to significantly improve the outcomes of rescue missions. The deployment of this technology not only enhances the efficiency of emergency response operations but also sets a new standard for leveraging AI in life-critical applications. With further refinements, such as incorporating thermal imaging and optimizing for low-resource devices, this model could serve as a cornerstone for next-generation disaster management systems.

**Keywords:**  
Fire emergency, deep learning, object detection, YOLOv8, Mediapipe, pose estimation, privacy preservation, face blurring, rescue operations, real-time video analytics, disaster management, CNN architecture, drone surveillance, posture recognition, ethical AI.

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**LIST OF TABLES**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sl. No.** | **Table Name** | **Table Caption** | **Page No.** |
| 1 | Table 1.1 | Software modules versus Reusable components | 5 |

**LIST OF FIGURES**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sl. No.** | **Figure Name** | **Caption** | **Page No.** |
| 1 | Figure 1.1 | Software modules versus Reusable components | 5 |

**TABLE OF CONTENTS**

|  |  |  |
| --- | --- | --- |
| **CHAPTER NO.** | **TITLE** | **PAGE NO.** |
|  | **ABSTRACT ACKNOWLEDGMENT** | **i**  **ii** |
| **1.** | **INTRODUCTION** | 1 |
|  | 1.1 Background | 1 |
|  | 1.2 Problem Statement | 2 |
|  | 1.3 Objectives | 5 |
| **2.** | **LITERATURE REVIEW** | **16** |

**3. Research Gaps of Existing Methods**

3.1 Challenges in Smoke Detection

3.2 Real-time Constraints

3.3 Integration with Emergency Services

**4. Proposed Methodology**

4.1 Overview

4.2 Detailed Workflow

4.3 Key Implementation Steps

4.4 Advantages of the Proposed System

4.5 Future Enhancements

**5. Objectives**

**6. System Design & Implementation**

6.1 Hardware Components

6.2 Software Components

6.3 Implementation Steps

**7. Timeline for Execution of Project**

**CHAPTER-1**

**INTRODUCTION**

* 1. **Background**

Natural and man-made disasters, including fires, frequently cause extensive damage and loss of life. Rapid response and effective decision-making are critical for minimizing their impact. In modern times, the availability of diverse datasets from sources such as social media, sensors, satellite imagery, and drones has grown exponentially. However, manually processing such large volumes of data for real-time decision-making is nearly impossible. AI, ML, and DL techniques have emerged as powerful tools to analyze, process, and visualize disaster data efficiently [1], [2]. These technologies are increasingly applied in geospatial analysis and situational awareness, where integrating spatial data from various sources enables precise tracking and identification of hazards [2].

Fire incidents present specific challenges, such as smoke-induced reduced visibility and delays in locating victims trapped in hazardous environments. Traditional fire detection systems, while effective to some extent, often fail to provide real-time insights. With advancements in AI and computer vision, emerging technologies like drones equipped with real-time monitoring capabilities offer a transformative approach to disaster management. For instance, integrating computer vision with fire detection systems has shown promising results in detecting fire sparks, smoke, and even human presence in challenging environments [3], [4].

Deep learning techniques, such as Convolutional Neural Networks (CNNs) and TinyML models, have demonstrated remarkable accuracy in image recognition tasks. These models, when deployed on low-power devices like Raspberry Pi or Banana Pi, offer a scalable solution for real-time monitoring in resource-constrained environments [5]. Enhanced systems like the modified YOLOv4 network have further advanced fire detection by improving accuracy and response times through data augmentation and network optimization [3]. Additionally, AI-based fire and smoke detection systems have introduced innovative features such as real-time visual analysis of fire and smoke, enabling quicker responses and reducing false alarms [4].

* 1. **Problem Statement**

Searching for trapped individuals in fire emergencies is labor-intensive, time-consuming, and hazardous. Smoke reduces visibility, and the lack of precise information about the number and location of victims exacerbates the situation. Current solutions lack the ability to provide real-time detection and prioritization of individuals in need of immediate attention.

* 1. **Objectives**

The primary objective of this project is to develop an advanced drone-based human detection system tailored for fire emergency scenarios. The system will employ cutting-edge deep learning algorithms to process live video feeds captured by drones, effectively identifying human faces and body poses in real-time. By leveraging this technology, rescue teams will gain critical insights into the conditions and locations of victims, allowing them to prioritize rescue operations and strategize their efforts more efficiently. Ultimately, the project aims to minimize casualties and enhance the effectiveness of rescue missions by providing a robust, real-time solution to detect and assess victims trapped in challenging environments, thereby saving lives and mitigating the devastating consequences of fire emergencies.

**CHAPTER-2**

**LITERATURE SURVEY**

* 1. **Introduction**

The challenges of fire detection and human identification in hazardous environments, such as fire emergencies, have driven significant advancements in AI and deep learning. The development of real-time detection systems integrating object detection, pose analysis, and privacy-preserving mechanisms enables rescue teams to respond more effectively and ethically. This chapter delves deeply into existing literature across these domains, exploring methodologies, key findings, and technological advancements to identify their implications for disaster management.

* 1. **Fire Detection**
* Fire detection technologies have transitioned from traditional threshold-based methods to advanced AI-driven approaches, addressing limitations such as environmental sensitivity and lack of robustness in complex scenarios. Early detection systems relied heavily on predefined thresholds for temperature, smoke density, or color patterns, often leading to false alarms and inefficiencies.
* Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have transformed fire detection. Doshi et al. (2020) applied CNNs for detecting fire in urban environments, achieving significant improvements in accuracy over traditional techniques. Their work demonstrated how convolutional layers could effectively extract spatial features critical for identifying fire patterns [11]. Yuan et al. (2021) further expanded on this by developing a hybrid CNN-RNN model designed for dynamic video sequences. This model excelled in identifying fire under varying lighting conditions and complex motion scenarios, showcasing its robustness and versatility [12].
* IoT-based fire detection has also gained traction, with studies emphasizing lightweight architectures for real-time applications. Li et al. (2022) proposed IoT-integrated deep learning models that balance computational efficiency with detection accuracy. Their system, optimized for constrained environments, proved effective in early fire detection across diverse settings [13]. Wei (2023) enhanced YOLOv8 by integrating a Squeeze-and-Excitation (SE) attention mechanism, which improved focus on critical regions within fire-affected environments. This modification demonstrated superior accuracy, particularly in dense smoke and low-light conditions [8].
* Multi-modal systems integrating RGB and thermal imaging have further expanded detection capabilities. Lin et al. (2023) employed a YOLOv8 framework for drone-mounted systems, combining RGB and thermal data to enhance detection precision in disaster zones. Their work emphasized the importance of multi-spectral data for overcoming challenges in visually complex scenarios [23].
  1. **Human Detection**
* Detecting humans during fire emergencies is pivotal for prioritizing rescue operations. Traditional methods, such as thermal imaging and motion-based detection, have limitations in environments with dense smoke and debris. Advances in deep learning frameworks, particularly the YOLO (You Only Look Once) architecture, have revolutionized this domain.
* Introduced by Redmon et al. (2016), YOLO’s real-time object detection capabilities set a new standard for efficiency and accuracy [14]. Subsequent iterations, including YOLOv4 and YOLOv8, have addressed challenges related to speed and precision. Nguyen et al. (2023) demonstrated YOLOv8’s superior performance in disaster scenarios, with a 10% improvement in mean Average Precision (mAP) compared to YOLOv5 [16]. Singh et al. (2023) highlighted YOLOv8’s robustness in identifying humans amidst smoke and debris, emphasizing its lower false positive rates and high reliability [17].
* Resource-constrained environments pose unique challenges for real-time human detection systems. Alsharif et al. (2024) validated YOLOv8’s adaptability in such settings, demonstrating its lightweight architecture and high accuracy on portable devices. Their findings highlight the framework’s suitability for drone-based and handheld applications in emergency scenarios [6].
  1. **Posture Analysis**
* The ability to analyse human posture during emergencies is critical for assessing the condition and priority of individuals. Posture analysis helps differentiate between standing, sitting, or lying individuals, allowing rescue teams to identify those in urgent need of assistance. This has become increasingly feasible with advancements in real-time pose estimation frameworks.
* MediaPipe, developed by Google, is a prominent tool for pose estimation due to its lightweight architecture and real-time capabilities. Zhang et al. (2022) combined MediaPipe with CNNs to develop a system capable of estimating body postures in disaster scenarios. Their work provided critical insights into improving situational awareness during rescue operations [18].
* Kang et al. (2023) introduced a novel approach by integrating MediaPipe with Spatio-Temporal Graph Convolutional Networks (ST-GCNs), which enhanced accuracy in dynamic and occluded environments. This hybrid model demonstrated superior performance in environments with frequent movement and partial obstructions [19].
* Sengar et al. (2024) optimized pose estimation models for resource-constrained environments, showcasing MediaPipe’s efficiency under challenging conditions such as low light and dense smoke [7]. Additionally, Kim et al. (2023) incorporated humanoid models into MediaPipe-based systems, significantly improving reliability and precision in complex scenarios [9].
  1. **Privacy Preservation**
* As video analytics become central to emergency response, privacy preservation has emerged as a crucial concern. Systems capturing video data during public emergencies must balance the need for effective detection with the ethical imperative to protect individual identities.
* Park et al. (2021) developed a real-time face blurring system that maintained detection accuracy while anonymizing individuals. Their approach addressed key ethical and legal challenges in video-based surveillance [20]. Similarly, Lee et al. (2023) introduced a privacy-aware AI pipeline integrating face detection and blurring mechanisms, ensuring compliance with data protection regulations. This system demonstrated that privacy-preserving methods could be implemented without compromising operational efficiency [21].
* Privacy preservation aligns with ethical AI principles, fostering public trust and promoting broader adoption of AI systems in disaster management. Future research must continue to address the trade-offs between detection capabilities and privacy requirements, ensuring systems are both effective and ethically sound.
  1. **Integrated Systems**
* Integrated systems combining fire detection, human identification, posture analysis, and privacy preservation represent a transformative approach to disaster management. Such systems leverage the strengths of individual components to provide comprehensive solutions.
* Kim et al. (2022) developed a multi-modal AI framework integrating YOLOv5 for object detection and MediaPipe for posture estimation. This system achieved high efficacy in simulated disaster scenarios, demonstrating the potential of integrated technologies [22]. Lin et al. (2023) emphasized the role of drones in enhancing situational awareness, combining RGB and thermal imaging to improve detection accuracy and speed in real-time [23].
* Avazov et al. (2022) highlighted the importance of smart city-compatible frameworks that integrate deep learning models with emergency protocols. Their work underscored the need for scalable, interoperable systems capable of addressing diverse disaster scenarios [3].
  1. **Methodological Insights**
* The reviewed literature highlights key methodological insights for developing effective AI-based disaster management systems. Robust data collection, including annotated datasets from diverse environments, is essential for training reliable models. Tools like CVAT and platforms like Roboflow have become invaluable for dataset annotation and augmentation.
* Model selection and optimization also play a critical role. Advanced architectures such as YOLOv8 and MediaPipe have demonstrated exceptional performance across various applications. However, integrating these technologies into cohesive frameworks requires careful consideration of system compatibility, computational constraints, and ethical considerations.
  1. **Conclusion**

The literature reveals significant progress in fire detection, human identification, posture analysis, and privacy preservation. While these advancements have paved the way for more effective disaster management systems, challenges remain in achieving real-time performance under resource constraints and integrating these technologies seamlessly with emergency protocols. Addressing these gaps requires continued research and innovation, building on the foundations established in the reviewed studies.

**CHAPTER-3**

**RESEARCH GAPS OF EXISTING METHODS**

**3.1 Challenges in Smoke Detection**

Fire emergencies often present environments filled with smoke, debris, and unpredictable heat signatures, posing significant challenges for existing detection technologies. Smoke can severely obstruct visibility, reducing the effectiveness of thermal imaging and standard object detection algorithms in identifying human presence. For instance, thermal cameras frequently misinterpret heat signatures from objects or flames as human activity, resulting in false positives. Additionally, the inability of many models to generalize across diverse environmental conditions, such as varying smoke densities or fluctuating heat patterns, further reduces their reliability during fire emergencies.

These challenges are compounded by the scarcity of high-quality, labeled datasets for training deep learning models specifically designed for fire events. The imbalanced nature of these datasets, with limited representation of diverse fire scenarios, restricts model adaptability. The integration of multiple data sources, such as satellite imagery, drone footage, and ground sensors, adds another layer of complexity due to variations in spatial resolution, temporal frequency, and data quality. Addressing these gaps requires models capable of operating effectively under adverse conditions while maintaining high accuracy in real-world scenarios [6].

**3.2 Real-time Constraints**

The demand for real-time processing and analysis is critical in fire emergency responses, yet many existing solutions fall short due to computational and hardware limitations. Advanced algorithms, such as CNNs and hybrid deep learning models, often require extensive processing power and high-performance hardware, which are impractical for deployment in drones or portable emergency setups. For instance, transmitting video feeds to centralized processing units introduces latency, delaying critical decision-making during rescue operations. Furthermore, many algorithms exhibit inefficiencies in computational resource optimization, leading to slower response times and reduced accuracy. The inability to process data efficiently in real-time becomes particularly problematic when dealing with large-scale scenarios involving UAVs or remote sensing systems. Enhancements, such as those seen in frameworks like MediaPipe, which improve pose estimation even under challenging conditions like low light and partial occlusions, demonstrate the potential for overcoming these constraints. These advancements highlight the need for adaptable and lightweight models that balance performance and resource efficiency [6], [7].

**3.3 Integration with Emergency Services**

A critical gap in existing fire detection and response systems lies in their integration with emergency services. Although technological advancements have enabled the development of sophisticated detection systems, they often lack compatibility with real-time rescue operations and centralized emergency protocols. Many systems fail to facilitate seamless data sharing between drones, rescue teams, and command centers, hindering actionable decision-making during crises.

Moreover, the absence of standardized evaluation metrics and protocols impedes the ability to compare and benchmark different models, slowing progress toward universally effective fire detection systems. Addressing this gap requires establishing standardized frameworks for integrating diverse technologies, such as drones equipped with advanced AI systems, portable communication networks, and centralized databases, into cohesive emergency response frameworks. Advances in pose estimation frameworks like MediaPipe, which adapt to challenging environments and overcome previous limitations, further underscore the potential for developing systems that integrate seamlessly with emergency services while maintaining robust performance [7].

**CHAPTER-4**

**PROPOSED MOTHODOLOGY**

**4.1 Overview**

The proposed methodology leverages cutting-edge drone technology and advanced deep learning models to address the challenges of locating and prioritizing individuals trapped during fire emergencies. This system integrates real-time video feed processing with algorithms like YOLOv8 for object detection and Mediapipe for pose estimation. By using drones equipped with high-resolution cameras, the system provides accurate identification of victims, their physical conditions, and their relative positions in the environment, enabling rescue teams to act swiftly and efficiently.

* 1. **Detailed Workflow**

Video Capture by Drone:

A drone equipped with high-resolution cameras captures live video footage of the fire-affected area. The cameras can operate under challenging visibility conditions, such as dense smoke, leveraging high-quality optics and thermal sensors when necessary.

Video Feed Transmission:

The captured video feed is streamed to a processing unit (either on the drone itself or remotely) equipped with sufficient computational power (e.g., GPU-enabled devices).

Data is transmitted via reliable wireless communication protocols to ensure uninterrupted processing.

Human and Fire Detection Using YOLOv8:

The YOLOv8 model processes the video frames to detect human faces and bodies with high accuracy. The model, trained on a diverse dataset of fire-rescue scenarios and specific movie clips which include fire scenarios, identifies individuals even in obscured environments, such as those affected by smoke or low light. [8]

Pose Estimation via Mediapipe:

Detected humans are further analyzed using Mediapipe to estimate body poses.

Pose estimation identifies critical physical conditions, such as whether an individual is standing, sitting or lying on the floor. This information is used to prioritize individuals requiring urgent medical attention.[9]

Data Visualization for Rescue Teams:

The processed information is displayed on a user-friendly interface accessible to rescue personnel. Metrics include the number of individuals detected, their locations, estimated conditions, and relative priorities for rescue operations.

The interface incorporates heatmaps or overlays to visualize victim distribution.

Real-time Feedback Loop:

The system continuously updates rescue teams with real-time data as the drone navigates through the environment. Feedback mechanisms allow for adjustments, such as redirecting the drone to new areas or focusing on specific regions with higher victim densities.

Integration with Rescue Protocols:

The system is seamlessly integrated with existing emergency protocols, ensuring it can be deployed with minimal additional training or setup.

Rescue teams can use the insights for strategic decision-making, optimizing response times and resource allocation.

**4.3 Key Implementation Steps**

Data Collection and Annotation:

Collect video footage from controlled fire-simulation environments, ensuring the dataset includes various scenarios such as dense smoke, varied lighting, and obstructed views.

Annotate the dataset using tools like Roboflow, labeling human faces, body poses, and environmental obstacles to enhance training accuracy.

Model Training and Validation:

Train the YOLOv8 model on the annotated dataset, optimizing for high accuracy and low inference times. Validate the model's performance on unseen data to ensure robustness in real-world conditions.

Integration of Pose Estimation Framework:

Incorporate Mediapipe's pose estimation pipeline into the system to analyze the conditions of detected individuals. Optimize the combined system to ensure real-time processing without compromising detection accuracy.[9]

System Testing in Simulated Environments:

Conduct extensive testing in controlled fire-simulation scenarios, assessing performance metrics like detection accuracy, false positive rates, and inference times.

Iterate on system design and algorithms to address any identified shortcomings.

Deployment and Real-world Application:

Deploy the system on drones for field testing in collaboration with emergency response teams.

Gather feedback and refine the system to improve usability and effectiveness in live scenarios.

**4.4 Advantages of the Proposed System**

Real-time Operation:

The system processes video feeds in real-time, enabling immediate detection and prioritization of individuals.

High Accuracy in Challenging Environments:

Advanced deep learning models ensure robust performance even in smoke-filled or obstructed conditions.

Enhanced Decision-making:

Rescue teams gain critical insights, including victim positions, conditions, and prioritization, facilitating strategic operations.

Scalability and Adaptability:

The system is designed to integrate with various drone platforms and emergency protocols, ensuring broad applicability across different scenarios.

Life-saving Potential:

By providing actionable data in real-time, the system significantly reduces response times, improving the chances of successful rescues and minimizing casualties.

**4.5 Future Enhancements**

Thermal and Multispectral Imaging Integration:

Future versions could incorporate additional sensors, such as thermal or multispectral cameras, to improve detection capabilities in extreme environments.

Cloud-based Analytics:

Integrating cloud processing would enable centralized data analysis and storage, supporting larger-scale operations and multi-drone coordination.

This methodology lays the foundation for an innovative and life-saving solution, combining the latest advancements in AI and drone technology to address critical challenges in fire emergency response.

**CHAPTER-5**

**OBJECTIVES**

The objectives of this project aim to address the critical challenges faced during fire emergencies, focusing on minimizing human casualties and enhancing rescue efficiency through technological innovation. The key objectives are:

* Reduce fatalities during fire emergencies: By deploying advanced deep learning models and drone technology, the project seeks to enable faster and more informed rescue operations, significantly reducing response times.
* Develop an efficient and scalable deep learning model: This involves creating a robust YOLOv8-based object detection system capable of identifying human faces and body poses in real-time, even in challenging environments such as smoke-filled areas and debris-covered spaces.
* Enhance situational awareness of rescue teams: By integrating real-time data visualization and prioritization metrics, the system provides rescue teams with actionable insights, enabling them to strategize and prioritize their efforts based on the condition and location of victims.
* Demonstrate the potential of AI-driven solutions: The project showcases the feasibility and impact of AI applications in life-saving scenarios, emphasizing the transformative role of advanced technology in emergency response systems.
* Provide a real-time detection and assessment framework: Utilizing a step-by-step methodology, the system captures live drone footage, processes it through a deep learning pipeline for human detection, analyzes body poses using Mediapipe, and delivers real-time visual metrics for decision-making.
* Ensure seamless integration with existing rescue protocols: The system is designed to work harmoniously with emergency equipment and communication systems, enhancing the overall effectiveness and adaptability of rescue operations.

By achieving these objectives, the project aims to set a benchmark for future AI-driven emergency response systems, ultimately contributing to saving lives and mitigating the devastating consequences of fire-related disasters.

**CHAPTER-6**

**SYSTEM DESIGN & IMPLEMENTATION**

**6.1 Hardware Components**

The proposed system relies on a set of sophisticated hardware components that are essential for its operation. These components are carefully selected to ensure robustness, scalability, and reliability in challenging environments like fire emergencies. Key components include:

1. **Drone with High-Resolution Cameras and Thermal Sensors:** The drone serves as the primary platform for data acquisition. Equipped with advanced optical systems, it captures both visible and thermal imagery of the environment, enabling detailed and multi-modal analysis. The high-resolution cameras ensure precise visual data collection, while thermal sensors aid in detecting heat signatures in low-visibility conditions, such as dense smoke.
2. **Portable GPU-Enabled Computing Devices:** These devices provide the computational power necessary for real-time processing of large video data streams. GPUs (Graphics Processing Units) are optimized for parallel processing, making them ideal for executing deep learning models like YOLOv8. These devices can be integrated onboard the drone or connected via ground stations to ensure minimal latency during operations.
3. **Communication Modules:** Reliable communication is critical for transmitting video feeds and analytical results from the drone to ground control stations or rescue teams. These modules employ robust wireless protocols, such as 5G, Wi-Fi 6, or dedicated RF communication channels, to ensure seamless and uninterrupted data transfer. Advanced error-correction algorithms are implemented to mitigate signal interference in disaster zones.
4. **Power Management Systems:** Drones and computing devices require efficient power management to sustain operations over extended periods. Lithium-polymer batteries with high energy density are used, complemented by real-time power monitoring systems to optimize battery usage and prevent mid-operation failures.
5. **Environmental Sensors:** Additional sensors, such as air quality monitors and GPS modules, are integrated to enhance situational awareness. These sensors provide auxiliary data that can be used to contextualize the drone’s findings and improve decision-making accuracy.

**6.2 Software Components**

The system integrates a range of advanced software technologies to enable its functionalities. These include:

1. **YOLOv8 Deep Learning Model:** YOLOv8 is the backbone of the object detection system. It offers state-of-the-art accuracy and real-time performance, making it ideal for detecting humans in complex environments. The model’s lightweight architecture ensures efficient deployment on resource-constrained hardware.
2. **Mediapipe Framework:** This framework facilitates precise body pose estimation, helping infer the physical condition of victims. Mediapipe’s ability to perform real-time pose tracking enables the system to prioritize rescue efforts based on detected postures.
3. **Python Libraries:** Essential libraries include OpenCV for image and video processing, NumPy for numerical computations, Matplotlib for data visualization, and Ultralytics for implementing YOLO models. These libraries provide a robust foundation for building and deploying the system’s functionalities.
4. **Roboflow:** This platform streamlines the process of dataset annotation, augmentation, and management. It supports efficient preparation of high-quality datasets, ensuring the YOLOv8 model is trained on diverse and representative data.
5. **Real-Time Visualization Tools:** User interfaces are designed to display processed data, including live video feeds, detected human locations, and inferred conditions. Interactive dashboards facilitate quick decision-making by rescue teams.
6. **Error Handling and Recovery Mechanisms:** The software incorporates fault-tolerant algorithms to handle data corruption, packet loss, or hardware failures. This ensures the system’s resilience during critical operations.

**6.3 Implementation Steps**

The implementation process involves a detailed and systematic approach to ensure the system functions effectively in real-world scenarios. The following steps outline the methodology:

1. **Data Collection:**
   * Video footage is captured from simulated fire environments to create a representative dataset. Controlled setups include varying levels of smoke, debris, and fire intensity to replicate real-world conditions.
   * Thermal imaging data is also collected to complement visual data, ensuring the model can operate effectively in low-visibility scenarios.
2. **Data Annotation:**
   * Using tools like Roboflow, the dataset is meticulously annotated. Human faces, body poses, and environmental features are labeled to create a high-quality training dataset. This step ensures the model is exposed to diverse scenarios, such as partial occlusions and variable lighting.
3. **Model Training:**
   * The YOLOv8 model is trained on the annotated dataset for multiple epochs. Hyperparameter tuning is conducted to optimize the model’s performance, focusing on metrics like detection accuracy, inference speed, and robustness against noise.
   * Data augmentation techniques, such as flipping, rotation, and scaling, are applied to enhance the model’s generalizability.
4. **System Integration:**
   * The trained YOLOv8 model is integrated into the drone’s onboard system. This enables real-time video feed processing for detecting humans and assessing their poses.
   * Mediapipe is incorporated to analyze detected poses and infer victim conditions, such as standing, lying down, or showing signs of distress.
   * A communication pipeline is established to transmit processed data to rescue teams via a user-friendly interface. The interface includes features like heatmaps and priority indicators for effective resource allocation.
5. **Testing:**
   * Comprehensive testing is conducted in simulated environments replicating real-world fire scenarios. Performance metrics, such as detection accuracy, inference speed, and system reliability, are evaluated.
   * Stress testing is performed to assess the system’s robustness under extreme conditions, including prolonged operation and high data loads.
6. **System Optimization:**
   * Feedback from testing is used to refine the system. This includes adjusting model parameters, enhancing software algorithms, and fine-tuning hardware configurations.
   * Continuous integration and deployment pipelines are established to streamline updates and improvements.
7. **Deployment:**
   * The final system is deployed on drones for real-world applications. Field trials are conducted in collaboration with emergency response teams to validate its effectiveness and usability.
   * Training programs are developed to familiarize rescue teams with the system’s functionalities and operational workflows.

**6.4 Future Enhancements:**

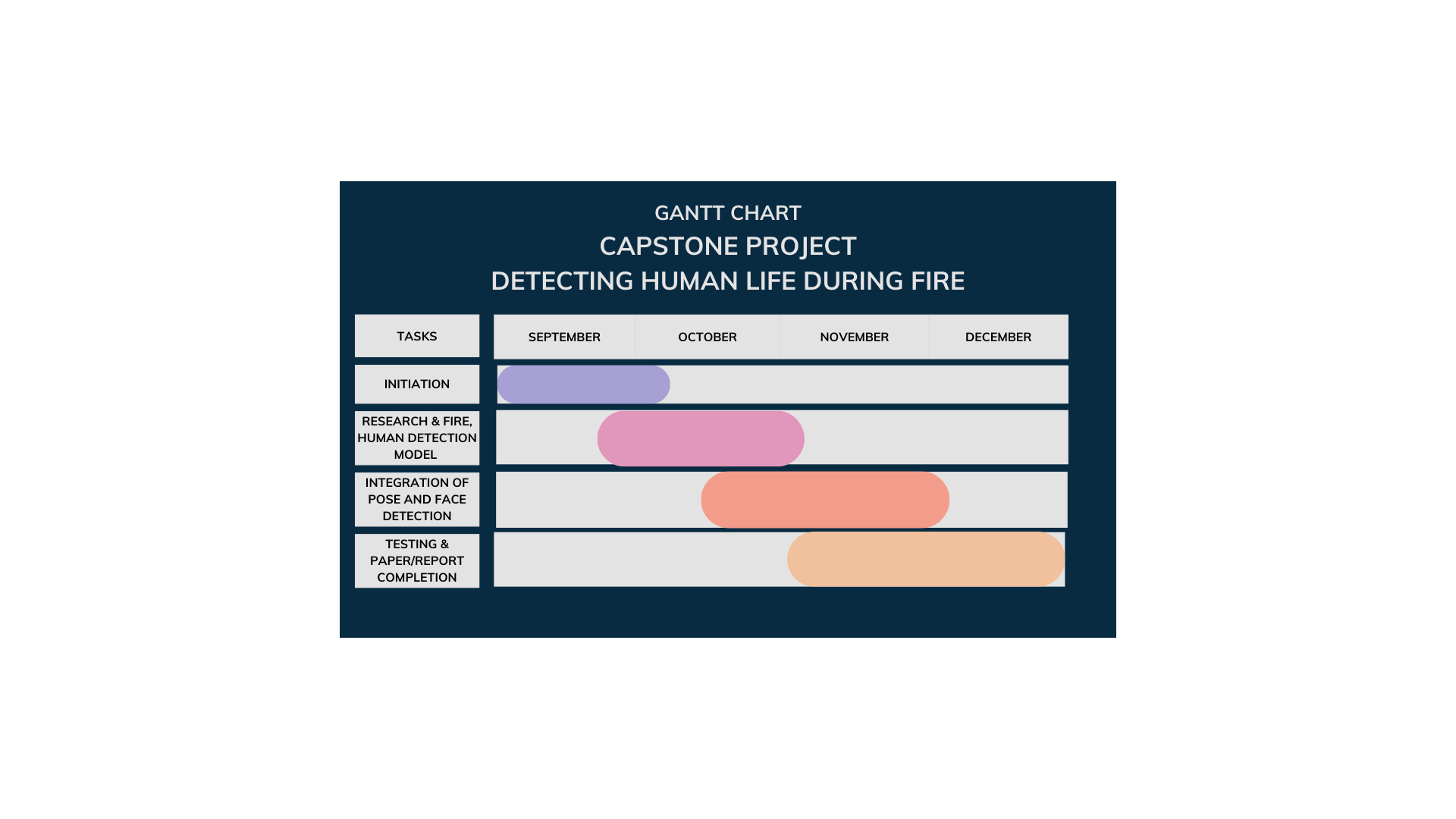
While the current system demonstrates significant potential, future iterations can include:

* **Thermal and Multispectral Imaging Integration:** Expanding sensor capabilities to improve detection accuracy in extreme environments.
* **Cloud-Based Analytics:** Leveraging cloud computing for centralized data processing, enabling multi-drone coordination and large-scale operations.
* **Edge AI Deployment:** Further optimizing models for deployment on ultra-low-power edge devices to enhance portability.
* **Autonomous Navigation:** Incorporating AI-driven navigation algorithms for drones to independently explore and map disaster zones.
* **Integration with IoT Systems:** Connecting with smart city infrastructures for seamless data exchange and coordinated emergency responses.

**CHAPTER-7**

**TIMELINE FOR EXECUTION OF PROJECT**

**(GANTT CHART)**

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**CHAPTER-8**

**OUTCOMES**

**CHAPTER-9**

**RESULTS AND DISCUSSIONS**

**CHAPTER-10**

**CONCLUSION**

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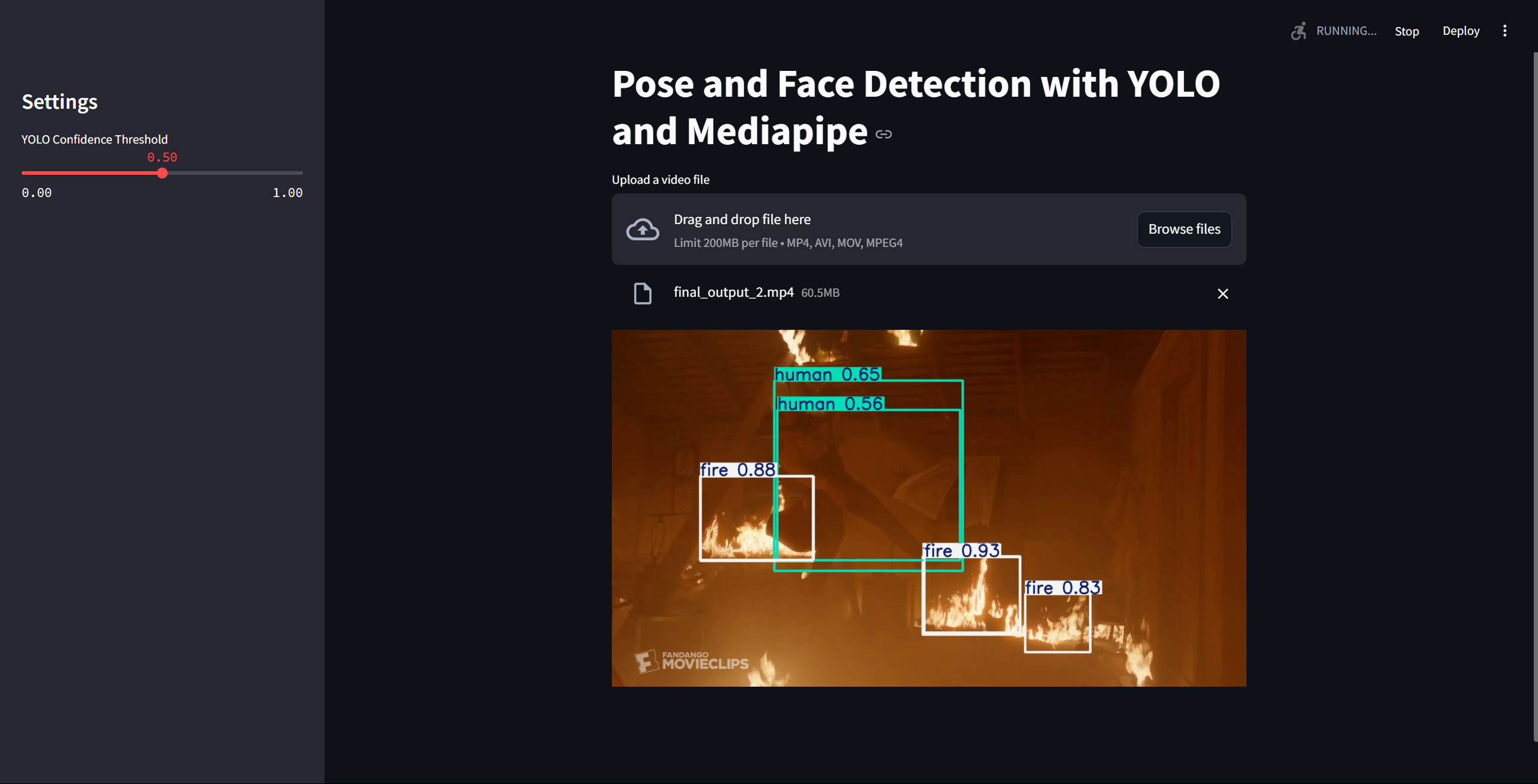
**APPENDIX-A**

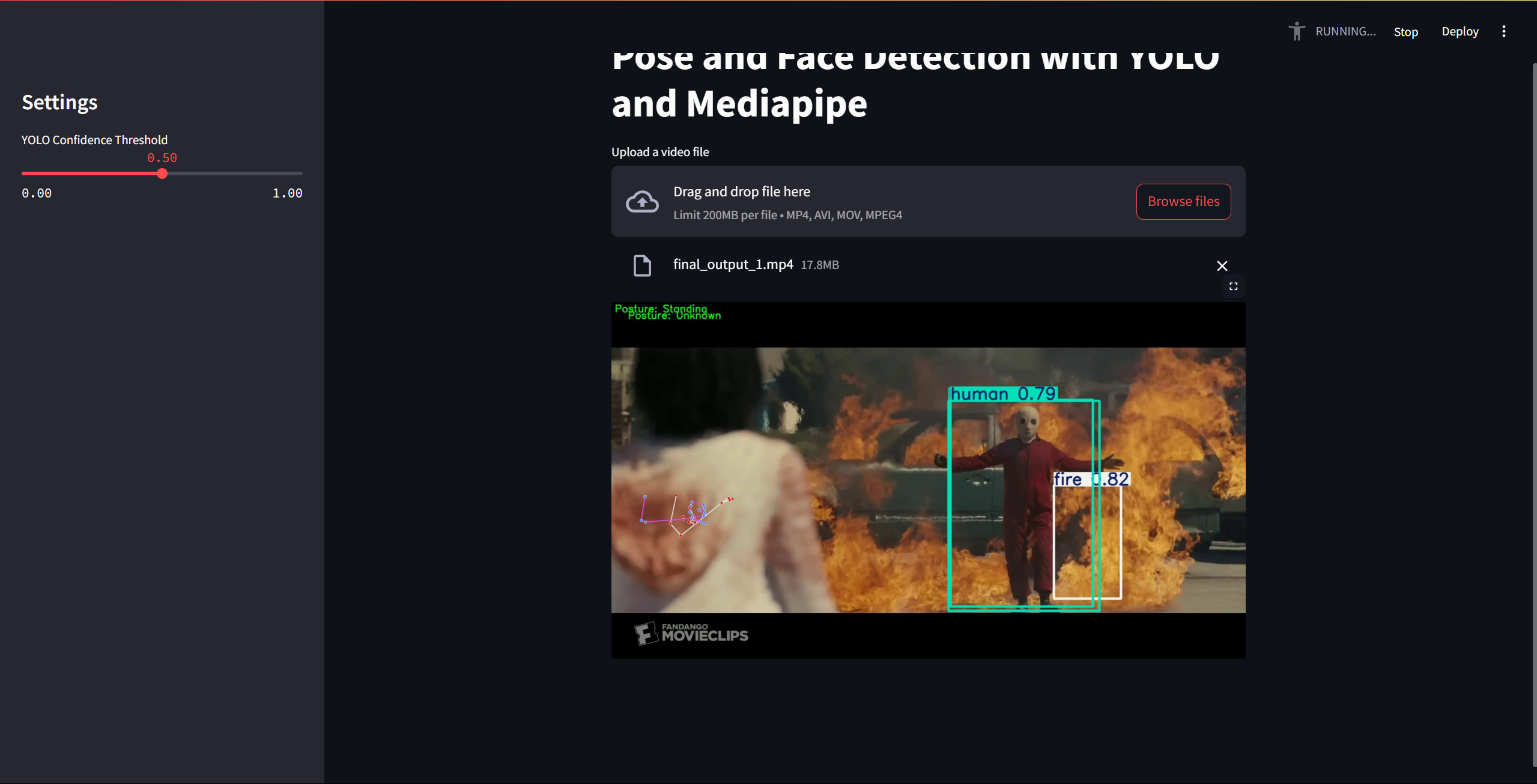
**PSUEDOCODE**

import streamlit as st  
import cv2  
import mediapipe as mp  
import numpy as np  
from ultralytics import YOLO  
import torch  
import gdown  
import os  
import tempfile  
import time  
import warnings  
  
# Suppress warnings  
warnings.filterwarnings("ignore")  
os.environ["TF\_CPP\_MIN\_LOG\_LEVEL"] = "3"  
  
# Ensure GPU is available  
DEVICE = "cuda" **if** torch.cuda.is\_available() **else** "cpu"  
  
# Download YOLO weights if not already present  
MODEL\_URL = "https://drive.google.com/uc?id=14KjAuw8JOox-YUHnQlocBwN\_0m\_3yi3p"  
MODEL\_PATH = "best.pt"  
  
**if** not os.path.exists(MODEL\_PATH):  
    **with** st.spinner("Downloading YOLO model weights..."):  
        gdown.download(MODEL\_URL, MODEL\_PATH, quiet=False)  
  
# Load YOLO model globally  
yolo\_model = YOLO(MODEL\_PATH).to(DEVICE)  
  
def process\_frame(frame, conf):  
    """Process a single frame for YOLO detection and gather metrics."""  
    results = yolo\_model.predict(frame, imgsz=640, conf=conf, verbose=False, device=DEVICE)  
    result = results[0]  
    annotated\_frame = result.plot()  
  
    # Extract metrics  
    metrics = {  
        "boxes\_count": len(result.boxes),  
        "class\_labels": result.boxes.cls.tolist() **if** len(result.boxes) > 0 **else** [],  
        "confidences": result.boxes.conf.tolist() **if** len(result.boxes) > 0 **else** []  
    }  
    return annotated\_frame, metrics  
  
# Initialize Mediapipe Pose and Face Detection  
mp\_pose = mp.solutions.pose  
mp\_drawing = mp.solutions.drawing\_utils  
mp\_face\_detection = mp.solutions.face\_detection  
  
def calculate\_angle(a, b, c):  
    """Calculate the angle between three points (a, b, c)."""  
    a = np.array(a)  
    b = np.array(b)  
    c = np.array(c)  
  
    radians = np.arctan2(c[1] - b[1], c[0] - b[0]) - np.arctan2(a[1] - b[1], a[0] - b[0])  
    angle = np.abs(radians \* 180.0 / np.pi)  
  
    **if** angle > 180.0:  
        angle = 360.0 - angle  
  
    return angle  
  
# Streamlit Interface  
st.title("*Detecting Human Life during Fire* ")  
st.sidebar.title("Settings")  
confidence = st.sidebar.slider("YOLO Confidence Threshold", 0.0, 1.0, 0.6, 0.01)  
video\_file = st.file\_uploader("Upload a video file", type=["mp4", "avi", "mov"])  
  
**if** video\_file:  
    **with** tempfile.NamedTemporaryFile(delete=False) as temp\_file:  
        temp\_file.write(video\_file.read())  
        temp\_video\_path = temp\_file.name  
  
    cap = cv2.VideoCapture(temp\_video\_path)  
    stframe = st.empty()  
  
    # Prepare output video  
    fourcc = cv2.VideoWriter\_fourcc(\*"mp4v")  
    output\_path = "annotated\_output.mp4"  
    out = None  
  
    inference\_times = []  
    **with** mp\_pose.Pose(min\_detection\_confidence=0.5, min\_tracking\_confidence=0.5) as pose, \  
         mp\_face\_detection.FaceDetection(min\_detection\_confidence=0.5) as face\_detection:  
  
        while cap.isOpened():  
            ret, frame = cap.read()  
  
            **if** not ret:  
                break  
  
            # Start inference timer  
            start\_time = time.time()  
  
            # Recolor image to RGB  
            image = cv2.cvtColor(frame, cv2.COLOR\_BGR2RGB)  
            image.flags.writeable = False  
  
            # Process pose detection  
            pose\_results = pose.process(image)  
  
            # Process face detection  
            face\_results = face\_detection.process(image)  
  
            # Recolor back to BGR  
            image.flags.writeable = True  
            image = cv2.cvtColor(image, cv2.COLOR\_RGB2BGR)  
  
            # Process YOLO detection  
            annotated\_frame, metrics = process\_frame(image, confidence)  
  
            # Analyze posture if pose landmarks are detected  
            **if** pose\_results.pose\_landmarks:  
                # Extract key landmarks  
                landmarks = pose\_results.pose\_landmarks.landmark  
                shoulder = [landmarks[mp\_pose.PoseLandmark.LEFT\_SHOULDER.value].x,  
                            landmarks[mp\_pose.PoseLandmark.LEFT\_SHOULDER.value].y]  
                hip = [landmarks[mp\_pose.PoseLandmark.LEFT\_HIP.value].x,  
                       landmarks[mp\_pose.PoseLandmark.LEFT\_HIP.value].y]  
                knee = [landmarks[mp\_pose.PoseLandmark.LEFT\_KNEE.value].x,  
                        landmarks[mp\_pose.PoseLandmark.LEFT\_KNEE.value].y]  
                ankle = [landmarks[mp\_pose.PoseLandmark.LEFT\_ANKLE.value].x,  
                         landmarks[mp\_pose.PoseLandmark.LEFT\_ANKLE.value].y]  
  
                # Calculate angles  
                upper\_body\_angle = calculate\_angle(shoulder, hip, knee)  
                lower\_body\_angle = calculate\_angle(hip, knee, ankle)  
  
                # Determine posture based on angles  
                **if** upper\_body\_angle > 160 and lower\_body\_angle > 160:  
                    posture = "Standing"  
                elif upper\_body\_angle < 160 and lower\_body\_angle < 90:  
                    posture = "Sitting"  
                elif upper\_body\_angle < 70 and lower\_body\_angle < 70:  
                    posture = "Lying Down"  
                **else**:  
                    posture = "Unknown"  
  
                # Display posture on the frame  
                cv2.putText(annotated\_frame, f"Posture: {posture}", (50, 50), cv2.FONT\_HERSHEY\_SIMPLEX,  
                            1, (0, 255, 0), 2, cv2.LINE\_AA)  
  
                # Draw landmarks  
                mp\_drawing.draw\_landmarks(  
                    annotated\_frame,  
                    pose\_results.pose\_landmarks,  
                    mp\_pose.POSE\_CONNECTIONS,  
                    mp\_drawing.DrawingSpec(color=(245, 117, 66), thickness=2, circle\_radius=2),  
                    mp\_drawing.DrawingSpec(color=(245, 66, 230), thickness=2, circle\_radius=2),  
                )  
  
            # End inference timer  
            end\_time = time.time()  
            inference\_times.append(end\_time - start\_time)  
  
            # Write to output video  
            **if** out is None:  
                height, width, \_ = annotated\_frame.shape  
                out = cv2.VideoWriter(output\_path, fourcc, cap.get(cv2.CAP\_PROP\_FPS), (width, height))  
            out.write(annotated\_frame)  
  
            # Display frame in Streamlit  
            annotated\_frame = cv2.cvtColor(annotated\_frame, cv2.COLOR\_BGR2RGB)  
            stframe.image(annotated\_frame, channels="RGB", use\_container\_width=True)  
  
    cap.release()  
    out.release()  
  
    # Display average inference time  
    avg\_inference\_time = np.mean(inference\_times)  
    st.success(f"Processing complete! Average inference time per frame: {avg\_inference\_time:.2f} seconds")  
  
    # Provide download link  
    **with** open(output\_path, "rb") as f:  
        st.download\_button("Download Annotated Video", f, file\_name="annotated\_output.mp4")

**APPENDIX-B**

**SCREENSHOTS**

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**APPENDIX-C**

**ENCLOSURES**

**1. Journal publication/Conference Paper Presented Certificates of all students.**

**2. Include certificate(s) of any Achievement/Award won in any project-related event.**

**3. Similarity Index / Plagiarism Check report clearly showing the Percentage (%). No need for a page-wise explanation.**

**4.** **Details of mapping the project with the Sustainable Development Goals (SDGs).**