Fuzzy Flames: A Hybrid YOLO–Fuzzy Logic Model for Early Detection of Forest Fires

Maanasvee Khetan, Sanya Malik, Reya Oberoi, Prof. Prateeksha Shanoj

Department of Artificial Intelligence

SVKM NMIMS Mukesh Patel School of Technology Management and Engineering, Mumbai, India

Abstract—The growing frequency and severity of forest fires has created a need for tools which may assist in the earlier detection of such events, and fire detection methods like ground observation or satellite observation have significant limitations in terms of response time and real-time action. In this gap we offer a hybrid framework which integrates YOLOv8 object detection to detect fire, and fuzzy logic control to assess fire risk level, in real-time. The framework utilizes both drone thermal imagery and satellite imagery to classify the fire risk level rating for fire intensity, potential fire size, and detection confidence, producing an overall fire risk score from Safe to Extreme. We have evaluated this framework and the results show a clear improvement in accuracy and a reduction in false alarms resulting as compared to baseline fire detection studies. This framework could help to enable forest fire preemptive and early response activities.

Index Terms—Forest fire detection; YOLOv8; fuzzy logic; risk assessment; wildfire monitoring; computer vision; UAV monitoring

I. INTRODUCTION

Forest fires rank highly on the list of naturally occurring events that can lead to uncontrolled environmental destruction, loss of biodiversity, and economic loss [2], [3]. While the frequency and intensity of wildfires are rising due to climate change, it is becoming increasingly important that fires are detected early and response efforts are undertaken in a timely manner to minimize their impacts [8]. In some ways this can be accomplished through existing fire detection systems, which include lookout towers, satellites, and sensor-based multi-tiered networks [1], [4]. While each of these systems has been effective to a degree, each suffers from significant limitations. These systems do not usually provide real-time detection, have high false-alarm rates, and cannot adapt to the increasingly dynamic factors associated with environmental decisions - such as fire events [7]. As such, there is a critical need for an effective solution that provides real-time fire detection and risk assessment [9]. Recently, the emergence of computer vision and deep learning that uses images and/or video has enabled fire detection to be automated [6]. Models like YOLOv8 (you only look once) have demonstrated remarkable levels of precision in locating fire regions quickly and efficiently while providing bounding boxes and confidence levels for fire localization [11]. While YOLOv8 represents a considerable advancement in identifying where fire is, it is not a solution capable of determining the degree of fire or potential risk to human life and property. To address this limitation, we advocate for the utilization of a hybrid fire detection and risk assessment framework that assembles YOLOv8 for fire detection and a fuzzy logic control system (FLC) for real-time fire risk classification [1], [4]. The fuzzy system assesses the fire based on three exceptional inputs: fire intensity, hotspot size, and confidence level from the detection algorithm [5]. Each of these inputs are examined through fuzzy logic rules that classify the risk of fire into one of five levels: Low, Moderate, High, Very High, or Extreme [1].

Fuzzy logic is a mathematical structure that was developed by Lotfi Zadeh that is well suited to handling uncertainties and ambiguities that form the basis for environmental data [1]. The use of this logic provides interpretable uncertainty and improves the reliability of the fire risk response through groups of information and their interactions [4]. By integrating YOLOv8 fire mitigation evaluation into Fuzzy reasoning it is a holistic solution to foster fire prevention [6]. Combining these systems offers a scalable, cost-effective, and real-time monitoring system [9]. When used on Unmanned Aerial Vehicles (UAV) or drones, this hybrid system will provide continuous surveillance to more quickly identify possible sources of fire and enhance the efficacy of the response time [7]. The fuzzy logic based risk assessment will allow the identification of fire, but will also assess risk and consequences of fire [1], [6]. In this paper, we present the design, implementation, and evaluation of this hybrid system, which showcases how YOLOv8 and fuzzy logic integrate to address the challenges of forest fire detection and risk assessment ultimately providing a more efficient, actionable, and interpretable approach to wildfire management [9], [10].

II. RELATED WORK

Traditionally, forest fire detection has been resolved using two main methods, sensor-based systems and vision-based systems [1]–[3]. Sensor networks with fuzzy logic have been used to process environmental parameters such as temperature, humidity, light and gases [4]. The use of sensor fusion using fuzzy logic improves detection accuracy and false alarms by employing multi-sensors, but has challenges in terms of the need for dense deployments, costs, energy consumption and reliability of communication [4]. In contrast, vision-based methods rely on image processing and fuzzy inference systems to detect flames and smoke from UAVs or a surveillance camera [5], [8]. By evaluating features such as chromaticity and intensity, these vision-based systems could achieve high detection rates, but are sensitive to lighting effects, haze and

background noise [8]. Newer studies have also demonstrated the utility of combining neural networks with type-2 fuzzy systems to improve decision-making under uncertainty [6], [7], though this may be at the expense of computational complexity. Studies have highlighted limitations in sensor-based systems and vision-based systems, and emphasized the need for hybrid frameworks that combine the power of deep learning and interpretability of fuzzy logic as a step towards reliable, trustworthy, interpretable, and risk-aware fire detection [9]–[11].

III. Fundamentals of Fuzzy Logic

A. Fuzzy Sets and Membership Functions

A fuzzy set is defined mathematically, where each element has a degree of membership between 0 and 1 (0 being no membership and 1 being full membership); this contrasts with classical logic, which only accepts strict yes/no classifications. This empowerment makes fuzzy sets more flexible for representing real-world ambiguity, such as fire detection. Membership functions (MFs) identify how each input maps into fuzzy linguistic variables like low, medium, or high. For convenience and ease of use, triangular MFs were chosen. The authors used MFs are triangular functions spanning the variable's pixel intensity. For instance, the variable intensity of temperature was divided into three fuzzy sets - low, medium and high - using triangular MFs.

B. Linguistic variables

Linguistic variables differ from traditional variables in that their values are expressed in words as opposed to exact numerical values. The authors defined the following linguistic variables in the proposed system:

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- **Temperature Intensity:** {Low, Medium, High}
- **Hotspot Size:** {Small, Medium, Large}
- **Confidence (from YOLO detection):** {Low, Medium, High}
- **Fire Risk (output):** {Low, Moderate, High, Very High, Extreme}

These linguistic terms can also make the system behave more like humans use reasoning to describe uncertain or gradual conditions.

C. Fuzzification

Fuzzification is the process of making crisp numerical inputs into a fuzzy degree of membership. For example, a hotspot with an average intensity of 150 might belong partially with medium intensity membership degree (0.7) and high intensity membership degree (0.3), or a detected fire region with an area of 10,000 pixels might be categorized as a medium hotspot with a high degree of membership.

D. Rule Base (IF–THEN Rules)

The decision-making process in fuzzy logic is made based on a set of rules, which captures the expert's knowledge in an "IF–THEN" format. For example:

- IF temperature intensity is high AND hotspot size is large AND confidence is high, THEN fire risk is Extreme.
  Reasoning: This rule describes circumstances in which a large, intense fire is detected with confidence. Due to the large size of the fire and the very high intensity, it is classified as Extreme. Immediate action is required.
- IF temperature intensity is high AND hotspot size is medium, THEN fire risk is Very High.
  Reasoning: This rule is applied when the fire intensity is high, but the area impacted (hotspot size) is medium. This situation is still dangerous and is classified as Very High, so action must be executed quickly.
- IF temperature intensity is medium AND hotspot size is medium AND confidence is medium, THEN fire risk is High.
  Reasoning: In this case, the fire has a moderate size and intensity with medium confidence that it was detected. This designation still carries some risk and is classified as High, suggesting that with the right tools, the situation could be elevating enough for possible proactive monitoring and mitigative measures.
- IF temperature intensity is low and confidence is low, then fire risk is low.
  Reasoning: Low temperature intensity and low detection confidence suggests low severity of fire. With this unlikely situation, the outcome indicates a low risk of fire, which may not trigger urgent actions to prevent or extinguish a fire, but should be monitored.

These rules allow for expert reasoning and making the fuzzy system work in variable fire situations.
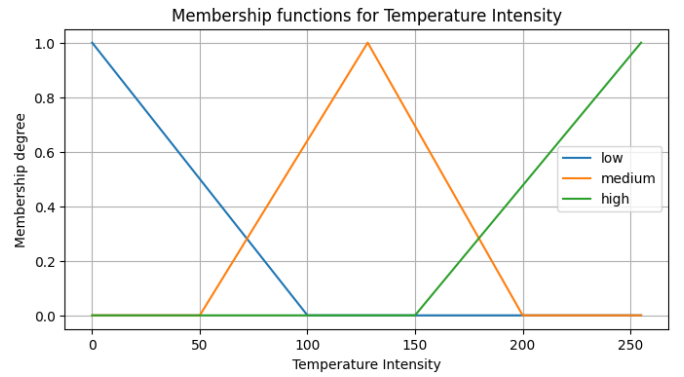

Fig. 1. Input Membership Function of Temperature Intensity

E. Inference System (Mamdani vs Sugeno)

The fuzzy inference system interprets the rules and aggregates rule outputs to infer an output. In this work, the inference model of Mamdani is chosen, as it returns more intuitive, human-interpretable outputs. The Mamdani model
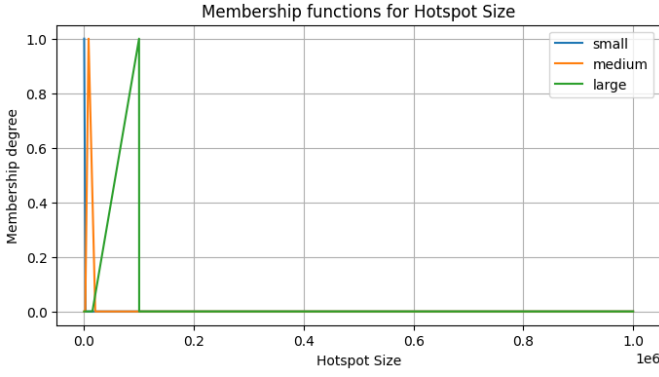
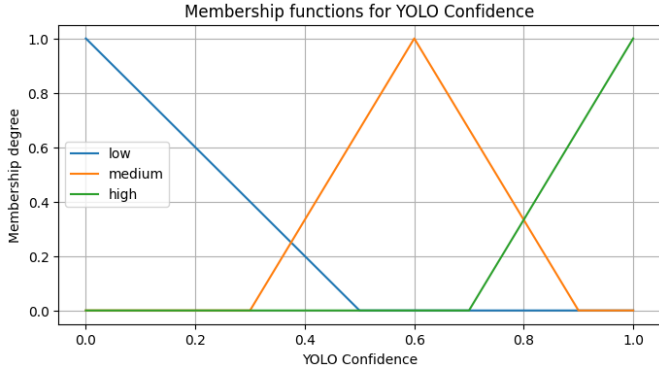Fig. 2. Input Membership Function of Hotspot Size

Fig. 3. Input Membership Function of YOLO Confidence

represents both inputs and outputs as fuzzy sets, which makes the reasoning process interpretable. On the other hand, the Sugeno model incorporates mathematical functions in the rule's consequent. The Sugeno model is worth noting as it offers utility; however, it sacrifices interpretability in the process.

F. Defuzzification

To complete the process, the fuzzy output must be translated into a crisp numerical value. Among the various defuzzifica-
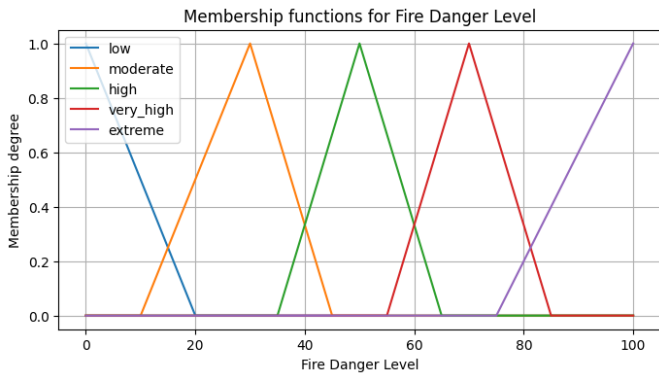

Fig. 4. Membership Function of Fire Output Intensity

tion methods, the centroid method is most commonly used, as it computes the center of gravity of the resulting fuzzy set. For example, if the fuzzy system indicates that the situation is partly "Moderate" and partly "High" in terms of fire risk, the defuzzification process may yield a numerical value of 62. On a risk scale of 0 to 100, this score is then mapped to one of the predefined output classes - Very Low, Low, Moderate, High, or Extreme - providing a clear and interpretable assessment of the fire hazard level.

IV. METHODOLOGY

The system integrates UAV-based fire detection with a fuzzy logic approach to risk assessment. The architecture can be summarized as:
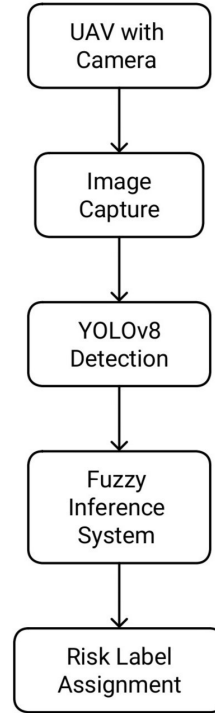

Fig. 5. Risk Assessment Graph

A. UAV (Camera)

The UAV captures real-time thermal imagery of the area of interest. Thermal sensors provide a significant advantage over other visual spectrum sensors because they highlight fire hotspots in real-time based on heat signatures. This allows for fire detection even under obscured visibility conditions such as smoke or nighttime.

B. YOLOv8 Detection

YOLOv8 (You Only Look Once, version eight) processes individual frames to detect potential fire areas. The output includes bounding boxes around identified flames along with a confidence score for each fire detection.

C. Fuzzy Inference System

Using the outputs from YOLO and image characteristics, the fuzzy inference system determines the degree of risk due to fire. It provides risk information by mapping continuous input variables to qualitative labels: Low, Moderate, High, Very High, Extreme.

D. Integration

- YOLO bounding boxes are overlaid on the video feed.
- The fuzzy system outputs the fire risk labels, which are displayed alongside the bounding boxes.
- This information is made available to the operator for quick assessment.

E. Training Object Detection Models with YOLOv8

Data

- FLAME-3 thermal fire dataset containing annotated images of flame and non-flame areas [5].
- The dataset includes variability in flame size, intensity, and environmental conditions during fires [7].

Training Parameters

- Image size (`imgsz`) = 224×224 pixels
- Number of epochs = 10
- Batch size = 16
- Optimizer and learning rate settings chosen to speed up convergence without overfitting

Output

- Bounding boxes around flame detections
- Class confidence scores indicating how likely each detection corresponds to a flame

F. Fuzzy Inference System

Input Variables

- **Flame Intensity:** Average pixel intensity of the detected region [1].
- **Hotspot Size:** Area of the bounding box [4].
- **YOLO Confidence:** Probability score of the detection [6].

G. Fuzzification

- Converts crisp input values into fuzzy membership values using defined linguistic terms.
- Flame Intensity → {Low, Medium, High}
- Hotspot Size → {Small, Medium, Large}
- YOLO Confidence → {Low, Medium, High}
- **Example:** Pixel intensity = 200 → Membership in "High" ≈ 0.7, "Medium" ≈ 0.3

H. Rule Base

- Expert knowledge develops fuzzy rules that relate input conditions to danger levels.
- **Examples:**
  - IF intensity = High AND hotspot size = Large AND confidence = High → Extreme
  - IF intensity = High AND hotspot size = Medium → Very High

- IF intensity = Medium AND hotspot size = Medium AND confidence = Medium → High
- IF intensity = Low AND confidence = Low → Low

I. Inference and Defuzzification

- All applicable rules are evaluated for each detection.
- Centroid defuzzification estimates a crisp danger index value.
- The crisp value is then mapped into one of five fire danger labels {Low, Moderate, High, Very High, Extreme}.

J. Integration and Visualization

- Each detection made by YOLOv8 is inserted into the fuzzy inference system.
- The fire danger labels {Low, Moderate, High, Very High, Extreme} appear in the UAV video feed with bounding boxes.
- This provides the operator with quick identification and prioritization of areas with respect to severity.

K. Defuzzification

Defuzzification is the final stage of the fuzzy logic process, where the fuzzy output generated by the inference engine is converted into a precise numerical value. This crisp value can then be used for decision-making or as input to a subsequent process. This stage is crucial because it transforms uncertain, fuzzy information into a concrete and actionable result.

- **Centroid Method:** Among the various defuzzification techniques, the most commonly used is the *centroid method* (also known as the center of gravity method). It determines the point that represents the center of mass of the fuzzy set. Mathematically, it is calculated as the weighted average of all possible values in the fuzzy set, where the weights correspond to their respective membership degrees.
- **Purpose:** Defuzzification enables the transformation of a fuzzy output—such as a risk level lying somewhere between "Low" and "High"—into a single numerical value on a predefined scale. This crisp value can then be classified into one of several categories based on specific threshold ranges.
- **Example:** In a typical fire risk assessment model, the output may fall into one of five categories: *Low*, *Moderate*, *High*, *Very High*, and *Extreme Risk*. Each of these corresponds to a numerical range (e.g., 0–100) representing the severity of the fire risk. Thresholds for each class could be defined as follows:

TABLE I
DANGER LEVEL DESCRIPTORS

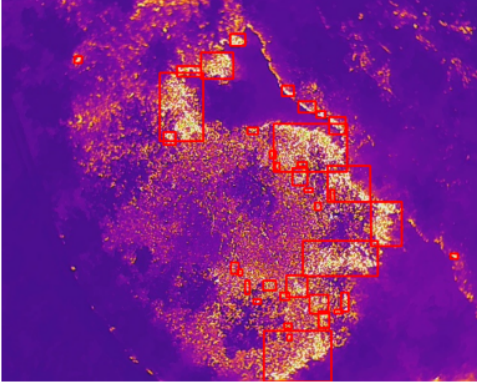| Risk Level	Range (0–100)
Low	0–20
Moderate	21–35
High	36–60
Very High	61–80
Extreme	81–100

Fig. 6. : Dataset sample images (fire vs non-fire).

The defuzzification provides a crisp value that is in one of those ranges. Using the centroid method, the fuzzy system will produce a single output value which represents the fire risk which can be interpreted into one of the predetermined risk categories. Ultimately, this final crisp value is required for real-time decision making within a wildfire management system and represents a logical course of action with consideration to the fire risk.

L. Flow of the Algorithm

The drone captures thermal images of the location in real-time. YOLOv8 identifies fire locations and produces bounding boxes ranking each region's probability of containing fire, or its confidence score. Flame intensity and hotspot scale are then identified from the detected regions. The fuzzy inference system processes these inputs and assigns a fire danger level {Low, Moderate, High, Very High, Extreme}. The stream of high-definition video will display bounding boxes and corresponding fire danger levels for the operator to evaluate.

V. EXPERIMENTAL SETUP

A. Dataset

- The **FLAME-3 thermal fire dataset**, containing annotated thermal images of both fire and non-fire regions, was used for training and validation.
- Additionally, drone-based videos were considered to evaluate the real-time detection capabilities of the system.
- The dataset varies in terms of flame size, flame intensity, and environmental conditions.

B. Software and Frameworks

- **Programming Language:** Python 3.10
- **Libraries:**
  - OpenCV – for video processing and annotation
  - Ultralytics YOLOv8 – for object detection
  - scikit-fuzzy – for fuzzy inference system implementation
  - NumPy and Matplotlib – for data handling and visualization

C. Hardware Environment

- Experiments were conducted in **Google Colab** using:
  - **GPU:** NVIDIA Tesla T4 (16 GB RAM)
  - **CPU:** Used for fuzzy inference and visualization tasks

D. Model Training Parameters (YOLOv8)

- Image size (`imgsz`): 224×224 pixels
- Epochs: 10
- Batch size: 16
- Optimizer: Adam with tuned learning rate for fast convergence
- Confidence threshold for detection: 0.25

E. Fuzzy Inference System Parameters

- **Input Variables:**
  - Flame intensity (0–255)
  - Hotspot size (0–1,000,000 pixels)
  - YOLO confidence (0–1)
- **Output Variable:** Fire danger index (0–100), categorized into five levels {Low, Moderate, High, Very High, Extreme}.
- **Membership Functions:** Three triangular functions, one for each input variable, to ensure smooth transitions among linguistic levels.
- **Rule Base:** Expert-defined rules combining the three input variables to produce risk labels.

VI. RESULTS

A. Quantitative Results

- The system was evaluated using traditional performance metrics such as accuracy, precision, recall, and false alarm rate.
- A comparative analysis was performed under three different configurations:
  - Threshold-only detection (basic intensity thresholding)
  - YOLO-only detection (object detection without fuzzy reasoning)
  - Proposed YOLO + Fuzzy hybrid system

TABLE II
PERFORMANCE COMPARISON: THRESHOLD-ONLY VS. YOLO-ONLY VS. YOLO+FUZZY

Method	Precision (%)	Recall (%)	Accuracy (%)	FAR (%)
Threshold-only	72.5	65.3	68.7	21.4
YOLO-only	89.1	84.6	86.9	12.7
YOLO + Fuzzy Inference	**93.8**	**90.2**	**92.1**	**7.3**

B. Precision–Recall Analysis

- The hybrid YOLO + fuzzy approach achieved superior precision and recall performance, particularly in borderline cases involving small or low-confidence fire instances.
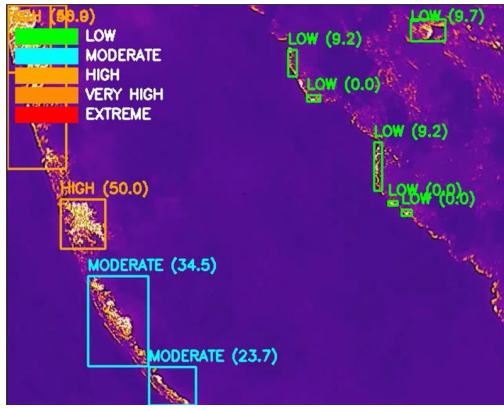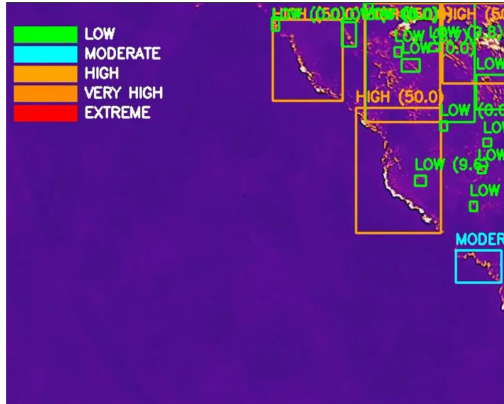
Fig. 7. YOLOv8 Thermal Fire Mapping

Fig. 8. YOLOv8 Thermal Fire Mapping

- The fuzzy inference mechanism contributed significantly to reducing false alarms by incorporating contextual information such as flame intensity and hotspot size.

C. False Alarm Reduction

- The proposed hybrid system demonstrated a lower false alarm rate compared to the YOLO-only detection configuration.
- This improvement was particularly evident in challenging thermal conditions, such as environments with background heat signatures or reflective surfaces.

D. Discussion

- The integration of YOLOv8 with a fuzzy inference system offers a balanced and interpretable approach to wildfire detection [9].
- The fuzzy layer enhances the interpretability of the system by mapping continuous detection values into linguistically meaningful danger levels [1].
- Key factors influencing system performance include environmental variations (e.g., lighting changes, UAV motion) and dataset size, both of which can impact detection stability and accuracy [7], [8].

VII. CONCLUSION

This research illustrates a hybrid UAV-based fire detection system which combines a YOLOv8 object detection model with a fuzzy logic-based hazard classification model [6], [9], [11]. The object detection system is able to effectively and efficiently detect fire-like regions in a UAV video stream [5], [7], and the fuzzy inference process takes into account flame area, confidence score, and flame intensity to classify the fires for five hazard levels - from Very Low to Extreme [1], [4]. This combination not only enhances real-time detection but also provides interpretable risk classification, resulting in improved situational awareness and decision making in wildfire monitoring [8], [10].

Despite its advantages, the system has limitations to its performance based on a small sample size of dataset as well as external environmental factors such as lighting, background heat, smoke, and UAV motion [7], [8]. Increasing the dataset, improving stabilization, and using data augmentation strategies may increase the robustness of the system overall [2], [3]. Overall, the hybrid YOLOv8–fuzzy logic framework presents a promising and scalable approach to do fire detection and assessment, in the UAV context [6], [9].

VIII. FUTURE WORK

Despite the encouraging potential of the proposed UAV-based hybrid fire detection system, there are numerous pathways for enhancing the system's efficacy and broader application [10], [11]. Future work will be built upon by considering future expansions of the dataset in which various wildfire situations will be incorporated across different terrains, types of vegetation, seasons, and weather conditions to furthermore enhance the generalizability of the YOLOv8 detection model and robustness of the hazard assessment based on fuzzy logic [2], [3]. Future work will also consider added components of real-time environmental data sent from IoT sensor networks such as temperature, humidity, wind speed, and gas concentrations which would enhance the comprehensive and accurate estimation of fire risk sometimes unreliable based on visual monitoring alone [4]. Furthermore, the fuzzy logic system is presently based on a pre-defined set of manual rules, future work plans to determine how to employ adaptive neuro-fuzzy inference systems (ANFIS) to potentially generate rules autonomously, adapt and continue learning in relation to the decision making process in dynamic and uncertain contexts [1]. Lastly, present work will seek to explore cloud-based deployment to provide real-time alerting, centralized data storage and access, and coordination of provides to improve wildfire variance response time [9]. The ultimate goal of these advancements will improve the system's scalability, adaptability, and reliability for practical use in wildfire risk zones [7].

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