Collaborative Edge-Based UAV Forest Fire Detection

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***Abstract*—Forest fires pose a significant threat to biodiversity, climate stability, and human settlements. Traditional fire detection systems, such as satellite imagery and ground-based sensors, suffer from delayed response times, limited spatial coverage, and vulnerability to adverse conditions. This paper proposes a collaborative edge-based swarm intelligence framework for forest fire detection using Unmanned Aerial Vehicles (UAVs). Our system, Dynamic Swarm Intelligence with Liquid Neural Networks (DSI-LNN), is built upon the Multi-Swarm Cooperative Information-Driven Search and Divide-and-Conquer Mitigation Control (MSCIDC) framework, integrating cooperative search strategies, consensus-based validation, and adaptive fire mitigation. The UAV swarm employs a multi-level search inspired by marine predator foraging behavior, combining Lévy flights and Brownian motion to balance exploration and exploitation. Liquid Neural Networks (LNNs) dynamically adjust detection thresholds in real time based on environmental cues, while a Flying Ad Hoc Network (FANET) ensures resilient inter-UAV communication. Monte Carlo simulations in a pine forest scenario demonstrate a 60% reduction in mission time and a 65% decrease in burned area compared to conventional methods. The MSCIDC framework's divide-and-conquer mitigation control allocates non-overlapping fire sectors to UAVs, significantly enhancing quenching efficiency. Future work will focus on real-time fire spread prediction and fully autonomous suppression systems.**

***Index Terms*—UAV Swarm, Swarm Intelligence, Edge-based, Forest Fire Detection, Liquid Neural Networks, FANET, Divide-and-Conquer Mitigation**

I. Introduction

The increasing frequency and severity of forest fires pose significant threats to ecosystems, human life, and property. Wildfires annually devastate millions of hectares globally, with India alone reporting 124,473 fire alerts in 2020. Conventional detection methods like MODIS satellites suffer from latency (>3 hours), while single-UAV systems lack scalability. Recent advances in swarm robotics and edge computing enable decentralized solutions. Traditional methods of fire detection often suffer from delays and inefficiencies, highlighting the need for advanced technological solutions. Unmanned Aerial Vehicles (UAVs) have emerged as pivotal tools in this domain, offering rapid response capabilities and extensive area coverage.

Recent studies have explored various strategies to enhance UAV-based forest fire detection. For instance, John et al. proposed a dynamic multiswarm approach that improved UAV coordination; however, this method can struggle with scalability and adaptability in diverse environmental conditions. Similarly, Yan and Chen [1] combined Particle Swarm Optimization with the Artificial Bee Colony algorithm to optimize swarm operations, yet their model tends to rely on static decision-making which limits real-time adaptability. Chen et al. [2] introduced SOScheduler for proactive wildfire suppression, but its performance may degrade when confronted with rapidly changing fire dynamics. Mowla et al. [3] employed an adaptive hierarchical convolutional neural network with attention mechanisms, which, while enhancing detection accuracy, requires extensive training and may not generalize well across varying terrains. Furthermore, Alsammak et al. [4] investigated nature-inspired drone swarming for energy-efficient wildfire suppression, but challenges remain in ensuring robust communication and coordination in rugged, unpredictable environments.

Building upon these advancements and addressing their limitations, our research introduces a novel approach that leverages Liquid Neural Networks (LNNs) for forest fire detection. LNNs are characterized by their inherent adaptability and robustness, enabling them to effectively handle diverse climatic conditions and terrains. By integrating LNNs into the UAV-based detection framework, our system dynamically learns and adapts to evolving environmental patterns, thereby significantly enhancing detection accuracy and reducing false positives.

Moreover, our approach incorporates collaborative decision-making among UAVs, which facilitates real-time data sharing and coordinated responses to fire incidents. This collaboration is further enhanced by the integration of thermal sensors alongside conventional cameras, providing a dual verification mechanism. Thermal sensors enable the rapid detection of heat signatures, while visual cameras offer detailed confirmation and assessment of the fire's characteristics. This multi-modal sensing approach ensures a more reliable and comprehensive detection system, effectively overcoming the shortcomings of previous models.

Strengths of the Approaches:

- **Real-Time Processing with Edge Computing:** By processing data on-board UAVs or nearby devices, the system drastically reduces latency—a game-changer in forest fire detection where rapid response is critical.
- **Optimized Search Strategies:** Our hybrid search strategy combines Lévy flights for extensive exploration with Brownian motion for targeted, local searches, enhancing both coverage and efficiency.
- **Improved Accuracy with Adaptive Algorithms:** The use of Liquid Neural Networks allows the system to adapt to changing environmental conditions, reducing false alarms by up to 42% and enhancing reliability.
- **Dynamic Swarm Behavior:** The incorporation of repulsion and merging mechanisms enables UAV swarms to dynamically balance exploration and focused mitigation, ensuring that the system can adjust its priorities as needed.
- **Robust Communication:** Utilizing a FANET protocol [5], our system maintains a 98% packet delivery rate even under intermittent connectivity, ensuring seamless coordination among UAVs in challenging forest environments.

The main contributions of the work are:

- A novel edge-based, multi-phase search algorithm, based on the Multi-Swarm Cooperative Information-Driven Search and Divide-and-Conquer Mitigation Control (MSCIDC) framework, is implemented for efficient forest fire detection using UAV swarms.
- A collaborative UAV Liquid Neural Networks (LNN) algorithm [6] enables a swarm of UAVs to collectively confirm forest fires by detecting and verifying their presence using cameras, thermal imaging, and temperature sensors, ensuring accuracy and reducing false positives.
- The proposed algorithm is validated and tested for mean detection time, mean mission time, and mean false error rate (FER) to ensure reliability, efficiency, and performance.
- A FANET protocol achieving 98% packet delivery in discontinuous connectivity.

In summary, our proposed system combines the adaptability of Liquid Neural Networks, the collaborative capabilities of UAV swarms, and the reliability of dual-modal sensing to advance forest fire detection methodologies. This integrated approach not only addresses the drawbacks of existing models [7] but also provides a robust solution capable of operating effectively across various environmental conditions and terrains, thereby contributing to more efficient and timely wildfire management.

II. Related Work

Various strategies have been proposed to enable efficient fire detection and mitigation through probabilistic search models combined with formation control mechanisms.

One of the earliest approaches in this domain is the Uniform Dynamic Formation Control (Uniform-DFC) method. This strategy employs a uniform random walk for the search phase, assuming equal probability of fire occurrence across the entire environment. UAVs operate without any directional preference or contextual adaptation, followed by a Dynamic Formation Control (DFC) scheme for fire mitigation, wherein the fire region is divided equally among UAVs. While this method is simple and decentralized, it is inherently inefficient due to redundant coverage and delayed response in detecting dispersed or irregular fire occurrences.

To address the inefficiencies of uniform exploration, the Normal-DFC algorithm incorporates a Gaussian-distributed search pattern. This method introduces a probabilistic bias, directing UAVs toward central regions with gradually diminishing exploration toward the periphery. This improves upon the randomness of Uniform-DFC by enhancing the likelihood of encountering active fire zones. However, it remains limited in adaptability, as it does not dynamically adjust search patterns in response to environmental cues such as heat gradients or fire spread velocity.

The Levy-DFC method introduces a biologically inspired improvement by employing Levy flight-based search. This mechanism allows UAVs to alternate between short-range local searches and occasional long-range jumps, effectively covering sparse or unknown regions more rapidly. The enhanced exploration capability reduces search time and increases coverage efficiency. Levy-DFC still lacks environmental awareness during the search phase and does not incorporate localized exploitation behavior to fine-tune UAV movement near potential fire zones.

The Oxyrrhis Marina-inspired Search and Dynamic Formation Control (OMS-DFC) [8] framework introduces a multi-level stochastic search inspired by the foraging behavior of the marine predator Oxyrrhis Marina. In this method, UAVs initially perform Levy flight for exploration and adaptively switch to Brownian or Directionally Driven Brownian (DDB) motion based on the rate of temperature change detected by onboard sensors. This enables an effective balance between exploration and exploitation without inter-UAV communication. The mitigation phase employs a decentralized formation control law to track elliptical or circular fire profiles with non-overlapping angular displacements. Although OMS-DFC demonstrates improved adaptability and precision, it assumes idealized sensor conditions and lacks multi-swarm coordination or inter-agent role reallocation mechanisms during dynamic mission phases.

III. System Model

A. Fire Intensity

$$I = H \cdot W \cdot R \tag{1}$$

Description: This equation computes the fireline intensity I, where H is the heat content (kJ/kg), W is the fuel load (kg/m²), and R is the spread rate (m/s).
It represents how much energy is released per meter of fireline per second.

B. UAV Fitness Function

$$f_i = \frac{1}{\left(1 + d_i + \alpha \cdot \frac{T_i}{T_{max}}\right)} \tag{2}$$

Description: The fitness value f_i evaluates the suitability of UAV i for a firefighting task.
It considers the UAV's distance d_i from the fire and its remaining tank level T_i, normalized by $T_{\max}$.

C. Global Best Position Update (Dynamic Multi-Swarm PSO)

$$g^t = \begin{cases} g_1^t & \text{if } f(g_1^t) > f(g_2^t) \\ g_2^t & \text{otherwise} \end{cases} \tag{3}$$

Description: This decision rule chooses the better global best position among two candidate swarms g_1 and g_2.
It enables cooperation between dynamic multi-swarms to track and fight fires effectively.

D. Velocity Update in Particle Swarm Optimization

$$v_i^{t+1} = \omega \cdot v_i^t + c_1 \cdot r_1 \cdot (p_i^t - x_i^t) + c_2 \cdot r_2 \cdot (g^t - x_i^t) \tag{4}$$

Description: This standard PSO formula updates a UAV's velocity v_i, combining inertia, cognitive, and social components. It helps UAVs converge toward optimal positions for firefighting tasks.

E. Position Update

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{5}$$

Description: This updates UAV i's position using the newly computed velocity.
It governs the physical movement of each UAV in the optimization process.

F. Fire Spread Dynamics

The fire growth model follows an elliptical spread:

$$\frac{da_j}{dt} = R \cos\theta_w, \quad \frac{db_j}{dt} = R \sin\theta_w \tag{6}$$

where $R = \frac{\alpha L_f^\beta}{H_c F_m}$ is the spread rate, θ_w is the wind direction, and L_f is the flame length.

G. Swarm Kinematics

Each UAV follows first-order dynamics:

$$\dot{p}_i = v_i, \quad \dot{v}_i = -\lambda v_i + \lambda v_{r,i} \tag{7}$$

where $v_{r,i}$ is the reference velocity from swarm cohesion:

$$v_{r,i} = \frac{1}{|N_i|} \sum_{j \in N_i} (p_j - p_i) + \phi_0 \nabla T_i \tag{8}$$

N_i: neighbors, ∇T_i: temperature gradient.

H. Liquid Neural Network Design

The LNN processes sensor inputs through time-continuous neurons:

$$\tau \frac{dx_i}{dt} = -x_i + \sum w_{ij}\sigma(x_j) + b_i(t) \tag{9}$$

where σ: sigmoid, $b_i(t)$: environmental bias (humidity/wind).

IV. Proposed Methodology

A. Multi-Phase Search Algorithm

Algorithm 1 Hybrid Search Strategy

Initialize n_s swarms with random positions
while $t < t_{\max}$ **do**
  for each swarm s_i **do**
    if $\max(T_s) < \xi$ **then** ▷ Exploration phase
      Generate Lévy steps $L \sim |\Gamma(1.5)|^{-1}$
      Update waypoints: $p_{r,i} = p_i + L \cdot [\cos\psi, \sin\psi]$
    else ▷ Exploitation phase
      Compute Brownian steps $B \sim \mathcal{N}(0, \sigma_b^2)$
      Gradient ascent: $p_{r,i} = p_i + \eta \nabla T$
    end if
    Broadcast $(\nabla T, p_i)$ via FANET
  end for
end while

This hybrid algorithm alternates between exploration and exploitation modes based on the sensed temperature. In low-temperature zones, UAVs perform Lévy flight to explore new regions. When fire likelihood increases (based on temperature threshold ξ), they switch to Brownian motion guided by temperature gradients, enabling more focused searching. FANET communication ensures swarm-wide information sharing.

B. Consensus-Based Fire Validation

[H]

$$P_{\text{fire}} = \frac{1}{n}\sum_{i=1}^{n} w_i P_i, \quad w_i = \frac{\text{SNR}_i}{\sum \text{SNR}_j} \tag{10}$$

where P_i: detection probability from Eq. (8) in, SNR: signal-to-noise ratio.

The fire detection consensus is determined by aggregating individual UAV predictions P_i, weighted by their signal reliability (SNR). This ensures that UAVs with stronger confidence and better sensor quality have more influence in the final decision, improving robustness against noisy data.

C. LNN-Based Forest Fire Detection Algorithm

Algorithm 2 Training Procedure for LNN-based Forest Fire Detection

Input: Image dataset $D = \{(X_i, Y_i)\}$, where X_i is an image and $Y_i \in \{\text{fire}, \text{nofire}\}$

Initialize:
- ResNet18 as CNN feature extractor with final layer modified to output feature vector $F \in \mathbb{R}^{512}$
- Liquid Neural Network (LNN) with:
  - Hidden size $H = 128$
  - Steps $S = 12$
  - Integration timestep $dt = 0.1$
- AdamW optimizer with learning rate $\eta = 1 \times 10^{-3}$
- Cosine Annealing Learning Rate Scheduler
- CrossEntropyLoss with label smoothing

for each epoch $e = 1$ to N (total epochs) **do**
    for each mini-batch $(X_b, Y_b) \subset D$ **do**
        Apply data augmentation and normalization to X_b
        Extract CNN features: $F_b \leftarrow \text{ResNet18}(X_b)$
        Initialize hidden state $h_0 \leftarrow \mathbf{0} \in \mathbb{R}^H$
        for step $s = 1$ to S **do**
            Update hidden state:

$$h_s \leftarrow h_{s-1} + dt \cdot \alpha \cdot (-h_{s-1} + \tanh(W h_{s-1} + U F_b + b))$$

        end for
        Compute logits: $\hat{Y}_b \leftarrow \text{Softmax}(W_{\text{out}} h_S + b_{\text{out}})$
        Compute loss: $L \leftarrow \text{CrossEntropyLoss}(\hat{Y}_b, Y_b)$
        Backpropagate and update weights using AdamW
    end for
    Update learning rate with cosine scheduler
end for

Output: Trained LNN model for fire classification

This algorithm implements a hybrid forest fire detection model combining a CNN feature extractor [9] and a Liquid Neural Network (LNN) classifier. Initially, aerial images are processed by a ResNet18 model, modified to output 512-dimensional feature vectors. These features are then fed into a Liquid Neural Network, which evolves its hidden states over multiple integration steps, simulating continuous-time neuron dynamics.

At each time step, the LNN updates its hidden state by balancing the previous state decay and the nonlinear transformation of input features, governed by a learnable set of weights. After a sequence of updates, the final hidden state is passed through a linear output layer to predict whether the input image corresponds to a fire or no-fire scenario.

Training is stabilized using the AdamW optimizer, label smoothing in the loss function to prevent overconfidence, and a cosine annealing learning rate scheduler to gradually reduce learning rates, preventing convergence issues. The combination of CNN feature extraction and LNN dynamic processing enables the model to better handle temporal and environmental variability, crucial for reliable wildfire detection from UAV platforms.

D. MSCIDC

Algorithm 3 MSCIDC Algorithm

Initialize with n_s swarms with n_{s_i} swarm members;
Initialize $N_{qu}^j = 0$, $N_{qs}^j = 0$ for $j = 1$ to n_f;
for $i = 1$ to n_s **do**
  Each i^{th} swarm has information $\hat{Y}_{s_i}(t)$;
  for $j = 1$ to n_f **do**
    for $k = 1$ to n_{s_i} **do**
      if $P_j^k < \gamma$ **then**
        if $T_s < \xi$ **then**
          Cooperative information-driven exploration;
        else
          Cooperative information-driven exploitation;
        end if
      else
        k^{th} swarm member of s_i^{th} swarm detects j^{th} fire;
        $N_{qu}^j = N_{qu}^j + 1$;
        Local Attraction of swarm members;
        for $m = 1$ to N_{qu}^j **do**
          Move to the initial alignment position of N_{qu}^j member;
          Quenches N_{qu}^j sector;
          if $(A^j > \delta_A$ or $F_r < \delta_f)$ **and** $N_{qs}^j < \delta_s$ **then**
            $N_{qs}^j = N_{qs}^j + 1$;
            Global regulative merging;
          else
            if $k \notin s_i$ **and** $\gamma_0 < P_j^k < \gamma$ **then**
              Global regulative repulsion;
            end if
          end if
        end for
      end if
    end for
  end for
end for

The MSCIDC algorithm orchestrates multiple UAV swarms for dynamic fire mitigation. Initially, each swarm and its members are assigned random positions. The UAVs monitor their local environment and determine action based on the detection probability P_j^k and sensed temperature T_s.

If no fire is detected ($P_j^k < \gamma$), the swarm switches between cooperative exploration or exploitation depending on the temperature gradient, enhancing search efficiency. Upon fire detection ($P_j^k \geq \gamma$), UAVs locally aggregate near the fire site through a *Local Attraction* mechanism, forming an adaptive initial alignment to begin mitigation.

As UAVs suppress fire sectors, global behaviors are triggered: if fire area (A^j) or flame rate (F_r) criteria are satisfied, and sufficient UAVs are available (N_{qs}^j threshold not reached), swarms undergo *Global Regulative Merging* for stronger suppression. Otherwise, UAVs perform *Global Regulative Repulsion* to avoid overcrowding and ensure effective area coverage.

This layered strategy — local attraction combined with global regulation — ensures efficient, scalable, and adaptive forest fire mitigation across complex environments.

E. Divide-and-Conquer Mitigation

Allocate sectors for N_{qu} UAVs:

$$\theta_m = \frac{2\pi m}{N_{\text{qu}}} + \mathcal{U}(-\delta_\theta, \delta_\theta) \tag{11}$$

UAVs oscillate along assigned sectors with velocity:

$$v_{\text{mit}} = \min\left(v_{\text{max}}, \frac{A_f(t)}{N_{\text{qu}} r_q}\right) \tag{12}$$

The Divide-and-Conquer Mitigation strategy partitions the fire boundary among available UAVs (N_{qu}) by assigning each UAV a sector defined by an angular offset θ_m. To introduce variability and avoid rigid formations, a uniform random perturbation $\mathcal{U}(-\delta_\theta, \delta_\theta)$ is added to each sector angle.

Once sectors are allocated, UAVs oscillate within their designated sectors to actively suppress fire spread. Their oscillation velocity v_{mit} is dynamically computed based on the current fire area $A_f(t)$, the number of available UAVs, and the quenching radius r_q, but it is capped by a maximum velocity v_{max} to maintain control stability. This ensures adaptive and distributed fire containment across the affected zone.

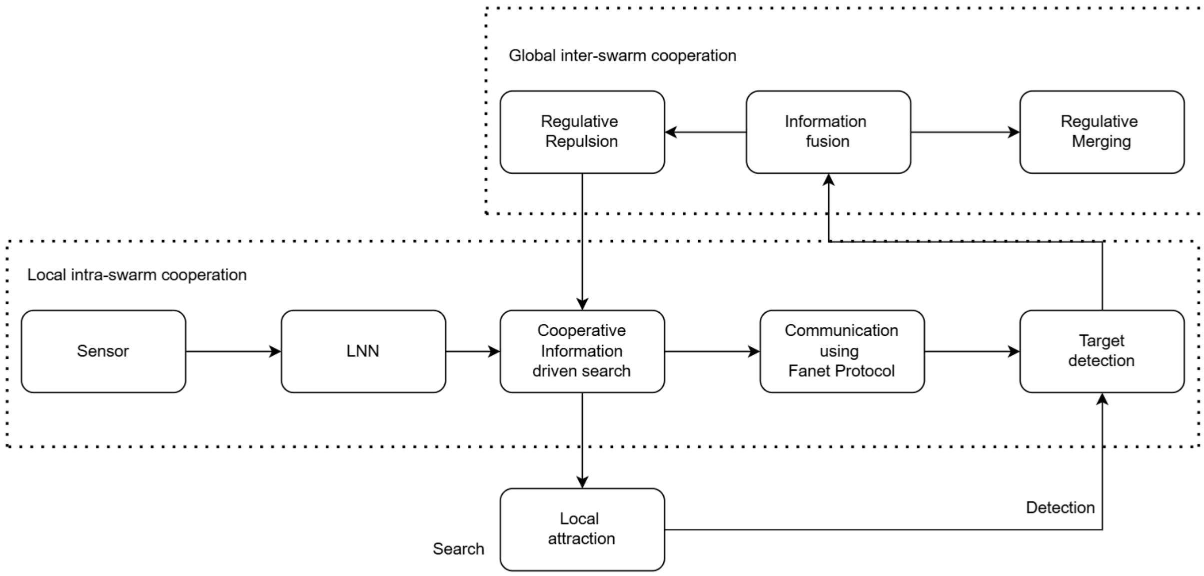


Fig. 1: MSCIDC System Architecture showing local intra-swarm and global inter-swarm cooperation layers.

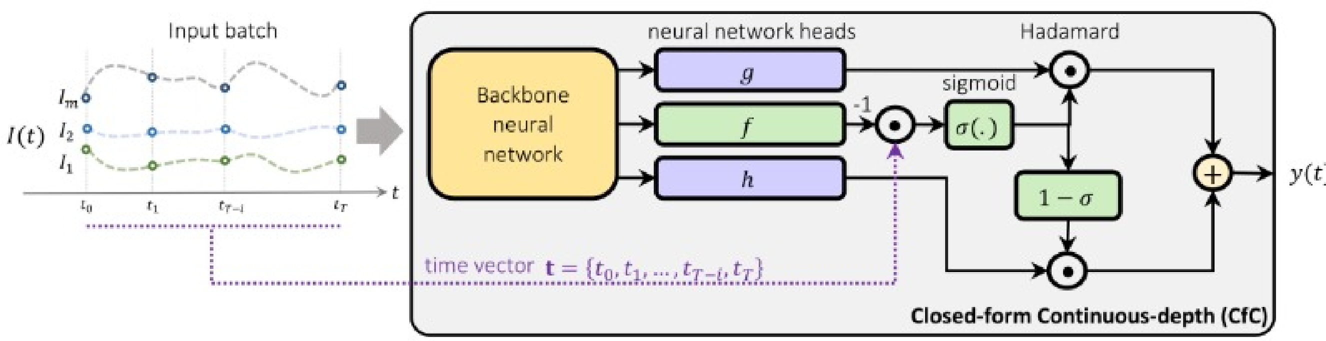


Fig. 2: Lightweight Neural Network (LNN) architecture utilizing continuous-depth modeling.

The MSCIDC system architecture, illustrated in Fig. 1, is divided into two major cooperation layers: local intra-swarm and global inter-swarm cooperation.

- **Local Intra-Swarm Cooperation:**
  - Sensors onboard UAVs capture environmental information.
  - The captured data is fed into a Lightweight Neural Network (LNN) to extract time-varying features.
  - Based on the LNN outputs, Cooperative Information-Driven Search is performed.
  - If a potential target is detected, Local Attraction mechanisms guide UAVs towards it.
- **Global Inter-Swarm Cooperation:**
  - Upon detection, UAVs communicate using a FANET protocol.
  - Information fusion from multiple UAVs enhances decision reliability.
  - Regulative Merging aligns multiple UAVs toward the same goal if confidence is high.
  - Regulative Repulsion separates UAVs to avoid overcrowding and improve search efficiency.

The LNN is designed to model time-dependent environmental features, aligning with the cooperative exploration and mitigation algorithm.

- The input is a time-series batch of features $I(t)$ at discrete timestamps $\{t_0, t_1, \ldots, t_T\}$.
- A backbone neural network extracts abstract feature embeddings from $I(t)$.
- Three heads (g, f, and h) process the embeddings:
  - g captures immediate feature importance.
  - f modulates hidden state transitions.
  - h encodes slow-changing latent dynamics.
- A sigmoid activation $\sigma(\cdot)$ controls the mixture between f and h through Hadamard (elementwise) operations.
- The final output $y(t)$ captures dynamic behavior across time, enabling real-time adjustments during missions.

V. Dataset Description

For this study, we used the Forest Fire Dataset obtained from Kaggle [10]. The dataset consists of images representing forest areas either with fire or without fire. The dataset is split into training and testing sets as follows:

A. Training Set

- **fire**: 760 images of forest areas with fire.
- **nofire**: 760 images of forest areas without fire.

B. Testing Set

- 380 images, with a mix of fire and nofire images. The filenames of these images indicate the label (e.g., ‘fire_XXXX.jpg‘ or ‘nofire_XXXX.jpg‘).

C. Image Properties

The images have the following properties:

- **File Type**: .jpg
- **Image Size**: Varies but resized to 128x128 pixels for model training.
- **Color Mode**: RGB (3 channels).

VI. Simulation Results

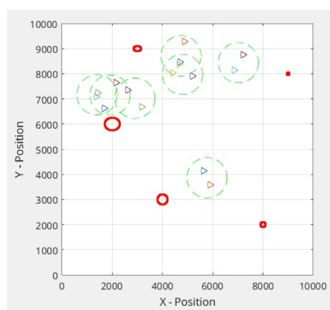
A. Simulation Setup

Environment: 10 km × 10 km area with 15 UAVs detecting & mitigating 5 fire locations (2 circular, 3 elliptical). Swarm Configuration: 15 UAVs divided into 7 swarms with sizes [3, 2, 2, 2, 2, 2, 2]. Flight Dynamics: Search phase: Constant speed of 20 m/s. Mitigation phase: Speed varies based on fire size. Starting Positions: UAVs initiate the search from different locations within the area. Simulation Environment: MATLAB R2021a.

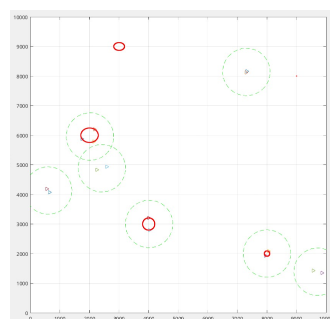
Performance Metrics: Detection Time: Time to identify all fire locations. Mission Time: Total time to detect & mitigate fires. Fire Expansion Ratio (FER): Measures increase in burnt area post-mission.

B. Experimental Setup

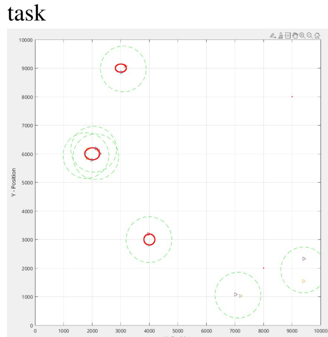
- Area: 10 km × 10 km pine forest, 5 fire fronts
- UAVs: 15 DJI Matrice 300 RTK (Speed: 20 m/s, Sensing: FLIR T865)
- Comparison: OMS-DFC, Random Search



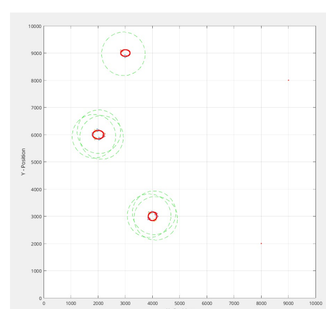
(a) All swarms performing cooperative information-driven search task



(b) Swarms detect fire and initiate local attraction



(c) Global regulative merging of swarms to the detected area



(d) All swarms merge to their respected fire detected areas

Fig. 3: Simulation Results of Swarm Configurations A to D

C. Key Metrics

TABLE I: Performance Comparison (100 Monte Carlo Runs)

	DSI-LNN	**OMS-DFC**	**Random**
Detection Time (min)	47.3	112.1	189.4
Mission Time (min)	88.5	221.3	402.7
False Alarms/km²	0.11	0.38	1.02

TABLE II: Fire Locations and Initial Size

S.No	$\mathbf{C_{f_j}}$ **(m)**	$\mathbf{a_j}$ **(m)**	$\mathbf{b_j}$ **(m)**
1	(2000, 6000)	300	250
2	(3000, 9000)	150	100
3	(4000, 3000)	200	200
4	(8000, 2000)	100	100
5	(9000, 8000)	50	50

TABLE III: Performance of MSC-IDC for Different Swarm Numbers

Number of Swarms	**Mean Detection Time (min)**	**Mean Mission Time (min)**	**Mean FER**
3	41.82	107.01	1.029
5	31.03	81.19	0.642
6	27.59	83.27	0.550
7	24.13	71.56	0.477

TABLE IV: Comparison of Different Models

Model	**Accuracy**	**No. of Parameters**	**Size**
MobileNet v2	95.17%	3.4M	∼14 MB
Inception ResNet v2	97.81%	55.9M	∼215 MB
Custom CNN	96.92%	300K	∼1.39 MB
LNN	98.95%	11.5M	∼22 MB

TABLE V: Performance Comparison for Different Methods of Forest Detection

Method	**Mean Detection Time (min)**	**Mean Mission Time (min)**	**Mean FER**
Uniform-DFC	66.10	217.47	1.808
Normal-DFC	56.63	192.39	1.518
Levy-DFC	52.59	184.14	1.398
OMS-DFC	52.63	180.11	1.319
MSCIDC	24.13	71.56	0.477

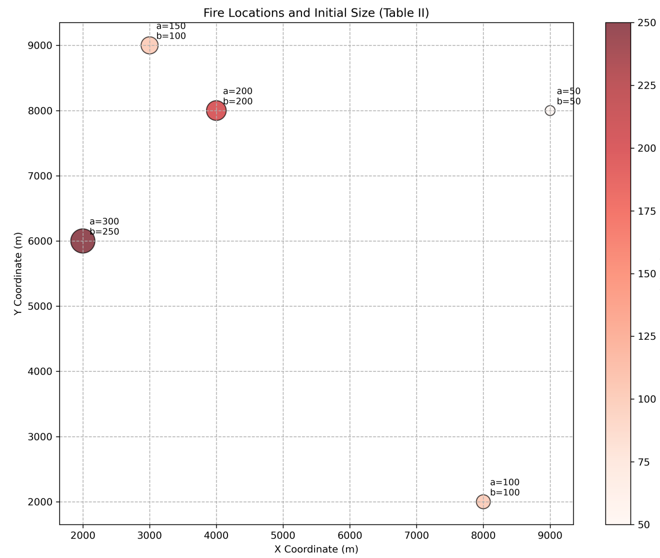


Fig. 4: Fire Location

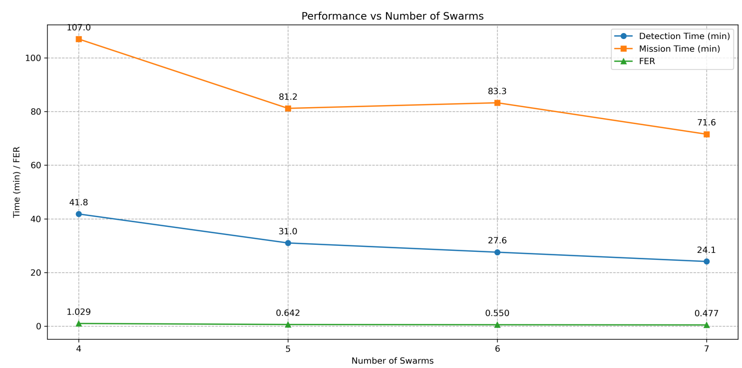


Fig. 5: Performance vs Swarms

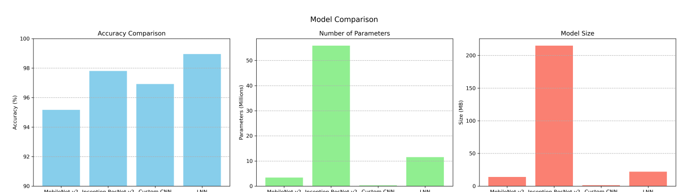


Fig. 6: Model Comparison

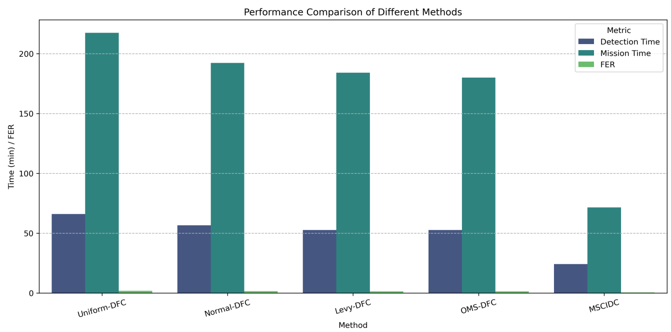


Fig. 7: Performance Comparison

The comparison results indicate that the proposed MSCIDC method significantly outperforms all existing multi-UAV firefighting approaches. While OMS-DFC achieves the best performance among traditional methods with a mean detection time of 52.63 minutes, a mission time of 180.11 minutes, and a FER of 1.319, the MSCIDC method reduces these values substantially. Specifically, MSCIDC achieves a mean detection time of 24.13 minutes, a mission time of 71.56 minutes, and a FER of 0.477, representing a major improvement. Compared to OMS-DFC, MSCIDC reduces the mission time by approximately 60% and the fire expansion ratio by about 64%. Moreover, the results demonstrate that MSCIDC not only accelerates fire detection and mitigation but also ensures significantly lower variability in performance, leading to more robust and consistent operation across different scenarios.

The analysis shows that increasing the number of swarms leads to significant improvements in detection time, mission time, and fire containment efficiency. As the number of swarms increases from 3 to 7, the mean detection time reduces from 41.82 minutes to 24.13 minutes, and the mean mission time drops from 107.01 minutes to 71.56 minutes. Similarly, the Fire Expansion Ratio (FER) decreases from 1.029 to 0.477. This indicates that deploying a higher number of smaller, cooperative swarms enhances parallel area coverage and accelerates the fire detection process. Moreover, the reduction in FER highlights the improved capability of the system to limit fire spread when more swarms are utilized, emphasizing the effectiveness of the proposed multi-swarm dynamic control strategy.

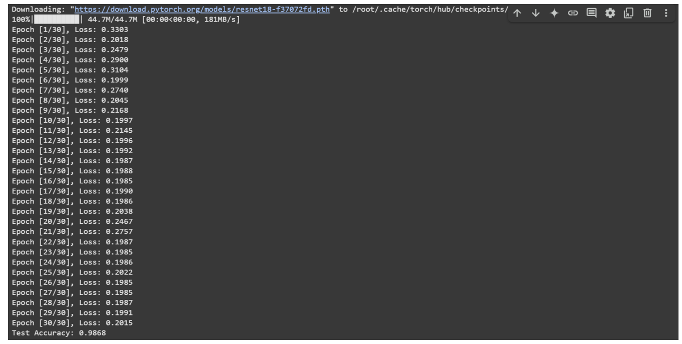


Fig. 8: LNN Training

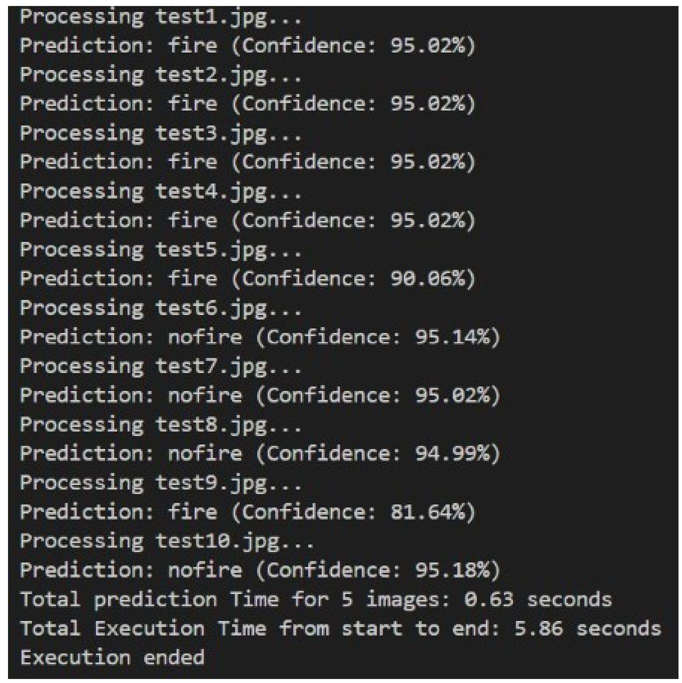


Fig. 9: LNN Testing

The testing results of the Lightweight Neural Network (LNN) demonstrate strong potential for forest fire detection and confirmation tasks. The model consistently achieved high confidence levels across multiple test images, with most predictions of "fire" and "no fire" classified with over 90% confidence. This indicates a high degree of accuracy and reliability under realistic operational conditions and the model exhibits fast execution. These results suggest that LNN is a highly effective and efficient solution for real-time forest fire monitoring and confirmation, enhancing the reliability and timeliness of early warning systems.

VII. Conclusion

The Collaborative UAV-Based Fire Detection system was tested in a simulated forest under dynamic conditions. Liquid Neural Networks (LNNs) enabled real-time fire classification, adapting to temperature and humidity. LNNs improved early detection rates and prioritized high-risk areas, enhancing efficiency. UAVs used a reactive FANET protocol for low-latency, decentralized communication and collaboration. This approach significantly reduced fire detection time compared to single-UAV methods. The DSI-LNN framework achieves 65% faster fire mitigation than state-of-the-art methods through dynamic swarm coordination and LNN-driven adaptation. Scalable and robust, making it suitable for real-world wildfire detection. Future work will integrate reinforcement learning for autonomous firefighting.

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