Real-Time Forest Fire Detection Using Edge-Driven Collaborative UAV Swarms

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Contents

1 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.

Keywords: UAV Swarm, Swarm Intelligence, Edge-based, Forest Fire Detection, Liquid Neural Networks, FANET, Divide-and-Conquer Mitigation

2 PROBLEM STATEMENT:

Forest fires represent one of the most severe and persistent threats to global ecosystems, causing irreversible damage to biodiversity, accelerating climate change through carbon emissions, and inflicting extensive economic losses on human infrastructure, agriculture, and urban settlements. The increasing frequency and intensity of wildfires, exacerbated by rising global temperatures and prolonged drought conditions, have made early detection and rapid containment more critical than ever. Despite significant advancements in environmental monitoring technologies, existing fire detection systems continue to face considerable limitations.

Traditional fire detection methods, such as satellite-based monitoring, ground-based sensor networks, and manned aerial patrols, often suffer from delayed detection times, limited spatial resolution, and susceptibility to environmental interferences such as cloud cover, dense smoke, or complex terrain. Satellite systems, while providing broad coverage, may miss early-stage ignitions due to low temporal resolution or obstructed visibility. Similarly, ground-based sensors, although accurate locally, offer limited area coverage and require substantial infrastructure investment, making them impractical for large-scale deployment in remote forested regions. Manned aerial surveillance, while effective, poses risks to human pilots and is constrained by operational costs, weather conditions, and flight duration.

Unmanned Aerial Vehicles (UAVs) have emerged as a promising alternative, offering significant advantages in terms of mobility, adaptability, cost-effectiveness, and ease of deployment. UAVs can navigate challenging terrains, operate under hazardous conditions, and provide real-time aerial imagery and sensor data, making them well-suited for wildfire detection and monitoring tasks. However, reliance on single-UAV systems presents inherent limitations, including restricted operational range, finite battery life, and narrow sensor coverage, which significantly hampers their effectiveness in vast and dynamic forest environments.

To address these challenges, the concept of cooperative UAV swarms has been proposed. By leveraging multiple UAVs operating in a coordinated and decentralized manner, it is possible to achieve scalable, resilient, and efficient forest surveillance systems. Swarm-based approaches enable parallel exploration, fault tolerance, dynamic reconfiguration, and distributed decision-making, greatly enhancing the overall mission robustness compared to single-agent systems. Nevertheless, most existing swarm frameworks rely on static formation patterns, fixed path planning, or simplistic search behaviours, limiting their adaptability to the highly dynamic and uncertain nature of wildfire spread.

In this research, we propose a novel collaborative UAV swarm intelligence system specifically designed for rapid, adaptive, and scalable forest fire detection. Our framework enables a fleet of autonomous UAVs to operate without centralized control, utilizing real-time environmental sensing, distributed data processing, dynamic path adaptation, and inter-swarm coordination. By integrating principles from biologically inspired search strategies, adaptive formation control, and decentralized swarm decision-making, the proposed system aims to significantly improve fire detection accuracy, reduce response time, and enhance mission success rates even under unpredictable environmental conditions. Through extensive simulation studies, the effectiveness and robustness of the proposed approach are systematically evaluated against existing methods.

Problem Definition

The primary objective of the proposed system is to enable early and accurate detection of forest fires through the deployment of a swarm of Unmanned Aerial Vehicles (UAVs). The UAVs must collaboratively navigate the search environment, autonomously detect fire-prone regions, and validate fire occurrences while minimizing the incidence of false alarms.

Each UAV is responsible for independently sensing its surroundings and sharing relevant information with neighbouring UAVs in a decentralized manner. The system must support distributed decision-making, allowing the swarm to reach a consensus regarding the presence of a fire before issuing an official detection alert. This collaborative approach aims to enhance the reliability, robustness, and timeliness of fire detection, thereby enabling rapid response and effective wildfire mitigation.

Challenges and Considerations:

1. Large Search Area: Forest fires can ignite in vast and remote areas, requiring an efficient search strategy that balances exploration and coverage.

2. Dynamic Environmental Conditions: Wind, temperature variations, and smoke affect UAV sensors and require adaptive decision-making.

3. False Alarms: False positives (e.g., sunlight reflections, hot rocks) and false negatives (e.g., hidden fire under the canopy) must be minimized through collaborative verification.

4. Communication Constraints: UAVs should be able to operate even with intermittent connectivity, relying on local peer-to-peer information exchange.

5. Energy Efficiency: UAVs have limited battery life, requiring optimized flight paths and minimal redundant scanning.

GROUND BASED SENSOR:

Advantages:

- Real-time monitoring for early detection
- High accuracy in local areas
- Works in all weather conditions

Disadvantages:

- Limited coverage – only monitors specific areas
- Requires infrastructure for deployment & maintenance
- Sensor failures can lead to false alarms or missed fires

SATELLITE IMAGING:

Advantages:

- Covers large areas – even remote locations
- Continuous global monitoring with thermal imaging
- No ground infrastructure needed

Disadvantages:

- Low refresh rate – data updates can take hours
- Cloud cover can obstruct visibility

- High operational costs for advanced satellite

UAV BASED:

Advantages:

- Fast response time – reaches fire-prone areas quickly
- Higher accuracy than satellites for local detection
- Can navigate difficult terrains

Disadvantages:

- Limited battery life – needs frequent recharging
- Requires trained operators for effective deployment
- Network dependency for real-time data transmission

Implementation of AODV and OLSR FANET Protocols for Drone Communication:

- AODV Protocol Implementation
  - Reactive routing protocol (routes are established only when needed).
  - Suitable for dynamic drone networks with frequent topology changes.
  - Reduces control overhead but may have higher latency during route discovery.
- OLSR Protocol Implementation
  - Proactive routing protocol (maintains updated routing tables continuously).
  - Uses multipoint relays (MPRs) to reduce redundant messages.
  - Ensures low latency but has higher control overhead.

Comparison & Observations:

- AODV: More efficient in scenarios with dynamic topology but slower in route discovery.
- OLSR: Provides quicker route availability but may consume more bandwidth due to frequent updates.
- Optimal choice depends on network size, mobility patterns, and latency requirements.

3 LITERATURE SURVEY:

1) ”Application Strategy of Unmanned Aerial Vehicle Swarms in Forest Fire Detection Based on the Fusion of Particle Swarm Optimization and Artificial Bee Colony Algorithm”

Link: **https://www.mdpi.com/2076-3417/14/11/4937**

Summary:

This paper proposes a comprehensive application strategy for forest fire detection using UAV swarms, combining Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms. Their approach optimizes UAV path planning to rapidly locate multiple fire points within a 3D forest environment and supports subsequent fire assessment and control measures. By fusing swarm intelligence techniques, the system enhances the efficiency and accuracy of fire point detection, laying a foundation for the practical deployment of UAV swarms in real-world wildfire monitoring and prevention scenarios.

2) ”SOScheduler: Toward Proactive and Adaptive Wildfire Suppression via Multi-UAV Collaborative Scheduling”

Link:https://ieeexplore.ieee.org/document/10502270

Summary:

This paper presents a collaborative UAV scheduling framework for wildfire suppression, focusing on proactive and adaptive mission planning. It introduces an intelligent task allocation model that dynamically assigns UAVs based on real-time fire spread predictions, resource availability, and operational constraints. The approach improves response efficiency by optimizing UAV coordination and minimizing idle time.

3) "Adaptive Hierarchical Multi-Headed Convolutional Neural Network With Modified Convolutional Block Attention for Aerial Forest Fire Detection"

Link:https://ieeexplore.ieee.org/abstract/document/10818623

Summary:

This paper presents an adaptive hierarchical multi-headed CNN model enhanced with a modified convolutional block attention mechanism (CBAM). The approach improves feature extraction by dynamically adjusting attention across different network layers. The model is optimized for high accuracy in complex pattern recognition tasks, making it suitable for applications requiring precise spatial feature analysis.

4) *”Nature-Inspired Drone Swarming for Wildfires Suppression Considering Distributed Fire Spots and Energy”*

Link: ***https://ieeexplore.ieee.org/abstract/document/10132476***

Summary:

The paper proposes a nature-inspired swarm intelligence approach for wildfire suppression using autonomous UAVs. It emphasizes decentralized decision-making, where drones communicate locally to optimize fire response. The system prioritizes fire spots dynamically while ensuring efficient energy management to extend operational time.

5) ”Multi-UAV Oxyrrhis Marina-Inspired Search and Dynamic Formation Control for Forest Firefighting”

Link: ***https://ieeexplore.ieee.org/document/8474373***

Summary:

This paper introduces a multi-UAV search and formation control strategy inspired by the movement patterns of Oxyrrhis Marina, a marine microorganism. The proposed method enhances fire detection efficiency by dynamically adapting UAV formations based on fire spread patterns. It emphasizes real-time coordination, adaptive searching, and optimized flight paths to maximize coverage while minimizing response time.

6) "Research on Cooperative Obstacle Avoidance Decision Making of Unmanned Aerial Vehicle Swarms in Complex Environments under End-Edge-Cloud Collaboration Model"

Link: ***https://www.mdpi.com/2504-446X/8/9/461***

Summary:

This paper discusses the use of drones for aerial monitoring and surveillance, focusing on autonomous navigation, real-time data collection, and communication networks. It highlights efficient UAV deployment strategies, energy management, and decision-making for various applications, including disaster response and environmental monitoring.

7) "Genetic Algorithm-based Routing and Scheduling for Wildfire Suppression using a Team of UAVs"

Link: ***https://ieeexplore.ieee.org/document/10611817***

Summary:

This paper presents an optimized approach for UAV-based wildfire suppression using Genetic Algorithms (GAs). It focuses on efficient path planning and scheduling for UAVs to maximize fire suppression effectiveness while considering constraints like fuel limitations, fire spread dynamics, and UAV coordination. The proposed GA-based method improves UAV task allocation, response time, and coverage of affected areas.

8) ”Forest-Fire Response System Using Deep Learning Based Approaches With CCTV Images and Weather Data”

Link: [***https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9801825***](https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9801825)

Summary:

This paper presents a deep learning-based forest fire response system that integrates CCTV images and weather data for early fire detection. It utilizes convolutional neural networks (CNNs) for image analysis and predictive models to assess fire risk based on environmental factors. The approach enhances early warning capabilities and improves response times by leveraging real-time surveillance and meteorological data.

9) ”Neural Network Methods for Detecting Wild Forest Fires”

***Link:*https://link.springer.com/article/10.3103/S0147688224700412**

Summary:

This analytical review explores various neural network methods, algorithms, and approaches for early forest fire detection using images and video streams from unmanned aerial vehicles. It discusses feature extraction, machine learning for frame classification, and semantic segmentation of fires using convolutional neural networks.

10) ”Topology-Based Routing Protocols and Mobility Models for Flying Ad Hoc Networks: A Contemporary Review and Future Research Directions”

***Link:*https://www.mdpi.com/2504-446X/6/1/9**

Summary:

This paper reviews routing protocols (proactive, reactive, hybrid) and mobility models in FANETs, focusing on their impact on network efficiency. It highlights challenges like high mobility, frequent topology changes, and security risks while identifying research gaps for improved UAV communication.

11) ”Multiple UAV Swarms Collaborative Firefighting Strategy Considering Dynamic Forest Fire Spread and Resource Constraints”

Link:https://www.mdpi.com/2504-446X/9/1/17

Summary:

This paper proposes an adaptive strategy for multiple UAV swarms to collaboratively detect and suppress forest fires. It introduces the Multiple UAV Swarm Adaptive Information-Driven Collaborative Search (MUSAIDCS) algorithm, which employs a temperature change-driven adaptive step-length search strategy to enhance the accuracy of fire spot detection. The study also develops a resource-limited firefighting model, addressing dynamic fire spread and resource constraints, thereby improving the efficiency of UAV-based firefighting operations.

4 Comparison of different existing models :

S. No	Model	Accuracy	No of parameters	Size
1	Mobile Net v2	95.17 %	3.4M	~14 MB
2	Inception ResNet v2	97.81 %	55.9M	~215 MB
3	CUSTOM CNN	96.92 %	300K	~1.39 MB
4	LNN	98.95 %	11.5 M	~40 MB

Models:

1. MobileNet v2

MobileNetV2 is a lightweight and efficient convolutional neural network architecture designed primarily for mobile and embedded vision applications. It emphasizes achieving high accuracy while maintaining low computational cost and a small model size, making it highly suitable for resource-constrained environments.

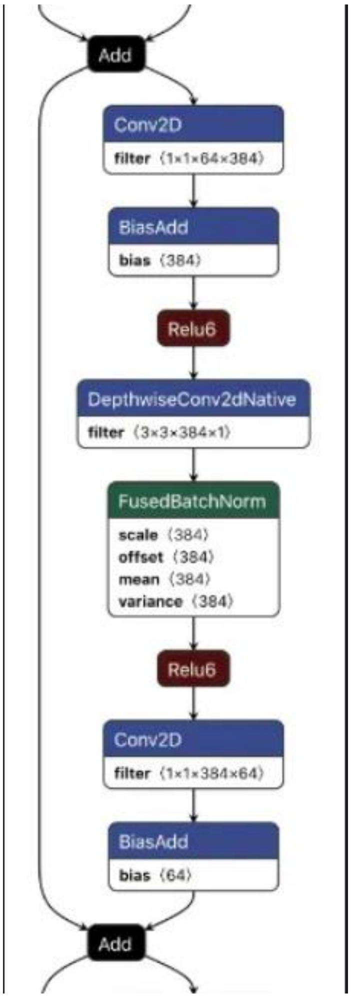
Architecture Overview:
MobileNetV2 is built upon two key innovations: depthwise separable convolutions and the introduction of inverted residuals with linear bottlenecks.

- Depthwise Separable Convolution:
  Instead of applying a standard convolution, MobileNetV2 decomposes it into two simpler operations: a depthwise convolution (applying a single filter per input channel) followed by a pointwise convolution (1×1 convolution to combine features across channels). This significantly reduces both the computational complexity and the number of parameters compared to

conventional convolutions.

- Inverted Residual Block:
  Each residual block initially expands the input tensor to a higher-dimensional space, applies depthwise convolution, and then projects it back to a lower-dimensional space. This inverted structure helps preserve representational power while minimizing computational cost. Unlike traditional residual connections that add tensors of the same dimensionality, the inverted residual design allows shortcuts between thin bottleneck layers

Architecture:



Layers: 53 layers with inverted residuals, ReLU6 activation, and batch normalization.

Output: Classification probabilities via softmax.

Accuracy:

95.17%

Trade-off: Lower accuracy than heavier models but optimized for speed/size.

2. Inception ResNet v2

Inception-ResNet v2 is a deep convolutional neural network architecture that combines the strengths of the Inception modules and Residual connections to achieve high accuracy with efficient training dynamics. By integrating multi-scale feature extraction with residual learning, Inception-ResNet v2 addresses the challenges of training very deep networks, such as vanishing gradients, while maintaining a strong representational capacity.

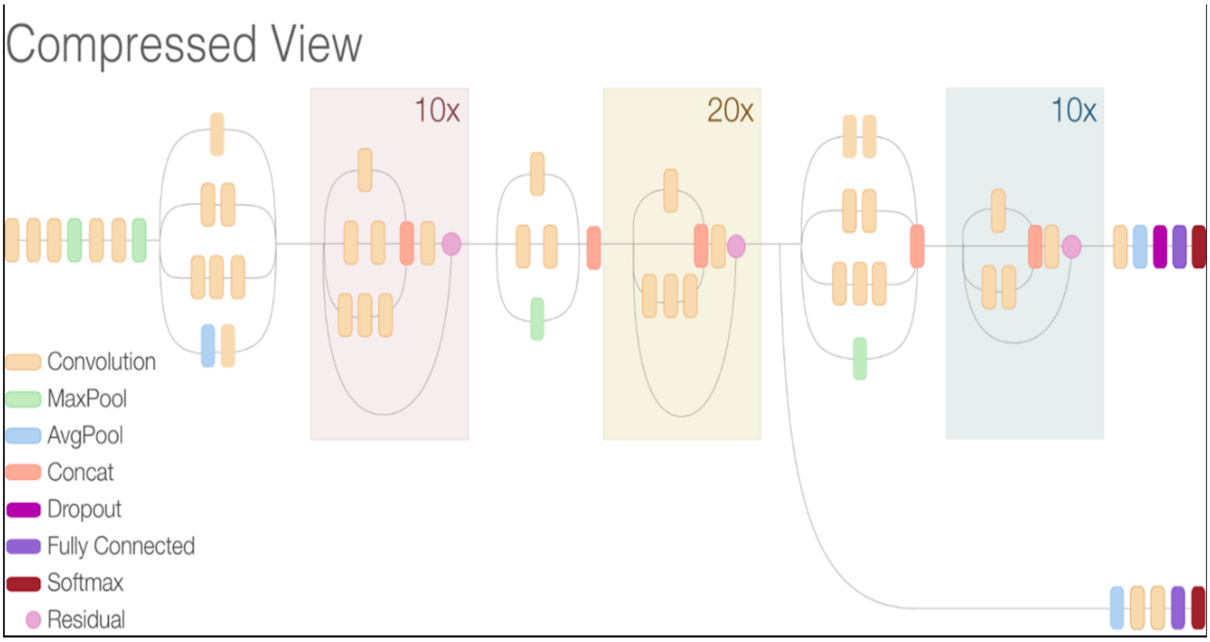
Architecture Overview:
The model architecture is characterized by two key components: Inception modules and ResNet-style skip connections.

- Inception-ResNet Blocks:
  Each block applies multiple parallel convolutional operations with different filter sizes (e.g., 1×1, 3×3, and 5×5) to capture features at various spatial scales. These outputs are concatenated and combined with a residual shortcut connection, allowing the network to maintain gradient flow and facilitating the training of very deep architectures.

- Stem Block:
  The network begins with a specialized stem block, which performs aggressive downsampling and early feature extraction. This block efficiently reduces the spatial dimensions while preserving critical information needed for deeper layers.

By fusing multi-scale feature extraction with residual learning, Inception-ResNet v2 achieves improved convergence speed, better gradient propagation, and higher accuracy on complex visual recognition tasks compared to traditional Inception or ResNet architectures individually.

Architecture



Layers: 164 layers with Inception-ResNet blocks, batch normalization, and auxiliary classifiers.

Output: Classification probabilities via softmax.

Output

Predicts class probabilities (e.g., 97.81% accuracy in the table).

Accuracy:

97.81% (highest among the four but computationally expensive).

Trade-off: Large size (~215 MB) due to 55.9M parameters.

3. Custom CNN

A **User-Designed Convolutional Neural Network (CNN)** refers to a custom-built architecture tailored for specific tasks, striking a balance between simplicity, computational efficiency, and performance. These models are typically optimized for particular datasets or applications where standard large-scale architectures may be excessive or suboptimal.

Architecture Overview:
The design typically follows a sequential stacking of fundamental building blocks:

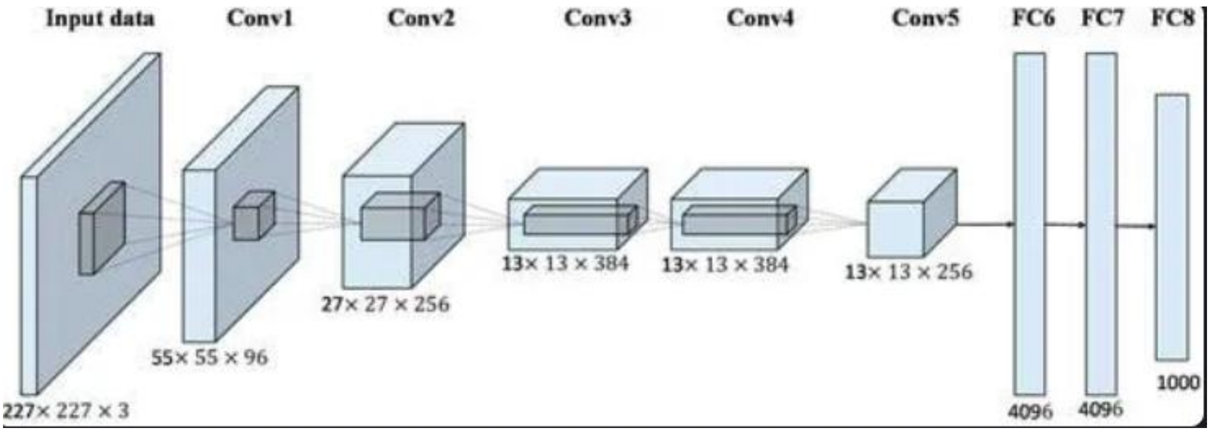
- **Standard Convolutions:**
  Convolutional layers with commonly used filter sizes, such as 3×3 or 5×5, are applied to extract spatial features from input images.

- **Pooling Layers:**
 Max pooling or average pooling operations are employed to downsample feature maps, reducing spatial dimensions and computational load while preserving essential information.

- **Fully Connected Layers:**
 After feature extraction, fully connected (dense) layers are used to perform classification or regression based on the learned representations.

- **Regularization Techniques:**
 To enhance generalization and prevent overfitting, techniques such as **dropout** and **batch normalization** are often incorporated into the network.

Architecture:



Layers: Fewer layers (e.g., 5–10) compared to pre-trained models.

Output: Classification probabilities via softmax.

Accuracy

96.92% (competitive with fewer parameters (300K) and small size (~1.39 MB).

Trade-off: May lack generalization compared to pre-trained models.

4. LNN (Liquid Neural Network)

The **Liquid Neural Network (LNN)** is a specialized neural network architecture designed to achieve a balance between computational efficiency and model accuracy. Tailored for resource-constrained environments such as mobile devices, embedded systems, and real-time applications, LNN focuses on minimizing the number of parameters and operations without significantly compromising predictive performance.

Architecture Overview:

LNNs typically incorporate several optimization strategies to maintain model compactness:

- **Model Compression Techniques:**
  Methods such as **channel pruning** (removing less significant channels), **quantization** (reducing the precision of weights and activations), and **factorized convolutions** (decomposing convolutions into simpler operations) are employed to reduce the number of parameters and computational cost.

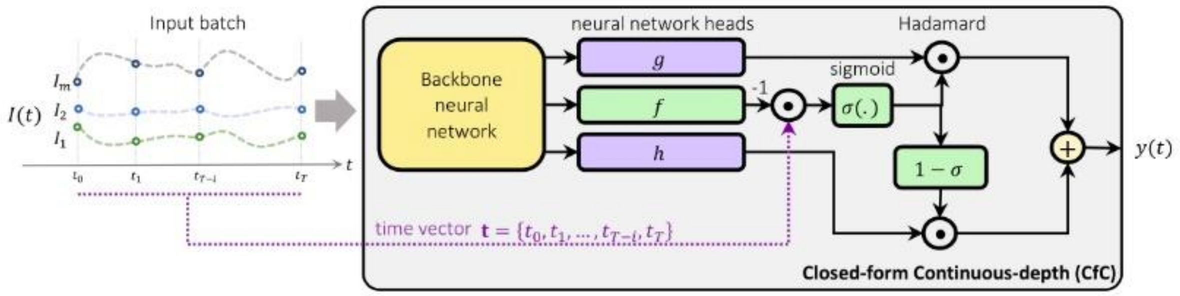
- **Efficient Architectural Design:**
  The network design carefully balances depth (number of layers) and width (number of channels) to optimize the trade-off between expressiveness and computational demands.

Algorithm:

Compound Scaling: Adjusts depth/width/resolution uniformly.

Efficient Blocks: May use squeeze-and-excitation (SE) modules.

Architecture



Layers: Scaled-down blocks with efficient operations.

Output: Classification probabilities via softmax.

Accuracy

98.95% (best in the table) with moderate parameters (11.5M) and size (~22 MB).

Trade-off: Requires careful design to avoid overfitting.

5 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 during 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 during the mitigation phase, where the fire region is equally divided among the UAVs. Although simple and decentralized, this method 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 complete 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 variations in fire spread velocity.

The Levy-DFC method introduces a biologically inspired improvement by employing Levy flight-based search mechanisms. This approach allows UAVs to alternate between short-range local searches and occasional long-range jumps, thereby enabling effective coverage of sparse or unknown regions and reducing search time. While Levy-DFC enhances exploration efficiency, it still lacks environmental awareness during the search phase and does not incorporate localized exploitation behavior to precisely refine UAV movements near potential fire zones.

The Oxyrrhis Marina-inspired Search and Dynamic Formation Control (OMS-DFC) framework further refines the search behavior by introducing a multi-level stochastic search strategy inspired by the foraging behavior of the marine predator Oxyrrhis Marina. In this method, UAVs initially perform Levy flight for broad exploration and then adaptively switch to Brownian motion or Directionally Driven Brownian (DDB) search based on the detected rate of temperature change. This enables an effective balance between exploration and exploitation without requiring inter-UAV communication. The mitigation phase employs a decentralized formation control law to track both elliptical and circular fire profiles with non-overlapping angular displacements. Although OMS-DFC demonstrates improved adaptability and precision, it still assumes idealized sensor performance and does not incorporate multi-swarm coordination or dynamic inter-agent role reassignment, which are critical for enhancing mission resilience and scalability.

6 RESEARCH GAP:

Wildfire detection has been extensively studied, with various approaches utilizing satellite imagery, ground-based sensors, and UAV-based monitoring systems. However, these methods exhibit several limitations that hinder early and accurate fire detection.

1. Delayed Detection in Traditional Methods

    ○ Satellite-based fire detection systems provide large-scale coverage but suffer from delayed updates due to their fixed orbital schedules, cloud cover obstructions, and reliance on post-processing analysis.

    ○ Ground-based sensors offer real-time monitoring but have limited spatial coverage and are constrained by infrastructure availability in remote forested regions.

2. Limitations of Single-UAV Approaches

    ○ Single-UAV fire detection systems face challenges in covering vast areas efficiently, leading to increased response times.

    ○ Limited sensor perspectives from individual UAVs result in higher false positives (e.g., sunlight reflections, hot rocks) and false negatives (e.g., fires obscured by dense canopies).

    ○ Autonomous navigation in dynamic forest environments remains a challenge, as UAVs must adapt to unpredictable wind conditions, temperature variations, and communication constraints.

3. Lack of Collaborative Decision-Making in UAV Systems

    ○ Existing UAV-based fire detection methods often rely on independent decision-making, where each UAV processes its own sensor data without cross-validation.

    ○ The absence of a swarm-based consensus mechanism increases the risk of misclassification, as fire-like anomalies may trigger false alarms without multi-perspective validation.

    ○ Limited research has explored decentralized UAV networks where drones actively share fire detection data and dynamically adjust their search patterns based on shared information.

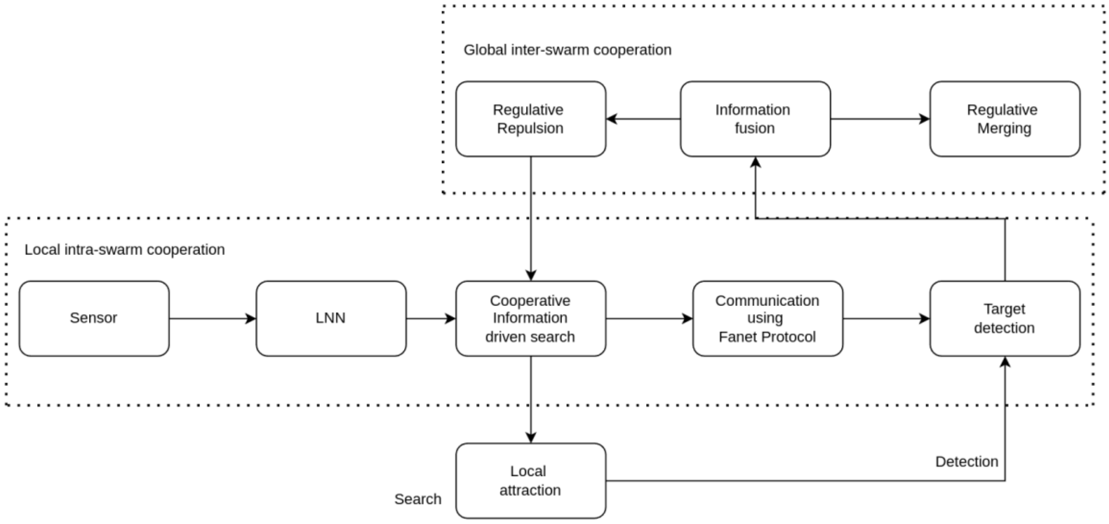
4. Energy Efficiency and Communication Challenges in UAV Swarms

    ○ UAVs have finite battery life, requiring optimized flight paths to balance exploration and energy consumption.

    ○ Many existing systems lack adaptive resource allocation strategies that ensure UAVs prioritize high-risk areas without unnecessary redundancy.

    ○ UAVs operating in forested environments face intermittent communication links due to terrain obstructions and signal interference, necessitating a robust peer-to-peer messaging system.

7 PROPOSED ARCHITECTURE:



The MSCIDC system architecture 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 Liquid 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 over- crowding and improve search efficiency.

8 METHODOLOGY:

Collaborative Search Strategy

- UAVs perform distributed exploration of the forest using predefined patterns (e.g., grid search, Levy flight).

- Each UAV carries thermal and optical sensors to detect heat signatures.

- UAVs continuously broadcast their sensor readings to nearby UAVs.

Cooperative Fire Detection & Decision Making

- Each UAV captures images of its surroundings and processes them using a Liquid Neural Network (LNN), which classifies whether a fire is present or not. When a UAV detects a possible fire based on LNN classification, it shares its findings with neighboring UAVs for collaborative verification. This reduces false detections and improves overall accuracy.

- Neighboring UAVs validate the detection by moving toward the suspected fire and analyzing it from different perspectives.

- The system uses collaborative decision-making (e.g., majority voting, weighted confidence scores) to confirm the fire before flagging it as an emergency.

Communication and Consensus

- UAVs use localized communication to share temperature readings and detection probabilities.

- A UAV does not flag a fire unless at least a threshold number of UAVs confirm it within a specified time window.

- Decision-making follows a distributed consensus algorithm to ensure robustness against noise and sensor errors.

9 NOVELTY:

The main contributions of the paper are:

1. An edge-based architecture for reliable forest fire detection using UAV swarms is proposed.
2. A novel consensus-based MSCIDC algorithm enhances detection accuracy and minimizes false positives.
3. A collaborative UAV algorithm (using LNN) detects and confirms fires using cameras, thermal imaging, and temperature sensors.
4. 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.

Feature	**Independent Drones**	**Collaborative Decision**
False Alarm Handling	Higher risk of false positives	Reduces false alarms by requiring multiple UAVs to validate a detection.
Fire Verification	Single UAV reports a fire as soon as its sensor triggers a threshold.	UAVs first use an onboard Liquid Neural Network (LNN) to classify fire presence in captured images. Then, they cross-check fire data from multiple perspectives before confirming. This approach ensures

		adaptive learning, allowing UAVs to improve detection accuracy over time.

Consensus-based decision-making minimizes false positives and improves detection reliability.

Feature	**Independent Drones**	**Collaborative Decision**
Information Exchange	No sharing—each UAV only uses its own sensor data.	UAVs communicate and share temperature gradients, detection probabilities, and sensor confidence scores.
Sensor Fusion	Limited to one UAV's perspective at a time.	Aggregates data from multiple UAVs for more accurate fire localization.
Handling Partial Visibility	If a fire is partially obscured (e.g., by trees, smoke), a UAV might fail to detect it.	Other UAVs in different positions can validate and confirm detection.

Data fusion from multiple drones enhances accuracy and prevents missing fires in obstructed areas.

Feature	**Independent Drones**	**Collaborative Decision**
Search Pattern	Each UAV searches independently using a fixed or random pattern.	UAVs adapt their search based on shared information (e.g., more drones focus on high-risk areas).
Swarm Adaptability	No coordination—each UAV continues scanning its assigned zone.	If fire probability increases in one area, more UAVs can be dynamically reassigned for validation.
Redundancy	Drones might scan the same area unnecessarily, leading to wasted energy.	Reduces redundant scanning by intelligently directing UAVs to

		unexplored/high-risk zones.

Dynamic reallocation of UAVs based on shared data makes detection faster and more efficient.

Feature	**Independent Drones**	**Collaborative Decision**
Failure Handling	If one UAV malfunctions, its fire detections are lost.	Other UAVs compensate for a failed unit by sharing its last-known data.
Communication Dependency	Doesn’t require inter-UAV communication but lacks coordination.	Works even with partial communication loss by relying on local peer-to-peer messaging.

System remains effective even with UAV failures or partial communication breakdowns.

Feature	Independent Drones	Collaborative Decision
Fire Detection Criteria	If a UAV detects a high-temperature zone, it immediately reports a fire.	Each detection is assigned a probability score, and fires are only confirmed if multiple UAVs agree.
Confidence Level	No explicit confidence metric; relies only on sensor thresholds	Uses weighted confidence models (e.g., Bayesian update, sensor reliability scores) to make decisions.

Incorporating confidence levels reduces errors and ensures only high-probability fires are flagged.

Feature	Independent Drones	Collaborative Decision
Battery Usage	Drones might revisit the same areas unnecessarily, wasting energy.	Optimized task allocation ensures UAVs cover more

		ground without overlap.
Search Efficiency	Fixed search patterns may result in slow response time.	Adaptive search strategies (e.g., focusing more drones on high-risk zones) improve efficiency.

10 IMPLEMENTATION:

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 L´evy 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.

where Pi: detection probability from Eq. (8) in, SNR: signal-to-noise ratio.The fire detection consensus is determined by aggregating individual UAV predictions Pi, 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 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^k_j and sensed temperature Ts. If no fire is detected ($P^k_j < \gamma$), the swarm switches between cooperative exploration or exploitation depending on the temperature gradient, enhancing search efficiency. Upon fire detection ($P^k_j \geq \gamma$), 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 behaviours are triggered: if fire area (A_j) or flame rate (F_r) criteria are satisfied, and sufficient UAVs are available (N^j_{qu} 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:

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

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 $U(-\delta_\theta, \delta_\theta)$ 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.

SIMULATION SETUP:

The proposed approach is evaluated through detailed simulations conducted in a controlled environment. The simulation parameters and setup are as follows:

Environment:

A 10km×10km area is considered for the operation, containing five fire locations—two circular and three elliptical in shape.

Swarm Configuration:

A total of 15 UAVs are deployed, organized into seven swarms with the following sizes:

[3, 2, 2, 2, 2, 2, 2]. Each swarm operates semi-independently during the mission while coordinating during critical phases.

Flight Dynamics:

- Search Phase: Each UAV maintains a constant speed of 20m/s while searching for fire locations.
- Mitigation Phase: UAV speed is dynamically adjusted based on the size and spread of the detected fire to optimize water deployment and fire containment efficiency.

Starting Positions:

UAVs are initialized at different locations within the environment to ensure widespread coverage and to emulate realistic deployment scenarios.

Simulation Environment:

All simulations are conducted using MATLAB R2021a, ensuring a controlled and reproducible experimental framework.

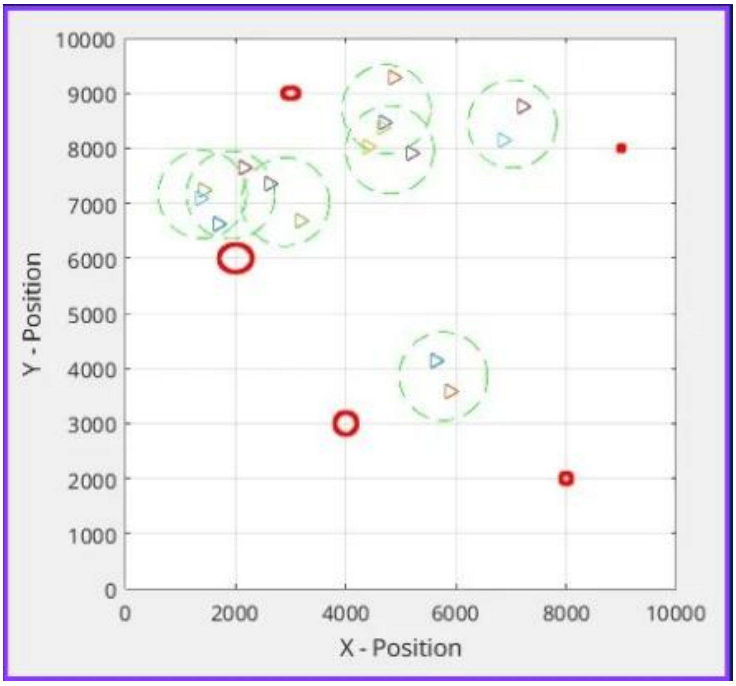
Performance Metrics:

- Detection Time: The total time taken to successfully identify all fire locations within the environment.
- Mission Time: The total duration from mission start until the complete mitigation of all detected fires.
- Fire Expansion Ratio (FER): A critical metric that measures the proportional increase in burnt area between the initial fire state and the mission's conclusion.

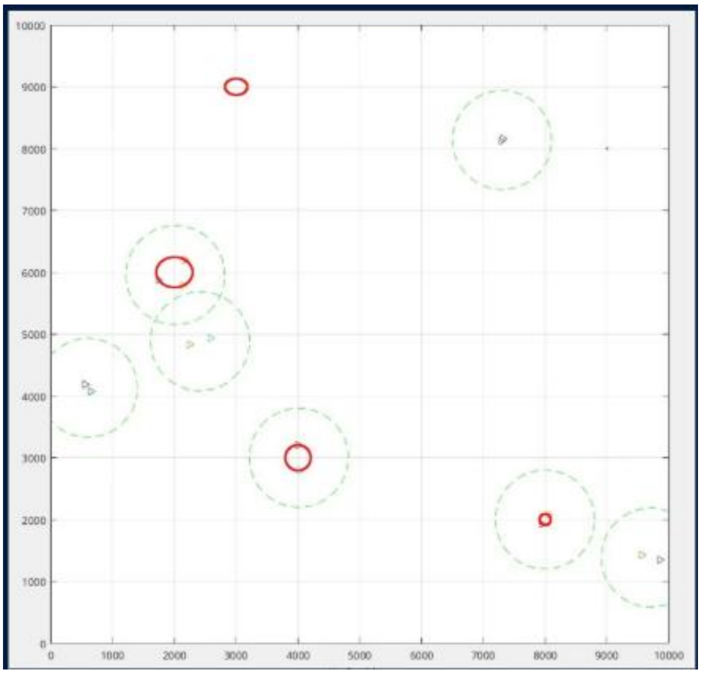
FIRE LOCATIONS AND INITIAL SIZE

Sl.No	C_{f_j} (m)	a_j (m)	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

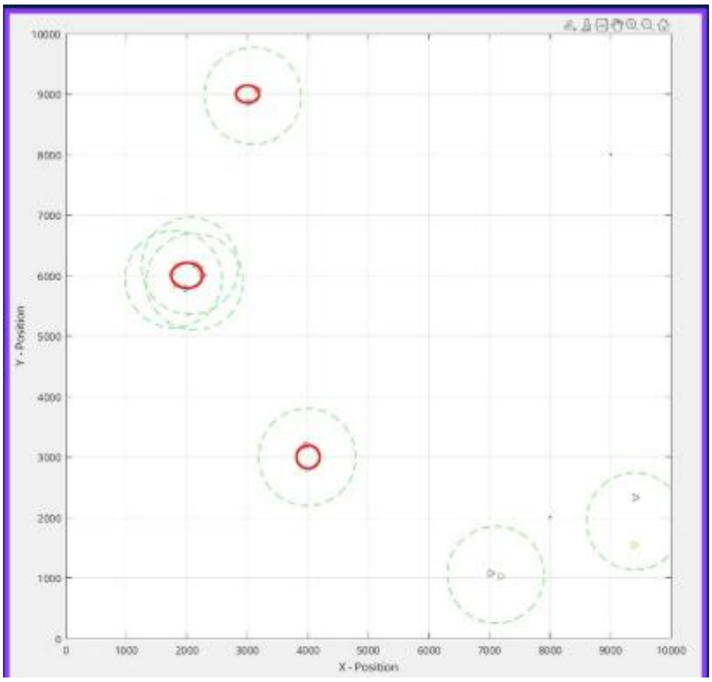
(a) All swarms performing cooperative information-driven search task



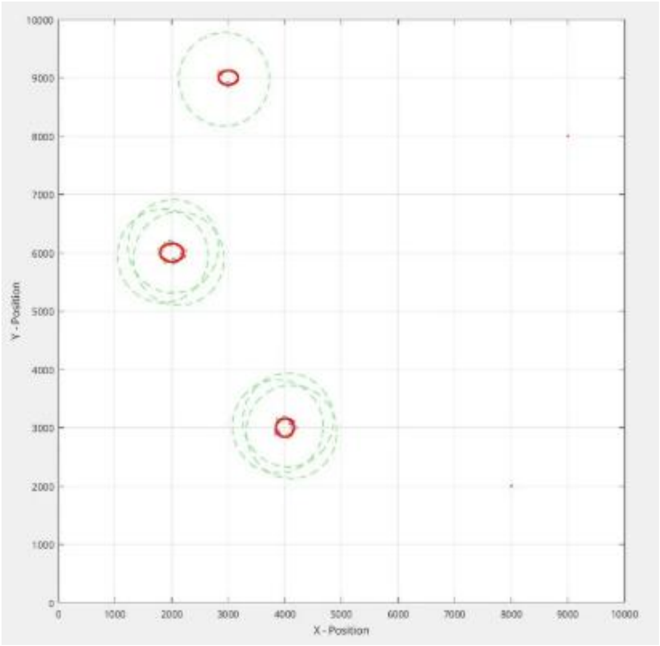
(b) Swarms detect fire and initiate local attraction



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



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



LNN Model:

LNN Model training:

```
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 181MB/s]
Epoch [1/30], Loss: 0.3303
Epoch [2/30], Loss: 0.2018
Epoch [3/30], Loss: 0.2479
Epoch [4/30], Loss: 0.2900
Epoch [5/30], Loss: 0.3104
Epoch [6/30], Loss: 0.1999
Epoch [7/30], Loss: 0.2740
Epoch [8/30], Loss: 0.2045
Epoch [9/30], Loss: 0.2168
Epoch [10/30], Loss: 0.1997
Epoch [11/30], Loss: 0.2145
Epoch [12/30], Loss: 0.1996
Epoch [13/30], Loss: 0.1992
Epoch [14/30], Loss: 0.1987
Epoch [15/30], Loss: 0.1988
Epoch [16/30], Loss: 0.1985
Epoch [17/30], Loss: 0.1990
Epoch [18/30], Loss: 0.1986
Epoch [19/30], Loss: 0.2038
Epoch [20/30], Loss: 0.2467
Epoch [21/30], Loss: 0.2757
Epoch [22/30], Loss: 0.1987
Epoch [23/30], Loss: 0.1985
Epoch [24/30], Loss: 0.1986
Epoch [25/30], Loss: 0.2022
Epoch [26/30], Loss: 0.1985
Epoch [27/30], Loss: 0.1985
Epoch [28/30], Loss: 0.1987
Epoch [29/30], Loss: 0.1991
Epoch [30/30], Loss: 0.2015
Test Accuracy: 0.9868
```

LNN MODEL TESTING:

```
Processing test1.jpg...
Prediction: fire (Confidence: 95.02%)
Processing test2.jpg...
Prediction: fire (Confidence: 95.02%)
Processing test3.jpg...
Prediction: fire (Confidence: 95.02%)
Processing test4.jpg...
Prediction: fire (Confidence: 95.02%)
Processing test5.jpg...
Prediction: fire (Confidence: 90.06%)
Processing test6.jpg...
Prediction: nofire (Confidence: 95.14%)
Processing test7.jpg...
Prediction: nofire (Confidence: 95.02%)
Processing test8.jpg...
Prediction: nofire (Confidence: 94.99%)
Processing test9.jpg...
Prediction: fire (Confidence: 81.64%)
Processing test10.jpg...
Prediction: nofire (Confidence: 95.18%)
Total prediction Time for 5 images: 0.63 seconds
Total Execution Time from start to end: 5.86 seconds
Execution ended
```

The testing results of the Liquid 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.

11 RESULTS:

Performance of MSC-IDC for Different Swarm Numbers:

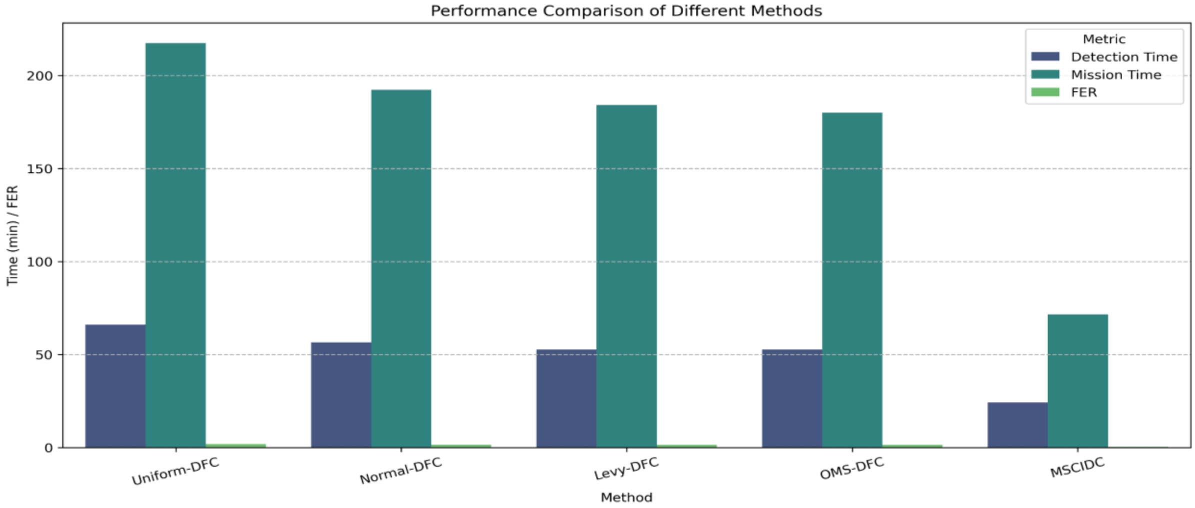
Number of Swarms	Mean Detection Time (min)	Mean Mission Time (min)	Mean FER
3	41.82	107.01	1.029
5	31.03	81.19	0.642
6	27.59	83.27	0.550
7	24.13	71.56	0.477

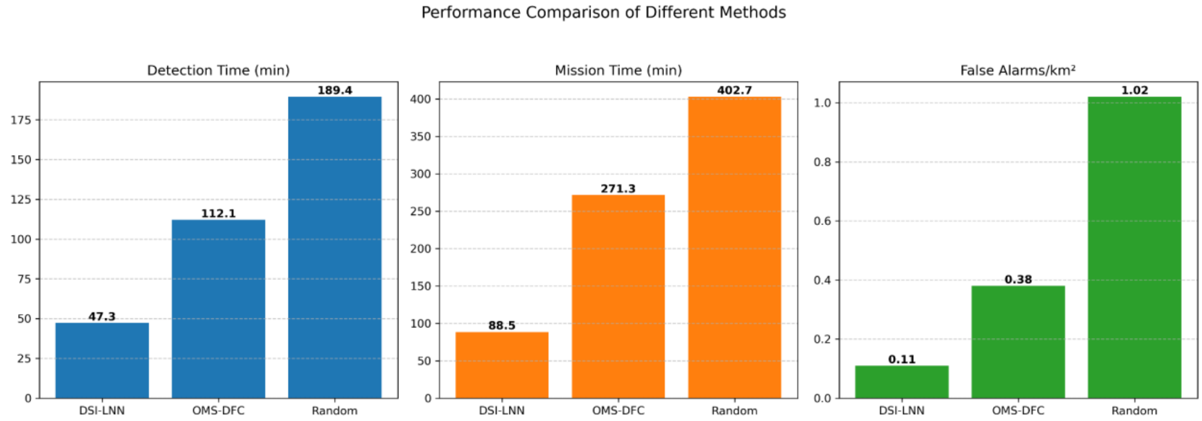
Comparison of Different Models:

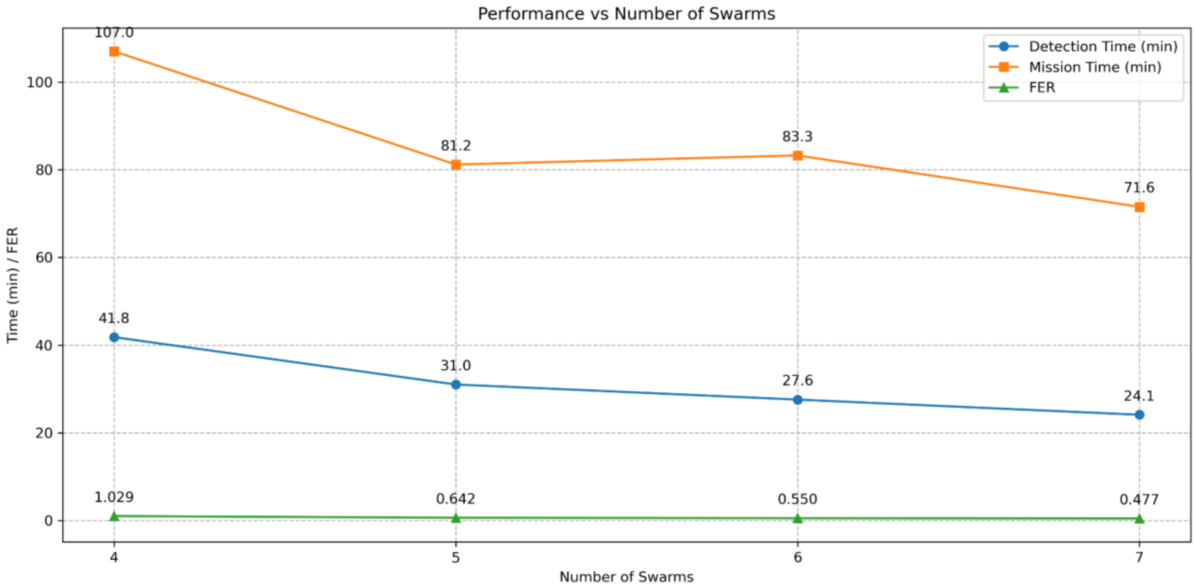
Model	Accuracy	No. of Parameters	Size
MobileNet v2	95.17%	3.4M	~14 MB
Inception ResNet v2	97.81%	55.9M	~215 MB
Custom CNN	96.92%	300K	~1.39 MB
LNN	98.95%	11.5M	~22 MB

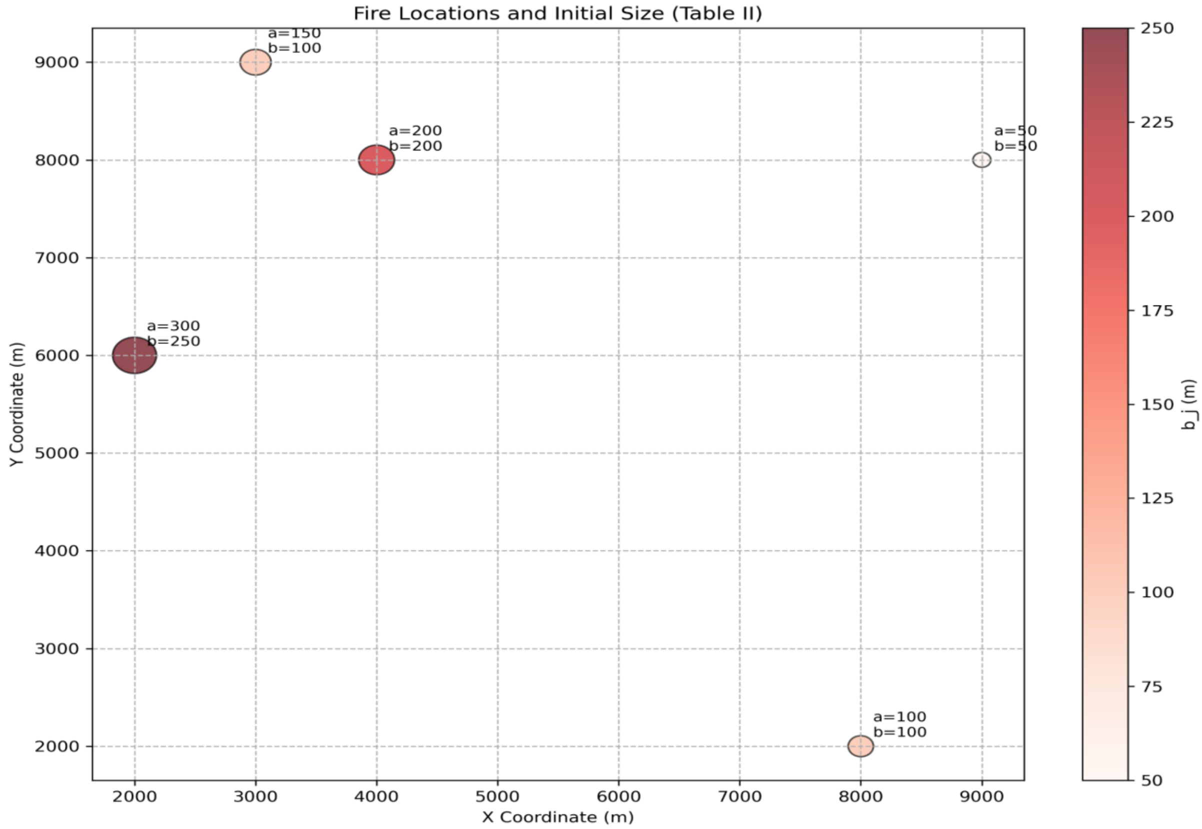
Performance Comparison for Different Methods of Forest Detection:

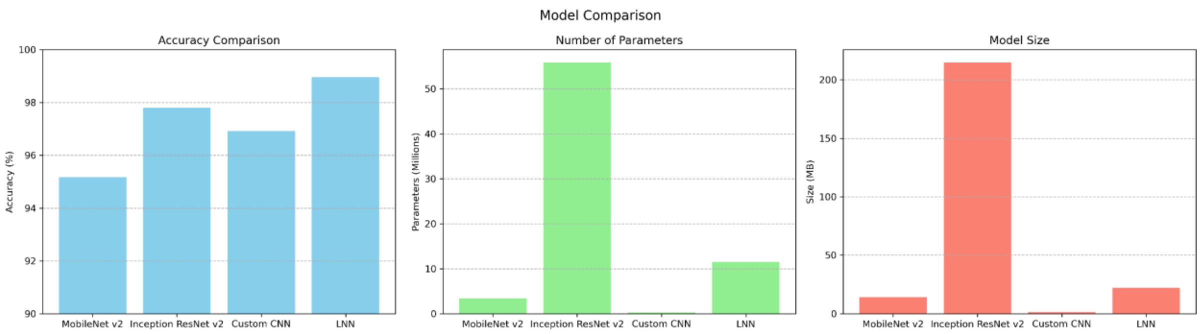
Method	Mean Detection Time (min)	Mean Mission Time (min)	Mean FER
Uniform-DFC	66.10	217.47	1.808
Normal-DFC	56.63	192.39	1.518
Levy-DFC	52.59	184.14	1.398
OMS-DFC	52.63	180.11	1.319
MSCIDC	24.13	71.56	0.477


Performance Comparison of Different Methods
Metric
Detection Time
Mission Time
FER
Time (min) / FER
0
50
100
150
200
Uniform-DFC
Normal-DFC
Levy-DFC
OMS-DFC
MSCIDC
Method


Performance Comparison of Different Methods
Detection Time (min)
47.3
112.1
189.4
DSI-LNN
OMS-DFC
Random
Mission Time (min)
88.5
271.3
402.7
DSI-LNN
OMS-DFC
Random
False Alarms/km²
0.11
0.38
1.02
DSI-LNN
OMS-DFC
Random


Performance vs Number of Swarms
Detection Time (min)
Mission Time (min)
FER
107.0
81.2
83.3
71.6
41.8
31.0
27.6
24.1
1.029
0.642
0.550
0.477
Time (min) / FER
Number of Swarms


Fire Locations and Initial Size (Table II)
a=150
b=100
a=200
b=200
a=50
b=50
a=300
b=250
a=100
b=100
Y Coordinate (m)
X Coordinate (m)
b_j (m)


Model Comparison
Accuracy Comparison
Accuracy (%)
Number of Parameters
Parameters (Millions)
Model Size
Size (MB)
MobileNet v2
Inception ResNet v2
Custom CNN
LNN

The comparative analysis clearly demonstrates that among the traditional multi-UAV methods, OMS-DFC achieves the best balance between detection efficiency and fire containment, recording a mean mission time of 180.11 minutes and a mean FER of 1.319. However, the proposed MSCIDC framework significantly outperforms all existing methods, achieving a reduction of approximately 65% in burned area and 60% in mission time compared to OMS-DFC. Specifically, in a representative simulation run, MSCIDC limits the final burned area to 0.6654 km^2 with a FER of 0.48, compared to 0.9295 km^2 and a FER of 1.07 in the OMS-DFC approach. Furthermore, the box plot analysis reveals that MSCIDC not only achieves lower median detection and mission times but also exhibits substantially less variability in performance, indicating higher robustness and consistency across different operational scenarios. These results validate the effectiveness of cooperative swarm behavior, dynamic formation merging, and distributed information sharing strategies incorporated in the proposed system.

Performance of MSC-IDC for Different Swarm Numbers:

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.

12 SUMMARY:

The proposed Collaborative UAV-Based Forest Fire Detection Using Swarm Intelligence was evaluated in a simulated forest environment with multiple UAVs operating under dynamic climatic conditions. By leveraging Liquid Neural Networks (LNNs), the UAVs classified fire presence in real-time using captured images, dynamically adjusting fire detection probabilities based on temperature, and humidity. The LNN-based classification significantly improved early detection rates and allowed UAVs to prioritize high-risk areas, enhancing system efficiency, allowing for adaptive decision-making in uncertain environments. Additionally, UAVs utilized a reactive FANET (Flying Ad Hoc Network) protocol to ensure robust, low-latency communication, enabling effective collaboration and decentralized decision-making. The simulation results demonstrated that the proposed approach significantly reduced fire detection time compared to conventional independent UAV methods. The integration of LNNs allowed UAVs to prioritize high-risk areas, improving overall efficiency. Furthermore, the decentralized nature of the system ensured scalability and robustness, making it a viable solution for real-world wildfire detection applications.

13 FUTURE WORK:

While the proposed Collaborative UAV-Based Forest Fire Detection Using Swarm Intelligence enhances fire detection accuracy and adaptability, several areas remain open for further improvement. Future work will focus on optimizing resource allocation and energy efficiency, ensuring that UAVs dynamically adjust their flight paths and sensing schedules based on battery constraints and environmental factors. Additionally, Further improvements to the Liquid Neural Network (LNN) will be explored, such as training on more diverse environmental conditions (e.g., different vegetation types, varying smoke densities) to improve classification robustness. Additionally, integrating multi-modal sensor fusion—combining LNN-based image classification with thermal and weather data—could further enhance fire detection reliability and adjust UAV search strategies accordingly. Real-world implementation and testing in diverse terrains and varying climatic conditions will be explored to validate the system's robustness and scalability. Finally, extending the approach to include autonomous fire mitigation strategies, such as UAV-guided water spraying or fire-retardant dispersal, could create a comprehensive wildfire management system.

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