Project Notes:

Project Title: An Unmanned Aerial Vehicle Module for Wildfire Detection with Image Recognition
Name: Samantha Wang

Note Well: There are NO SHORT-cuts to reading journal articles and taking notes from them. Comprehension is paramount. You will most likely need to read it several times, so set aside enough time in your schedule.

Contents:

Knowledge Gaps:

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved

Literature Search Parameters:

These searches were performed between (Start Date of reading) and XX/XX/2019.
List of keywords and databases used during this project.

Database/search engine	Keywords	Summary of search

Tags:

Tag Name	

Article #1 Notes: Title

Article notes should be on separate sheets

KEEP THIS BLANK AND USE AS A TEMPLATE

Source Title	
Source citation (APA Format)	
Original URL	
Source type	
Keywords	
#Tags	
Summary of key points + notes (include methodology)	
Research Question/Problem/ Need	
Important Figures	
VOCAB: (w/definition)	
Cited references to follow up on	
Follow up Questions	

Article #1 Notes: MXene artificial muscles based on ionically cross-linked Ti3C2Tx electrode for kinetic soft robotics

Article notes should be on separate sheets

Source Title	**MXene artificial muscles based on ionically cross-linked Ti3C2Tx electrode for kinetic soft robotics**
Source citation (APA Format)	Umrao, S., Tabassian, R., Kim, J., Nguyen, V. H., Zhou, Q., Nam, S., & Oh, I.-K. (2019). MXene artificial muscles based on ionically cross-linked Ti3C2Tx electrode for kinetic soft robotics. *Science Robotics*, *4*(33), eaaw7797. https://doi.org/10.1126/scirobotics.aaw7797
Original URL	https://www.science.org/doi/10.1126/scirobotics.aaw7797
Source type	Research article
Keywords	Soft robots, actuators, electrode
#Tags	Robotics, automation, mechanical, biomimicry
Summary of key points + notes (include methodology)	The article describes the development of a new type of artificial muscle made from MXene, a two-dimensional material with a high bending strain and a fast response speed. MXene artificial muscles have the potential to make soft robots more powerful, agile, and responsive. They successfully applied the artificial muscle to make a wearable robot and a kinetic art piece.
Research Question/Problem/ Need	*How does MXene perform when used for soft robotics as an artificial muscle?*
Important Figures	
VOCAB: (w/definition)	
Cited references to follow up on	
Follow up Questions	1. What kind of force can MXene artificial muscles apply? 2. How much voltage variation can MXene materials withstand? 3. Are the MXene artificial muscles consistent throughout environmental changes?

Article #2 Notes: Sunlight-powered self-excited oscillators for sustainable autonomous soft robotics

Article notes should be on separate sheets

Source Title	**Sunlight-powered self-excited oscillators for sustainable autonomous soft robotics**
Source citation (APA Format)	Zhao, Y., Li, Q., Liu, Z., Alsaid, Y., Shi, P., Khalid Jawed, M., & He, X. (2023). Sunlight-powered self-excited oscillators for sustainable autonomous soft robotics. *Science Robotics*, *8*(77), eadf4753. https://doi.org/10.1126/scirobotics.adf4753
Original URL	https://www.science.org/doi/10.1126/scirobotics.adf4753
Source type	Research article
Keywords	Soft robots, self-excited, polymer
#Tags	Robotics, automation, mechanical, sustainable
Summary of key points + notes (include methodology)	The article presents a new design for soft robots that are made of a polymer that transforms light to heat effectively, is very flexible, and responds to changes in the environment rapidly. This allows the robots to oscillate under sunlight, which can be used to power their movement. The authors demonstrated the feasibility of their design by creating a small robot called the "LiLBot" that can be used as an actuator in larger mechanisms.
Research Question/Problem/ Need	*Does this new design of a light-driven robot have potential in autonomous robotics?*

Important Figures

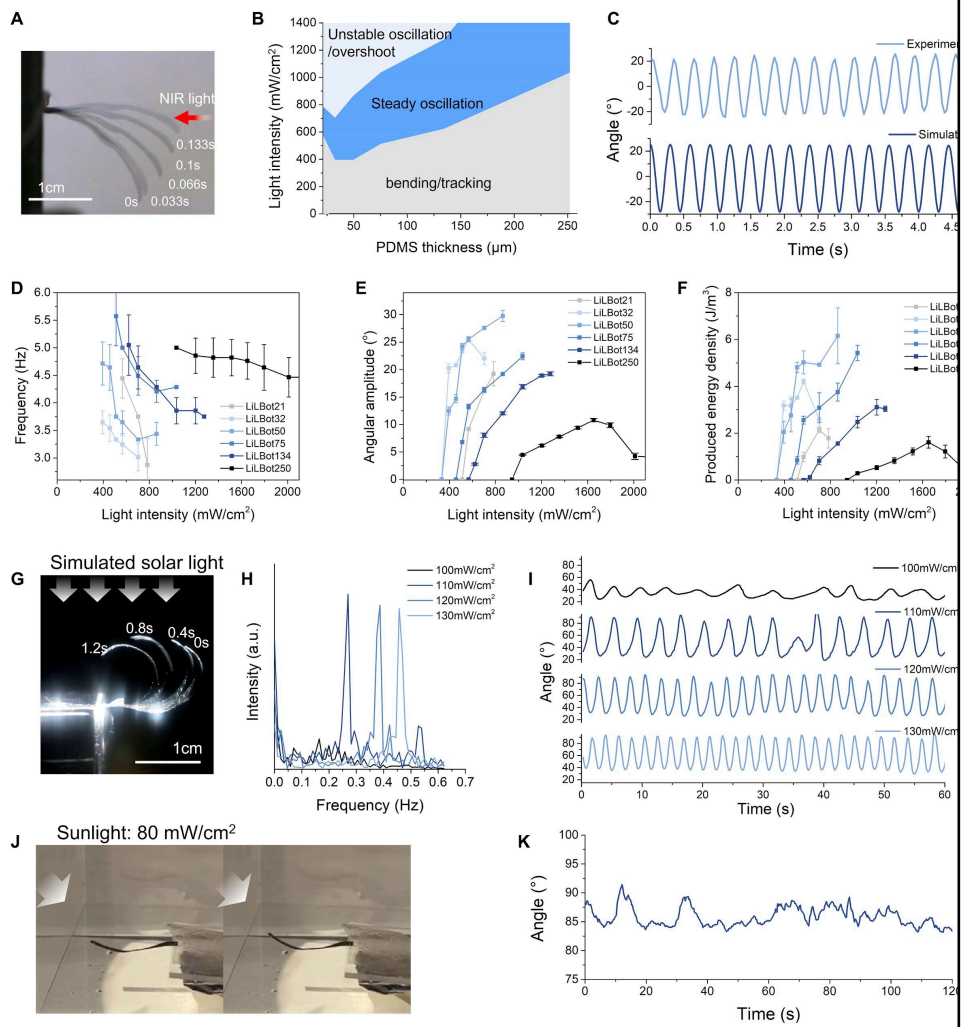


Fig. 2. Characterization of LiLBot.

(**A**) Superimposed sequential snapshots of the oscillator during a half oscillation cycle using a horizontal illumination mode. (**B**) Oscillation operation window with respect to different PDMS thicknesses and light intensities. (**C**) Comparison of simulation and experimental results. PDMS thickness of 50 µm, length of 2.2 cm, and NIR light intensity of 700 mW cm-2. (**D** to **F**) Frequency changes, angular amplitude changes, and produced energy densities of oscillation at different light intensities using a horizontal illumination mode. The error bars represent the SDs of the mean values obtained from five different measurements. (**G** to **I**) Superimposed sequential snapshots, angle changes, and frequencies of oscillation powered by a solar simulator using a vertical illumination mode. Light intensity in (G) is 130 mW cm-2, and those in (H) and (I) range from 100 to 130 mW cm-2. *Y* axis in (H) is the Fourier transform intensity of frequency. (**J** and **K**) Superimposed sequential snapshots and angle changes of oscillation powered by natural sunlight (light intensity of 80 mW cm-2).

Specific conditions that the robot operates under

	Note light frequency + intensity and material thickness
VOCAB: (w/definition)	Photothermal Conversion: the ability of the material to efficiently convert sunlight into heat Storage and Loss Modulus: properties that describe how a material stores and dissipates energy when subjected to mechanical forces Material Responsiveness: how quickly materials can respond to changes in external conditions
Cited references to follow up on	C. Laschi, B. Mazzolai, M. Cianchetti, Soft robotics: Technologies and systems pushing the boundaries of robot abilities. *Sci. Robot.* **1**, eaah3690 (2016). Y. Zhai, T. N. Ng, Self-sustained robots based on functionally graded elastomeric actuators carrying up to 22 times their body weight. *Adv. Intell. Syst.* **2100085**, 2100085 (2021). X. Q. Wang, C. F. Tan, K. H. Chan, X. Lu, L. Zhu, S. W. Kim, G. W. Ho, In-built thermo-mechanical cooperative feedback mechanism for self-propelled multimodal locomotion and electricity generation. *Nat. Commun.* **9**, 3438 (2018).
Follow up Questions	1. How far up in size can this robot be scaled? 2. Can differently shaped robots produce the same result? 3. Are there other materials that might react to similar energy sources in the same way?

Article #3 Notes: Image fire detection algorithms based on convolutional neural networks

Article notes should be on separate sheets

Source Title	Image fire detection algorithms based on convolutional neural networks
Source citation (APA Format)	Li, P., & Zhao, W. (2020). Image fire detection algorithms based on convolutional neural networks. *Case Studies in Thermal Engineering*, *19*, 100625. https://doi.org/10.1016/j.csite.2020.100625
Original URL	https://www.sciencedirect.com/science/article/pii/S2214157X2030085X
Source type	Research article
Keywords	Image recognition, object detection, neural networks, fire detection, algorithms
#Tags	fire, yolo (v3)
Summary of key points + notes (include methodology)	1. Advantages a. Over traditional methods (smoke/heat detectors) i. early fire detection, high accuracy, flexible system installation, and the capability to effectively detect fires in large spaces and complex building structures b. Over existing algorithms i. only use image classification (categorizing the entire image as “fire” or “no fire” as opposed to identifying where the fire is in the image) ii. leads to decreased accuracy if the fire is only visible in a small part of the image 2. Process a. Image preprocessing i. Editing images in dataset to have consistent size, pixel values, etc. with each other b. Feature extraction i. Extracting features such as the presence of certain patterns or textures in the image c. Fire detection - core component i. Done with tools such as support vector machines, random forests, and CNNs (the topic of this article) ii. CNN architecture 1. Input layer - receives image/video data 2. Convolutional layer - applies filters to sections of image, assigning value based on features

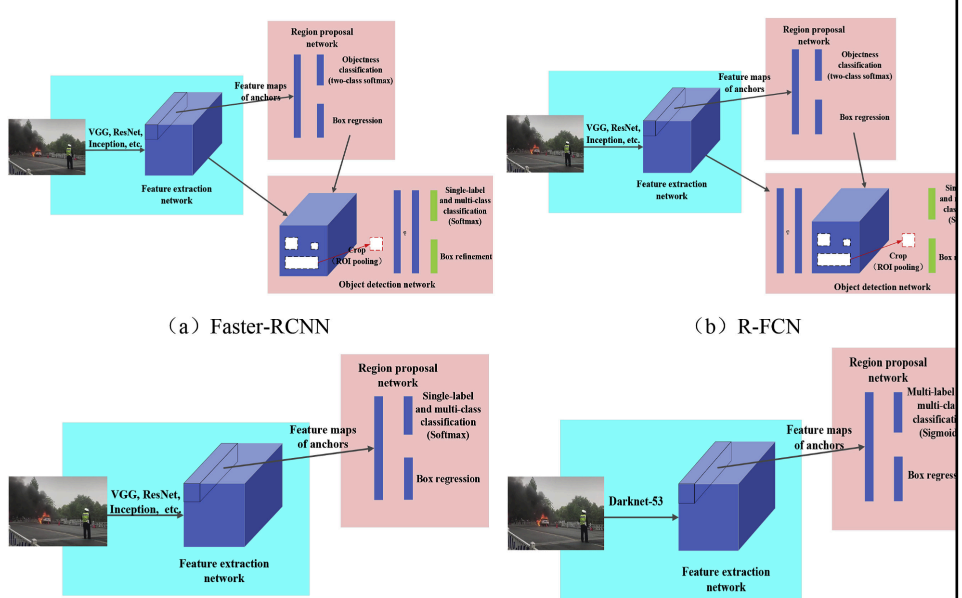
3. Pooling layer - reduce dimensionality of data, extracts only most important features from convolutional layers
4. Fully-connected layer - classify features using a probability distribution
5. Output layer - outputs final prediction based on probability values of features in data

3. What was tested
4. ***duplication of data
    a. Dataset of 29180 images taken from multiple databases
        i. Existing datasets are too small to sufficiently train models
    b. 4 different CNN architectures
        i. Faster-RCNN (Faster Regions With CNN Features)
            1. Stage 1: Region proposal generation
            2. In the first stage, Faster-RCNN uses a feature extraction network to generate feature maps of the input image. The feature extraction network is typically a pre-trained CNN, such as VGG or ResNet.
            3. Faster-RCNN then uses a Region Proposal Network (RPN) to predict region proposals from the feature maps. The RPN is a small CNN that is trained to predict objectness scores and bounding box locations. The objectness score indicates how likely it is that a region proposal contains an object.
            4. The RPN outputs a large number of region proposals, typically several thousand. The region proposals are then ranked based on their objectness scores, and the top scoring region proposals are selected for the second stage.
            5. Stage 2: Object classification and bounding box refinement
            6. In the second stage, Faster-RCNN classifies the region proposals from the first stage and refines their bounding boxes.
            7. To classify the region proposals, Faster-RCNN crops features from the same intermediate feature map that was used to generate the region proposals. This is done using ROI pooling. ROI pooling is a technique that allows Faster-RCNN to extract features from regions of different sizes.
            8. The extracted features are then fed to a fully connected network to predict class-specific scores. The class-specific scores indicate the probability that a region proposal belongs to a particular object class.

9. Faster-RCNN also uses a bounding box regression layer to refine the bounding boxes of the region proposals. The bounding box regression layer predicts the offset between the predicted bounding box and the ground truth bounding box.
10. Sharing computation
11. One of the key advantages of Faster-RCNN is that it shares computation between the two stages. In particular, the feature extraction network is shared between the two stages. This allows Faster-RCNN to be much faster than other two-stage object detection algorithms, such as R-CNN.
12. Speed
13. The detection speed of Faster-RCNN depends on the number of proposal regions from the RPN. The more proposal regions there are, the slower Faster-RCNN will be. However, Faster-RCNN is still significantly faster than other two-stage object detection algorithms, such as R-CNN.

ii. R-FCN (Region-based Fully Convolutional Network)
iii. SSD (Single-Shot Multibox Detector)
iv. YOLOv3 (You Only Look Once Version 3)

1. Small object detection superiority
    a. Small objects are less sensitive to translation, which makes them harder to localize
    b. They also produce less complex features, which makes them difficult to distinguish
2. Down and up sampling
3. Also concats instead of just adding feature maps
4. Independent functions for multilabeling, which increase accuracy when objects of different classes appear simultaneously
    a. Using a residual network architecture: A residual network architecture allows YOLO v3 to extract complex features from small feature maps.
    b. Using a multi-scale feature pyramid: YOLO v3 uses a multi-scale feature pyramid to detect objects at different scales. The multi-scale feature pyramid consists of three feature maps at different scales: 8, 16, and 32 times down sampled from the original image.
    c. The feature maps at different scales are used to detect objects at different sizes.

<table>
<tr><td></td><td>The smaller feature maps are used to detect larger objects, while the larger feature maps are used to detect smaller objects.
d. YOLO v3 also uses a technique called feature concatenation to combine the information from the different feature maps. Feature concatenation allows YOLO v3 to combine the location information from the smaller feature maps with the complex features from the larger feature maps.
e. The multi-scale feature pyramid is a technique that is used to combine feature maps at different scales. This is done by up sampling the smaller feature maps and concatenating them with the larger feature maps.
f. The up sampling process allows YOLO v3 to maintain the location information of the original image. The concatenation process allows YOLO v3 to combine the location information from the smaller feature maps with the complex features from the larger feature maps.</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>Can convolutional neural networks be used to develop an optimized fire detection algorithm?</td></tr>
<tr><td>Important Figures</td><td>

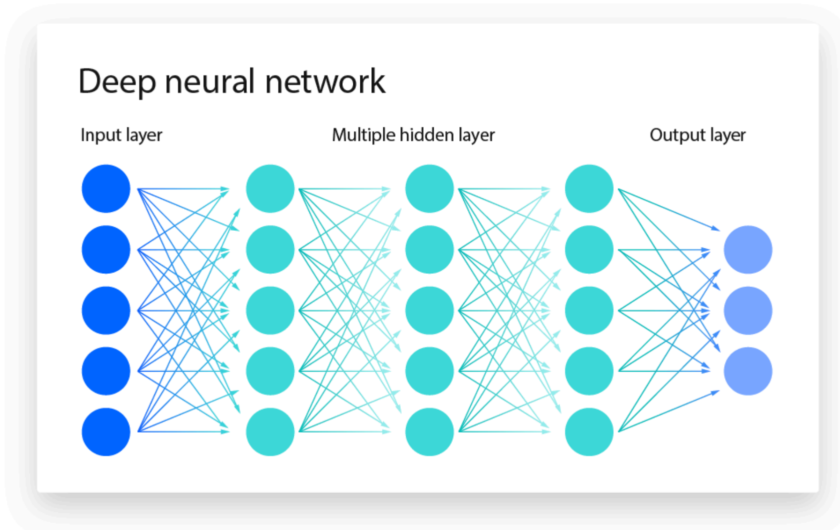
(a) Faster-RCNN (b) R-FCN (c) SSD (d) YOLO v3</td></tr>
</table>

	Diagrams of 4 different network architectures tested in the study
VOCAB: (w/definition)	down/up sampling - changing resolution of feature maps for different types of features Multi-scale feature pyramid - feature maps downsampled by 8,16,32x to detect differently sized objects Residual network architecture - concatenates feature maps in order to retain dimensionality of data, allowing for detection of more complex features
Cited references to follow up on	Real-time fire detection for video-surveillance applications using a combination of experts based on color, shape, and motion
Follow up Questions	What causes the major differences between CNN architectures? How are different CNN architectures optimized for different tasks?

Article #4 Notes: What are Neural Networks?

Article notes should be on separate sheets

Source Title	What are Neural Networks?
Source citation (APA Format)	*What are Neural Networks? | IBM*. (n.d.). Retrieved November 10, 2023, from https://www.ibm.com/topics/neural-networks
Original URL	https://www.ibm.com/topics/neural-networks
Source type	General article
Keywords	Neural network, deep learning, machine learning, artificial intelligence
#Tags	Ai, cnn
Summary of key points + notes (include methodology)	Neural networks ● Type of machine learning ● Structure is similar to a human brain ● If the output of any node is over a threshold, it is activated and sends information to the next layer ● Uses training data to learn and improve accuracy ● Can classify data once trained ● Speech recognition and image recognition can be done with neural networks ● Convolutional neural networks are used for image recognition ● Recurrent neural networks use temporal data for future outcomes Components and processes ● Nodes and layers ● Forward propagation ● Back propagation ● Gradient descent ● Weights and biases ● Activation function Training ● Use training data to learn and improve accuracy ● Calculate the error from prediction to actual outcome ● Adjust parameters accordingly Applications ● Image recognition ● Speech recognition ● Natural language processing ● Machine translation ● Medical diagnosis ● Fraud detection

	• Many other AI tasks
Research Question/Problem/ Need	What are neural networks?
Important Figures	 Diagram of a deep neural network (many layers)
VOCAB: (w/definition)	Activation function - node fires if output meets a certain threshold Gradient descent - optimization of function Backpropagation - adjusts function based on error
Cited references to follow up on	https://developer.ibm.com/articles/l-neural/ Pattern learning with backpropagation
Follow up Questions	How do neural networks process images? How deep should a neural network be when performing object detection? Are there different types of layers?

Article #5 Notes: TPH-YOLOv5++: Boosting Object Detection on Drone-Captured Scenarios with Cross-Layer Asymmetric Transformer

Article notes should be on separate sheets

Source Title	TPH-YOLOv5++: Boosting Object Detection on Drone-Captured Scenarios with Cross-Layer Asymmetric Transformer
Source citation (APA Format)	Zhao, Q., Liu, B., Lyu, S., Wang, C., & Zhang, H. (2023). TPH-YOLOv5++: Boosting Object Detection on Drone-Captured Scenarios with Cross-Layer Asymmetric Transformer. *Remote Sensing*, *15*(6), Article 6. https://doi.org/10.3390/rs15061687
Original URL	https://www.mdpi.com/2072-4292/15/6/1687
Source type	Research article
Keywords	Drone, image recognition, object detection, neural networks
#Tags	yolo
Summary of key points + notes (include methodology)	Drone-captured images are challenging for object detection due to a number of factors, including: **Low resolution**: Drone-captured images are often low resolution, making it difficult to distinguish small objects. **Obstruction**: Objects in drone-captured images are often obstruction by other objects, making it difficult to detect them. **Background clutter**: Drone-captured images often have complex backgrounds, which can make it difficult to distinguish objects from the background. **Methods** TPH-YOLOv5 and TPH-YOLOv5++ (Transformer Prediction Head YOLOv5) two-phase hybrid models that combine the advantages of one-stage and two-stage object detectors The first phase is based on the anchor-free head of YOLOv5 The anchor-free head is a lightweight network that predicts the bounding boxes of objects starting from the center of the object, instead of the corners Feature extraction -> bounding box proposal The second phase is based on the RetinaNet architecture

RetinaNet is a two-stage object detector that uses a focal loss function to address the problem of class imbalance
Focal loss function - weights less common classes more and more common classes less
Used in the case where datasets are imbalanced
Classification head -> regression head
Proposal class prediction -> refined bounding boxes

Improvements
inserted into the classification and regression phases

Cross-layer asymmetric transformer (CAT)
composed of two parts: a cross-layer attention module and an asymmetric transformer encoder.

The cross-layer attention module allows the model to learn long-range dependencies between features at different layers.
Assigns attention weights to features based on importance in previous to current layers

The asymmetric transformer encoder is a lightweight transformer encoder that is specifically designed for object detection.
Takes features from the previous layer and attention weights and outputs a new set of features that take into account the long-range dependencies between features at different layers

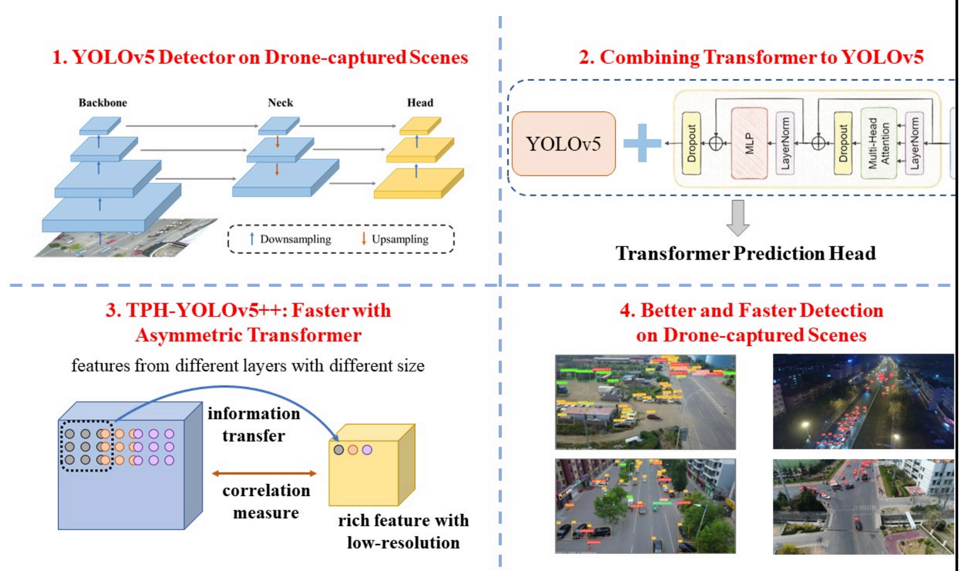
Pyramid feature fusion (PFF)
composed of two parts: a top-down pathway and a bottom-up pathway.

The top-down pathway fuses features with less complex features from lower layers

The bottom-up pathway fuses features with more complex features from higher layers

Experimental results
two datasets: VisDrone2021 and UAVDT.
VisDrone2021 is a large-scale dataset of drone-captured images with annotations for a variety of object categories.
UAVDT is a dataset of drone-captured images with annotations for vehicles.

On the VisDrone2021 dataset, TPH-YOLOv5++ achieved an mAP of 56.8%, which outperformed all previous methods. On the UAVDT dataset, TPH-YOLOv5++ achieved an mAP of 67.3%, which also outperformed all previous methods.

	On the VisDrone2021 dataset, the TPH-YOLOv5 model achieved an average precision (AP) of 39.18%, which is 1.5% higher than the previous state-of-the-art model. The TPH-YOLOv5++ model achieved an AP of 40.73%, which is 1.55% higher than the TPH-YOLOv5 model. On the UAVDT dataset, the TPH-YOLOv5 model achieved an AP of 45.53%, which is 2.3% higher than the previous state-of-the-art model. The TPH-YOLOv5++ model achieved an AP of 47.16%, which is 1.63% higher than the TPH-YOLOv5 model. **Conclusion** In this article, the authors proposed two new methods for object detection on drone-captured images: TPH-YOLOv5 and TPH-YOLOv5++. These methods improve upon the YOLOv5 method by adding two phases: a target proposal phase and a classification and regression phase. The authors evaluated their methods on two datasets: VisDrone2021 and UAVDT. TPH-YOLOv5++ outperformed previous methods on both datasets, achieving an mAP of 56.8% on VisDrone2021 and 67.3% on UAVDT.
Research Question/Problem/ Need	Drone-captured images are challenging for object detection due to a number of factors.
Important Figures	 Graphical abstract of article. Describes how model is broken down into parts, how the transformer head is applied, and how up and down sampling assist in increasing performance.
VOCAB: (w/definition)	**Cross-layer asymmetric transformer (CAT)**: CAT module allows the model to learn long-range dependencies between features at different layers

	Pyramid feature fusion (PFF): PFF module allows the model to fuse features from different scales, which improves its detection performance for small objects
Cited references to follow up on	https://web.stanford.edu/class/cs231a/prev_projects_2016/deep-drone-object__2_.pdf
Follow up Questions	How are incompatibilites between heads of models resolved? Are most image detection architectures easy to transfer data between? What is the true significance of mAP?

Article #6 Notes: Object Detection in 2024

Article notes should be on separate sheets

Source Title	Object Detection in 2024: The Definitive Guide
Source citation (APA Format)	Boesch, G. (2023, February 21). *Object Detection in 2024: The Definitive Guide*. Viso.Ai. https://viso.ai/deep-learning/object-detection/
Original URL	https://viso.ai/deep-learning/object-detection/
Source type	General article
Keywords	Neural network, object detection, image recognition
#Tags	yolo

Summary of key points + notes (include methodology)	Object detection can solve a variety of tasks such as identifying people, captioning images, tracking objects, autonomous driving, and more. Object detection deep learning models can be categorized into two types: two-stage detectors and one-stage detectors. In addition, these detectors each have their own set of benefits and performances on standardized benchmarks.
	
	- Object detection is a large field in AI and can detect objects in visual images or videos
	- Object detection can detect people from different views, and it can count the number of people in an image
	- Applications include healthcare monitoring, autonomous driving, video surveillance, robot vision, etc
	- Image processing does not use deep learning but uses various manual techniques to perform tasks on images
	- Deep learning uses past history of images and training to perform a task well
	- A common benchmark is the MS COCO
	- YOLO
	    - A single-stage detector and is much faster than two-stage detectors
	    - Good for small object classifications but worse for larger objects
	    - ImageAI can train custom YOLO models without much programming
	    - YOLO scores different regions in the image based on whether it thinks an object appears there
	    - Detections are identified as positive areas

	- YOLOv3 has a 57.9% mAP on COCO and uses overlapping areas when training
	- YOLOv4 improves more features such as geoimaging, implement self-adversarial training, and more
	- SSD
	  - A one-stage detector
	  - Has much higher accuracies and better for smaller images
	  - It outputs bounding boxes as different aspect ratios and scales for each object detected
	  - It then scores each object in each box and adjusts the boxes to better fit the detected object
	  - It is easy to train
	- RNN
	  - Two-stage detector
	  - Much slower but has higher accuracies
	  - First selects regions of an image - anchor boxes
	  - Labels the bounding boxes and categories within each one
	  - Then use CNN to extract detections or features
	  - RNN's are computationally heavy
	  - Fast/Faster-RCNN help improve speed by reducing the number of iterations run through the image
	- SqueezeDet
	  - Object detector built for autonomous driving
	  - Is extremely fast
	  - Uses convolution layers as intermediate and output layers
	  - Can find bounding boxes and identify objects
	- MobileNet
	  - Based on SSD and is for smaller applications
	  - Was implemented using Caffe deep learning framework
	  - Outputs a vector for each object with bounding box coordinates within
	- YOLOR
	  - New object detector
	  - Uses implicit and explicit knowledge and improves accuracy and greatly improves speed
	  - It is currently the fastest object detector

Research Question/Problem/ Need	What is object detection and how does object detection work using neural networks?

Important Figures	 Example of object detection, done with YOLOv7. Note the bounding boxes and confidence levels
Cited references to follow up on	https://viso.ai/deep-learning/object-tracking/
Follow up Questions	What is the true significance of mAP? What makes MS COCO a good benchmark?

Article #7 Notes: Deep Drone: Object Detection and Tracking for Smart Drones on Embedded System

Article notes should be on separate sheets

Source Title	Deep Drone: Object Detection and Tracking for Smart Drones on Embedded System
Source citation (APA Format)	Han, S., Shen, W., & Liu, Z. (n.d.). *Deep Drone: Object Detection and Tracking for Smart Drones on Embedded System*.
Original URL	https://web.stanford.edu/class/cs231a/prev_projects_2016/deep-drone-object__2_.pdf
Source type	Research article
Keywords	Drone, object detection, image recognition, neural networks
#Tags	yolo
Summary of key points + notes (include methodology)	● The text discusses a project called "Deep Drone" from Stanford University that focuses on object detection and tracking for drones using embedded systems ● The project aims to enable drones to perform automatic object detection and tracking to capture high-quality images and videos ● They implemented their system on various hardware platforms, including desktop GPUs (NVIDIA GTX980) and embedded GPUs (NVIDIA Tegra K1 and Tegra X1), and evaluated the frame rate, power consumption, and accuracy ● The system achieved real-time performance at 71 frames per second for tracking and 1.6 frames per second for detection on the NVIDIA TX1 platform ● The project addresses challenges related to computer vision and real-time constraints for drones ● It discusses various deep neural networks, including AlexNet, VGGNet, GoogleNet, ResNet, and SqueezeNet, highlighting their characteristics and differences ● The paper mentions Fast R-CNN, Faster R-CNN, YOLO Detector, KCF, and MDNet as object detection and tracking algorithms ● The text explains that they used a shallow and small network for image feature extraction to ensure real-time performance on embedded devices ● They used the KCF tracker for tracking, which runs at a high frame rate and is less accurate than MDNet but meets the real-time requirements

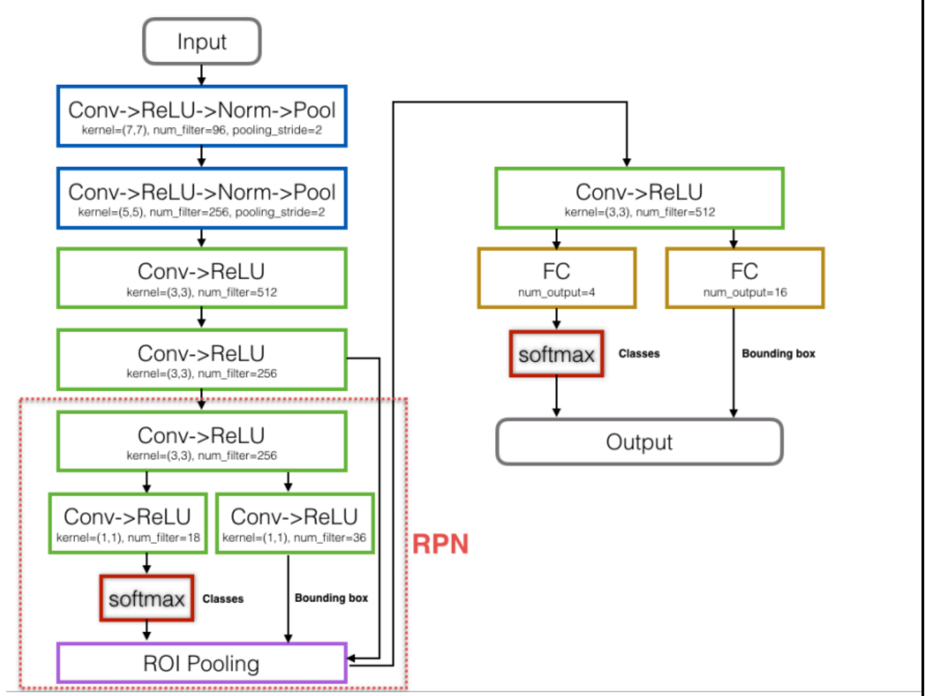
	● The paper details the hardware platforms used for testing, including GTX 980, TX1, and TK1, and their respective power consumption and processing times for detection and tracking ● It mentions the challenges of fitting the hardware onto drones due to size and weight constraints ● The paper describes the software architecture of their vision system, which consists of two components: a detection algorithm using CNN and a tracking algorithm using HOG feature and KCF ● The detection algorithm is evaluated based on its accuracy and runtime on different hardware platforms ● The tracking algorithm, KCF, is chosen for its speed, even though other algorithms have better accuracy ● The hardware platforms are compared in terms of speed and power consumption, with the TX1 platform being the most suitable in terms of speed and power, despite size constraints ● They discuss the implementation and experimentation challenges faced during the project, including issues with CUDA and compiler incompatibility for the embedded systems
Research Question/Problem/ Need	How can embedded systems help improve object detection and tracking for drones?
Important Figures	 Figure 1. The CNN architecture that we used for detection Architecture of neural network used for recognition. Differs from traditional architectures in depth layer complexity
VOCAB: (w/definition)	HOG features: Histogram of Oriented Gradients, a feature descriptor used for

	image recognition and tracking
Cited references to follow up on	S. Ren, K. He, R. B. Girshick, and J. Sun. Faster R-CNN: towards real-time object detection with region proposal networks. CoRR, abs/1506.01497, 2015.
Follow up Questions	What is the computational difference between object detection and tracking?

Article #8 Notes: Forest fire and smoke detection using deep learning-based learning without forgetting

Article notes should be on separate sheets

Source Title	Forest fire and smoke detection using deep learning-based learning without forgetting
Source citation (APA Format)	Sathishkumar, V. E., Cho, J., Subramanian, M., & Naren, O. S. (2023). Forest fire and smoke detection using deep learning-based learning without forgetting. *Fire Ecology*, *19*(1), 9. https://doi.org/10.1186/s42408-022-00165-0
Original URL	https://fireecology.springeropen.com/articles/10.1186/s42408-022-00165-0
Source type	Research article
Keywords	Drone, neural network, image recognition, object detection, deep learning
#Tags	fire
Summary of key points + notes (include methodology)	Abstract: ● Forests are crucial for humankind, facing threats like forest fires impacting global warming and life's existence. ● Automatic forest fire detection is essential for disaster mitigation. ● The research focuses on AI-based computer vision for fire/smoke detection using Convolutional Neural Networks (CNN). ● Transfer learning is used to address the limitations of pre-trained CNN models, and learning without forgetting (LwF) is introduced to retain original dataset classification abilities. Results: ● Transfer learning on models (VGG16, InceptionV3, Xception) enhances efficiency with a smaller dataset, reducing computational complexity. ● Xception excels with 98.72% accuracy. ● Learning without forgetting (LwF) significantly improves accuracy: Xception achieves 91.41% for a new dataset (BowFire) and 96.89% for the original dataset. Conclusion:

- Proposed models outperform current state-of-the-art methods.
- Learning without forgetting (LwF) successfully categorizes novel datasets.

Introduction:

- Forest fires, natural or man-made, cause economic losses and ecological damage.
- Interest in automated observation and detection systems for forest fires is rising.
- Various techniques, including sensor-based and vision-based systems, have been explored.

Literature Survey:

- CNNs, like Inception, VGGNet, and Xception, applied to fire/smoke detection.
- Transfer learning and deep learning improve detection accuracy.
- Machine learning and deep learning outperform traditional methods.
- Previous research highlights challenges, datasets, and potential solutions.

Research Focus and Contributions:

- Research Questions:
    - Adaptable nature of pre-trained models.
    - Categorization of new dataset images by pre-trained models.
    - Effectiveness of fine-tuning hyperparameters.
    - Transferability of knowledge between datasets.
- Contributions:
    - Examined pre-trained CNN models and exploration methods.
    - Developed low-cost computation models and analyzed their performance.
    - Optimized hyperparameters using Bayesian optimization.
        - Bayesian optimization allows the algorithm to focus its search on areas that are likely to contain the optimal solution, making it an efficient and effective method for optimizing expensive or noisy functions.
        - Core concepts of Bayesian optimization
            - Surrogate model: A statistical model that approximates the true objective function.
            - Acquisition function: A function that guides the search by balancing exploration and exploitation.
            - Exploration: Evaluating the objective function at points that are poorly understood, to improve the surrogate model.
            - Exploitation: Evaluating the objective function at points that are likely to be close to the optimum, to find the best solution.
        - Steps in Bayesian optimization

	● Initialize the surrogate model: Start with a simple surrogate model, such as a Gaussian process. ● Evaluate the acquisition function: Select the next point to evaluate based on the acquisition function, which balances exploration and exploitation. ● Evaluate the objective function: Evaluate the true objective function at the selected point. ● Update the surrogate model: Update the surrogate model with the new evaluation. ● Repeat steps 2-4: Continue evaluating the acquisition function, evaluating the objective function, and updating the surrogate model until a stopping criterion is met. ■ Applications of Bayesian optimization ● Bayesian optimization has been applied to a wide range of problems, including: ○ Hyperparameter optimization: Tuning the parameters of machine learning models. ○ Experiment design: Selecting the best set of experiments to run in order to learn about a phenomenon. ○ Sensor placement: Determining the optimal placement of sensors to monitor a system. ○ Optimization of expensive functions: Finding the best solution to problems where evaluating the objective function is time-consuming or expensive. ■ Advantages of Bayesian optimization ● Efficient: Bayesian optimization is particularly efficient for optimizing expensive or noisy functions. ● Effective: Bayesian optimization can find good solutions to problems with complex or non-convex objective functions. ● Adaptive: Bayesian optimization can adapt to changes in the objective function as it is explored. ■ Disadvantages of Bayesian optimization ● Computationally expensive: Bayesian optimization can be computationally expensive, especially for problems with high-dimensional input spaces. ● Requires a good surrogate model: The performance of Bayesian optimization is dependent on the quality of the surrogate model.

- May not find the global optimum: Bayesian optimization is a stochastic algorithm, so it may not always find the global optimum.
- Transferred knowledge to a challenging dataset using Learning without Forgetting (LwF).

Conclusion:

- The study proposes effective models for fire/smoke detection using AI-based techniques.
- Learning without forgetting (LwF) proves crucial for maintaining model accuracy on original datasets.
- The research contributes to the field by addressing transfer learning challenges.

Future Directions

- The conclusion section mentions a direction for future works without specifying details.

Note

- The research is focused on AI-based fire/smoke detection using CNNs, emphasizing the importance of transfer learning and introducing Learning without Forgetting (LwF) to maintain model capabilities. The study contributes valuable insights into improving accuracy and adaptability in fire detection models.

Research Question/Problem/ Need

Automatic warning systems are necessary to mitigate the destructive potential of wildfires

Important Figures

References	Models	Accuracy (%)
(Li and Zhao 2020)	YOLO v3	83.7
(Mahmoud 2022)	Deep ANN and AlexNet	95 and 98
(Cheng 2021)	VGG16 with TL	97.83
(Guede-Fernández et al. 2021)	Faster R-CNN	80
(Luo et al. 2018)	CNN	90
(Muhammad et al. 2018)	CNN	94.39
(Jeon et al. 2021)	CNN with feature-squeeze block	97.89
Proposed models	VGG16 – Feature Extractor	94.38
	VGG16 – Fine Tuner	95.46
	InceptionV3 – Feature Extractor	92.04
	InceptionV3 – Fine Tuner	97.01
	Xception – Feature Extractor	97.77
	Xception – Fine Tuner	**98.72**

Table in which the developed models are shown against previous research. Uses “validation percent accuracy”, a metric based on past recognition of similar images as well as standard percent accuracy

VOCAB: (w/definition)

Bayesian optimization: a global optimization technique that uses Bayes' theorem to update a probabilistic model of the objective function as it is evaluated

Cited references to follow up on

Jeon, M., H.-S. Choi, J. Lee, and M. Kang. 2021. Multi-scale prediction for fire detection using convolutional neural network. *Fire Technology* 57 (5):

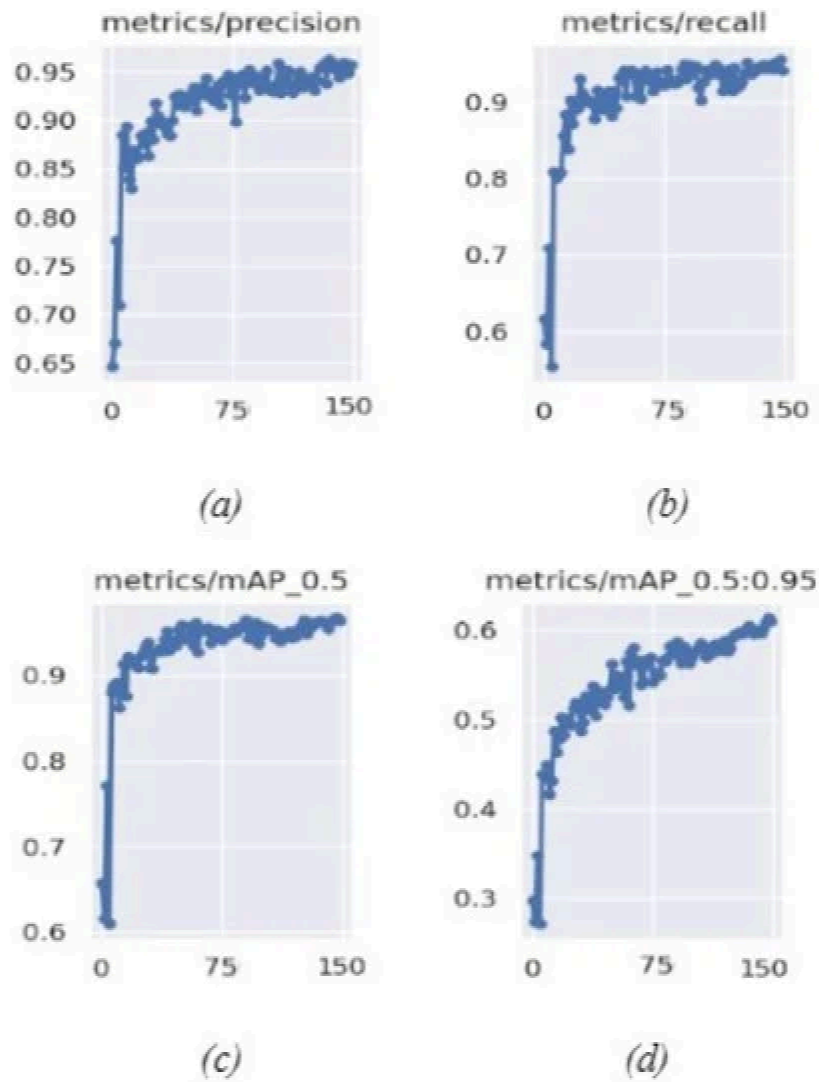
	2533–2551. Kaulage, A., S. Rane, and S. Dhore. 2022. *Satellite Imagery-Based wildfire detection using deep learning: 'Data Science'*. 213–220. Chapman and Hall/CRC.
Follow up Questions	How resource-efficient are hyperparameters to implement? What are the pros and cons of different optimization techniques? What metric is best to use when evaluating the success of an image recognition algorithm?

Article #9 Notes: Application of Image Processing Techniques for UAV Detection Using Deep Learning and Distance-Wise Analysis

Article notes should be on separate sheets

Source Title	Application of Image Processing Techniques for UAV Detection Using Deep Learning and Distance-Wise Analysis
Source citation (APA Format)	Dewangan, V., Saxena, A., Thakur, R., & Tripathi, S. (2023). Application of Image Processing Techniques for UAV Detection Using Deep Learning and Distance-Wise Analysis. *Drones*, *7*(3), Article 3. https://doi.org/10.3390/drones7030174
Original URL	https://www.mdpi.com/2504-446X/7/3/174
Source type	Research article
Keywords	Drone, object detection, image recognition, deep learning
#Tags	yolo
Summary of key points + notes (include methodology)	1. Introduction: ● UAVs or drones are remote-controlled or pre-programmed aircraft used in various industries. ● Applications include military surveillance, cargo delivery, commercial use, photography, etc. ● Government regulations exist due to security and privacy concerns, with measures against rogue UAVs. ● Current challenges include detection of UAVs for security reasons, leading to the need for accurate identification systems. 2. Related Work and Contributions: ● YOLO algorithm, especially versions like YOLOv5 and YOLOv7, is widely used for real-time UAV detection. ● Previous studies compared different versions of YOLO for UAV detection efficiency. ● Some studies utilized deep learning techniques, multi-dimensional signal features, and radar detection. ● Various experiments were conducted using datasets like Det-Fly, focusing on deep learning methods for visual UAV identification. ● Edge computing, image processing, and novel YOLO versions were

	proposed to enhance detection accuracy. ● Critique of previous works includes overfitting, lack of range-wise analysis, and not using diverse image processing techniques. 3. Methodology: ● Object detection in computer vision involves identifying and classifying objects in images or videos. ● Deep learning-based object detectors perform two tasks: finding objects and classifying each item. ● Two approaches: one-stage detectors and two-stage detectors, with YOLO being a significant one-stage technique. ● YOLO algorithm (versions like YOLOv5 and YOLOv7) uses a single forward pass for object detection. ● Image preprocessing techniques like grayscale conversion, hue augmentation, and edge enhancement are applied. ● Dataset used for testing includes various types of UAVs in diverse terrains to avoid overfitting. ● Recent YOLO versions are employed, addressing issues from previous studies and providing higher accuracies. ● Distance-wise analysis evaluates model performance at close, mid, and far ranges. 4. Image Preprocessing Techniques: ● Grayscale conversion removes color information, simplifying algorithms and reducing computational requirements. ● Hue augmentation modifies color channels to prevent memorization of colors, aiding in model generalization. ● Edge enhancement sharpens edges in images, enhancing contrast. 5. Overall Contributions: ● Addressed shortcomings of previous works by using a diverse dataset, applying various image processing techniques, and employing recent YOLO versions. ● Achieved higher accuracies and conducted distance-wise analysis for better understanding of model performance in different scenarios.
Research Question/Problem/ Need	Drones pose a significant risk to privacy due to their growing ubiquity.

Important Figures	 **Figure 1.** YOLOv5 Hue augmentation validation curves; (**a**) precision vs. epoch curve; (**b**) recall vs. epoch curve; (**c**) mAP score at 0.5 IoU threshold vs. epoch curve; (**d**) mAP (0.5:0.95) vs. epoch curve. a) Precision percentage vs number of epochs for which model was trained b) Recall percentage vs number of epochs for which model was trained c) Median accuracy percentage at 0.5 intersection over union threshold (ratio of overlap between predicted and expected bounding boxes) vs number of epochs for which model was trained d) Median accuracy percentage between 0.5 and 0.95 intersection over union threshold vs number of epochs for which model was trained
VOCAB: (w/definition)	Edge computing: Edge computing brings computing resources and services closer to the devices or "edge" of the network, where data is generated. This reduces latency and enables real-time processing and analysis of data.
Cited references to follow up	Lu, Z.; Yueping, P.; Zecong, Y.; Rongqi, J.; Tongtong, Z. Infrared Small UAV Target

on	Detection Algorithm Based on Enhanced Adaptive Feature Pyramid Networks. *IEEE Access* **2022**, *10*, 115988–115995. [**Google Scholar**] [**CrossRef**] Aydin, B.; Singha, S. Drone Detection Using YOLOv5. *Eng* **2023**, *4*, 416–433. [**Google Scholar**] [**CrossRef**]
Follow up Questions	What is the true significance of mAP? Does the resource drain of image post-processing affect the speed at which the model is trained?

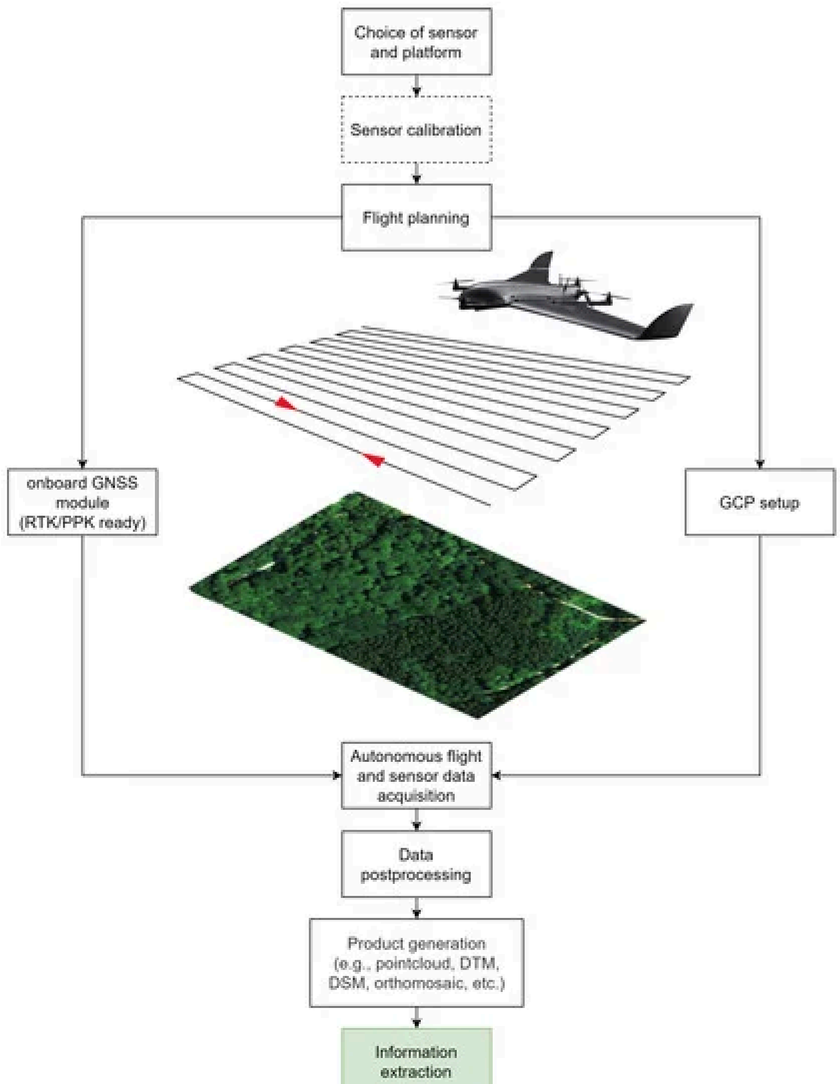
Article #10 Notes: Multi-UAV Surveillance over Forested Regions

Article notes should be on separate sheets

Source Title	Multi-UAV Surveillance over Forested Regions
Source citation (APA Format)	Leng, G., Qian, Z., & Govindaraju, V. (2014). Multi-UAV Surveillance over Forested Regions. *Photogrammetric Engineering & Remote Sensing*, *80*(12), 1129–1137. https://doi.org/10.14358/PERS.80.12.1129
Original URL	https://www.mdpi.com/2072-4292/14/13/3205
Source type	Research article
Keywords	Drone, surveillance uav
#Tags	drone
Summary of key points + notes (include methodology)	Introduction: ● S-UAVs (Small-Unmanned Aerial Vehicles) are a low-cost alternative for aerial surveillance over forests. ● However, their limited coverage due to low altitudes and short endurance necessitates optimal flying paths for maximum ground visibility. ● Vegetation occlusion in forests is generally neglected in visibility computations. ● This paper proposes a probabilistic sensing model incorporating both terrain and vegetation occlusions in visibility computations. ● A two-step approach determines near-optimal flight paths: ○ Strategically deploy waypoints (observation points) using centroidal Voronoi tessellation. ○ Design a flyable path along waypoints that obeys S-UAV kinematic constraints using the improved Clustered Spiral-Alternating algorithm. ● Simulations on synthetic and reconstructed terrains show the proposed method's effectiveness in improving terrain visibility compared to grid-based waypoints. Relevant Literature: ● Watchman Routing Problem ○ The problem of finding a shortest path that also satisfies some visibility requirements is known as the Watchman Routing Problem (WRP).

	○ The WRP has been well-studied in the field of computational geometry. ○ For surveillance and inspection applications, the WRP is often solved as a multi-objective optimization problem, where both the travel cost and the view-cost are minimized. ● Visibility Exposure Models ○ Understanding visibility of a terrain from an observation point is very important for determining the optimal viewpoints. ○ Visibility exposure models, such as isovist and viewshed models, are widely used in the areas of urban planning, optimal placement of watch-towers, and line-of-sight communication problems. ○ Isovist modeling accesses building footprint polygons to compute visibility and is more suited to urban areas, whereas viewshed analysis uses terrain models and is more suitable in rural regions. ● Visibility Calculations ○ De Floriani and Magillo (2002) provide a detailed survey on the visibility calculations using different DEM representations and algorithms. ● Visibility from UAVs ○ Very few papers in the literature have considered visibility of the terrain from the UAV. ○ For example, the papers Kim and Kim (2008) and Semsch et al. (2009) incorporate the complete occlusions in the visibility from UAVs. ○ However, partial occlusion due to vegetation has been neglected. ● Partial Visibility through Vegetation ○ Several researchers have studied partial visibility through vegetation. ○ Vegetation growth in forests is highly random and very difficult to model. ○ Therefore, vegetation is modeled as a form of a clutter field for simpler analysis. ● Exponential Attenuation Model of Visibility ○ The exponential attenuation model of visibility is used in this paper for measuring the visibility of a point on the ground beneath the vegetation from the UAV. ○ This visibility of a ground point depends on the length of the path travelled by the Line-of-Sight (LOS) beam and the density of the vegetation through which the LOS beam travels. ● Forest Canopy Cover ○ Forest canopy cover is defined as the proportion of the forest floor covered by the vertical projection of the tree crowns. ○ Satellite imagery has played a pivotal role in generating information about the global forest canopy cover. ○ Forest cover data is freely available through electronic download. ● Centroidal Voronoi Tessellation

	○ The centroidal Voronoi tessellation is one of the most common methods to minimize distance cost functions in facility location problems. ○ The same method is used to solve for the near-optimal waypoints (observation locations), which iteratively enhances the ground visibility. ● Flyable Path Planning ○ A flyable path is a path that satisfies the kinematic constraints of the flying vehicle, such as minimum turning radius and minimum climb angle. ○ In order to make the path planning simpler, fixed wing S-UAVs are generally assumed to be a Dubin's vehicle (a vehicle that travels in a straight line or turn at a constant turning radius). ○ In this paper, a combination of the alternating algorithm and the Spiral Algorithm is used to improve the effectiveness of surveillance and usability. Methods: ● Visibility Decay Model ○ The visibility of a ground point from an S-UAV is determined using a probabilistic visibility model that accounts for both terrain occlusions and vegetation occlusions. ○ The probabilistic visibility model is based on the Beer-Lambert law, which describes the exponential decay of visibility with depth. ○ The decay constant in the Beer-Lambert law is proportional to the forest crown cover, which can be estimated from satellite imagery. ○ Complete occlusion of a ground point due to the terrain is checked by comparing the Line-of-Sight (LOS) Beam with the DEM. ○ The LOS beam is traced from the S-UAV to the ground point, and the elevation of intermediate points is compared to the elevation of the LOS beam at that point. ○ If the elevation of an intermediate point is more than the elevation of the LOS beam at that point, then the ground point is not visible from the S-UAV. ○ The length of the LOS beam is calculated using geometric relations. ○ The model is implemented using a regular square grid representation of DEM. ○ The decay constant in the Beer-Lambert law can be assumed to be constant only over small distances due to the non-uniform nature of forest crown cover. ○ The Beer-Lambert law is used to model the decrease in intensity of light through materials with different attenuation factors. ○ The Mean Vegetation Height, T, is used to calculate the length of the LOS beam due to the unavailability of the exact Digital Surface Model (DSM) of the forest.

	○ The elevation of intermediate points of the LOS is compared to the elevation of ground points directly vertical to them to check for complete occlusion of a ground point due to the terrain. ○ The regular square grid representation of DEM is used to analyze the visibility. ○ The length of the LOS beam plays an important role when the UAV is flying at altitudes that are comparable to the mean vegetation height.
Research Question/Problem/ Need	Forests are a difficult environment to surveil because of their many complex and irregular features.
Important Figures	 Diagram of process by which the drones acquire and process information. Search pattern is variable.
VOCAB: (w/definition)	Terrain Visibility: The ability of an S-UAV to see the ground beneath vegetation and

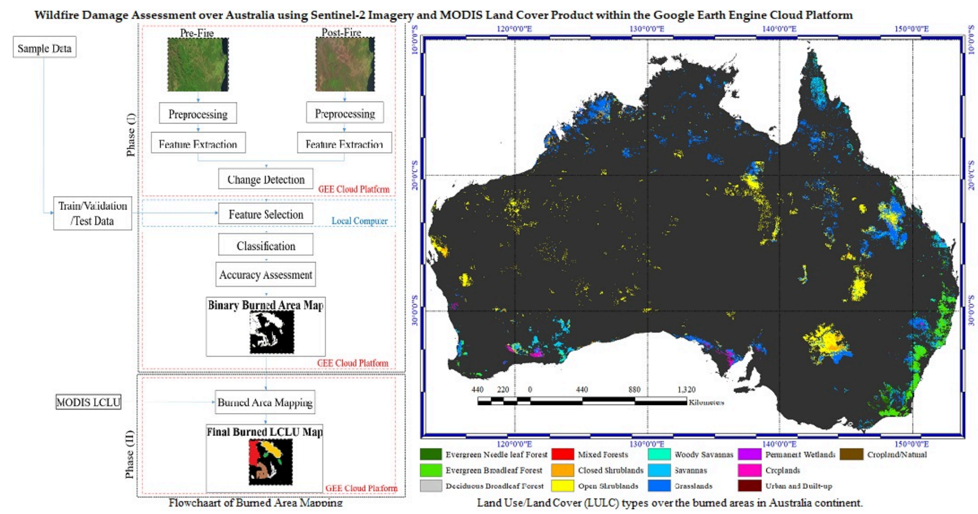
	other obstacles. Watchman Routing Problem (WRP): Finding the shortest path for an observer (e.g., an S-UAV) that also maximizes its visibility of a certain area. Visibility Exposure Models: Tools like isovists and viewsheds that analyze how much of an area is visible from a specific point. Line-of-Sight (LOS) Beam: The imaginary path light travels from the S-UAV to a point on the ground. Centroidal Voronoi Tessellation: A method for dividing an area into regions closest to specific points (waypoints). Dubin's Vehicle: A simplified model of an aircraft that can only fly straight or turn at a constant radius. Visibility Decay Model: A probabilistic model that estimates how likely a point on the ground is visible from the S-UAV, considering both terrain and vegetation occlusions. Beer-Lambert Law: A physical principle describing the exponential decrease in light intensity as it travels through a material. Digital Surface Model (DSM): A map of the top surface features (e.g., treetops) in an area. Digital Elevation Model (DEM): A map of the ground elevation in an area.
Cited references to follow up on	Seifert, E.; Seifert, S.; Vogt, H.; Drew, D.; van Aardt, J.; Kunneke, A.; Seifert, T. Influence of Drone Altitude, Image Overlap, and Optical Sensor Resolution on Multi-View Reconstruction of Forest Images. *Remote Sens.* **2019**, *11*, 1252.
Follow up Questions	If an area of forest has already been mapped, is it feasible for a UAV to retain that information?

Article #11 Notes: Wildfire Damage Assessment over Australia Using Sentinel-2 Imagery and MODIS Land Cover Product within the Google Earth Engine Cloud Platform

Article notes should be on separate sheets

Source Title	Wildfire Damage Assessment over Australia Using Sentinel-2 Imagery and MODIS Land Cover Product within the Google Earth Engine Cloud Platform
Source citation (APA Format)	Seydi, S. T., Akhoondzadeh, M., Amani, M., & Mahdavi, S. (2021). Wildfire Damage Assessment over Australia Using Sentinel-2 Imagery and MODIS Land Cover Product within the Google Earth Engine Cloud Platform. *Remote Sensing*, *13*(2), 220. https://doi.org/10.3390/rs13020220
Original URL	https://www.mdpi.com/2072-4292/13/2/220
Source type	Research article
Keywords	wildfire
#Tags	fire
Summary of key points + notes (include methodology)	Abstract and Introduction: ● Wildfires are significant natural disasters with global impacts on safety, ecosystems, and climate. ● Remote Sensing (RS) images, particularly Sentinel-2 and MODIS, are used for accurate wildfire burn area estimation. ● A framework based on change analysis is implemented in two phases: (1) binary mapping of burned areas; (2) estimating burned areas for different Land Use/Land Cover (LULC) types. ● The study focuses on Australian wildfires and utilizes Google Earth Engine (GEE) for efficient processing of RS data. Methodology: ● Study Area: Mainland Australia, affected by wildfires from September 2019 to February 2020. ● Satellite Data: Sentinel-2 optical satellite images used for their high spatial resolution. ● Reference Data: Generated from reports of wildfire locations and visual

	interpretation of Sentinel-2 time series imagery. ● MODIS LULC Product: Used to determine LULC types over burned areas. ● Landsat Burned Area Product: Utilized for assessing the results of the proposed method. Proposed Method: ● Phase 1 - Binary Burned Areas Mapping: ● Preprocessing: Conducted in Google Earth Engine (GEE). ● Spatial-Spectral Feature Extraction: Utilized original spectral bands, spectral indices, and texture features. ● Change Detection: Predicted burned areas by differencing pre-fire and post-fire layer-stacked images. ● Feature Selection: Employed Harris's Hawk Optimization (HHO) algorithm. ● Binary Burned Area Mapping: Applied supervised classifiers to selected features. ● Phase 2 - LULC Estimation: Determined LULC types over burned areas using MODIS LULC products. Results: ● The proposed framework showed high potential in detecting burned areas with an overall accuracy (OA) of 91.02% and kappa coefficient (KC) of 0.82. ● Evergreen needle leaf forests exhibited the greatest burned area among different LULC classes, with a burning rate of over 25%. Conclusion: ● The study successfully mapped Australian burned areas at a higher spatial resolution compared to previous GEE studies. ● Introduced an innovative approach for estimating burned areas for different LULC types. ● Implemented a novel feature selection algorithm (HHO) and compared the performance of different classifiers for burned area mapping. Challenges and Recommendations: ● Challenges in existing methods include moderate spatial resolution, complexity, computational efficiency, and the need for dynamic thresholding. ● Recommendations include exploring higher spatial resolution imagery, improving computational efficiency, and addressing issues related to burned area mapping and monitoring. Overall Implications: ● The study contributes valuable insights and methods for accurate and detailed wildfire mapping using RS data, particularly within the GEE platform.
Research Question/Problem/ Need	Wildfires are a very significant naturally occurring disaster, but assesment of their damage on forests is difficult.

Important Figures	
VOCAB: (w/definition)	Remote Sensing (RS): Techniques for collecting and analyzing data about the Earth's surface from airborne or spaceborne sensors. Sentinel-2 and MODIS: Satellites that collect multispectral data used in various environmental applications, including wildfire monitoring. Google Earth Engine (GEE): A cloud-based platform for processing and analyzing large geospatial datasets. Sentinel-2: A European Earth observation satellite constellation providing high-resolution optical imagery. MODIS LULC Product: A dataset classifying land cover types based on MODIS satellite data. Landsat Burned Area Product: Another dataset identifying burned areas derived from Landsat satellite data. Binary Mapping: Classifying areas with a binary value (in this case, burned or unburned) Spatial-Spectral Feature Extraction: Creating new features from the satellite data that capture both spatial and spectral information (e.g., texture, vegetation indices). Harris's Hawk Optimization (HHO): A nature-inspired algorithm used for feature selection in this study. Supervised Classifiers: Algorithms trained on labeled data (e.g., reference data) to classify new data points. Overall Accuracy (OA): The percentage of correctly classified pixels in the entire

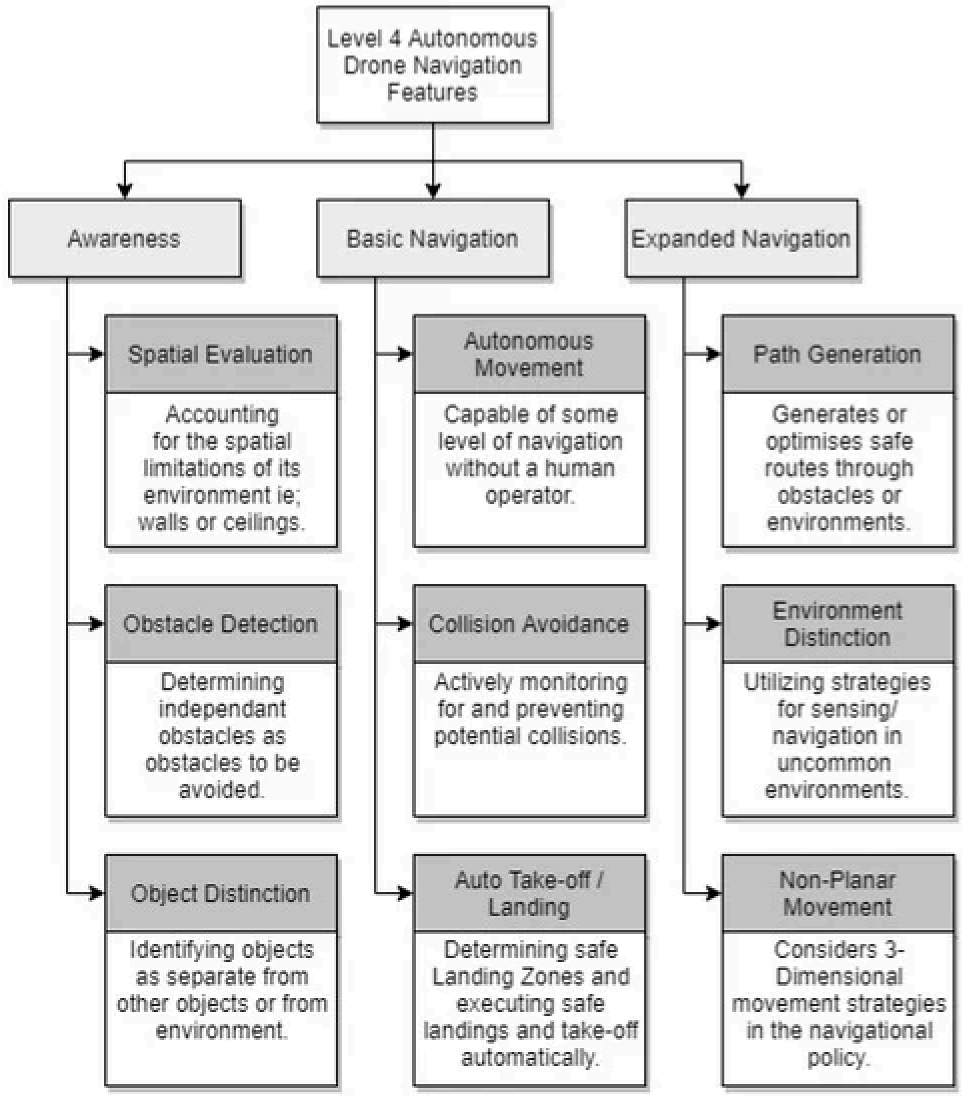
	dataset. Kappa Coefficient (KC): A statistical measure of agreement between two classifications.
Cited references to follow up on	Oliva, P.; Schroeder, W. Assessment of VIIRS 375 m active fire detection product for direct burned area mapping. *Remote Sens. Environ.* **2015**, *160*, 144–155.
Follow up Questions	How reliable is a binary mapping strategy when dealing with variable values?

Article #12 Notes: Flying Free: A Research Overview of Deep Learning in Drone Navigation Autonomy

Article notes should be on separate sheets

Source Title	Flying Free: A Research Overview of Deep Learning in Drone Navigation Autonomy
Source citation (APA Format)	Lee, T., Mckeever, S., & Courtney, J. (2021). Flying Free: A Research Overview of Deep Learning in Drone Navigation Autonomy. *Drones*, *5*(2), Article 2. https://doi.org/10.3390/drones5020052
Original URL	https://www.mdpi.com/2504-446X/5/2/52
Source type	Research article
Keywords	Drone, deep learning, autonomy
#Tags	yolo
Summary of key points + notes (include methodology)	Article Overview: ● Focus on drone autonomy, specifically in navigation, with a deep learning approach. ● Establishes a taxonomy of drone navigation autonomy by mapping to vehicular autonomy levels. ● Examines research works in drone navigation tasks, emphasizing deep learning-based solutions. ● Aims to guide research in drone autonomy, identifying key works and areas for future development. Introduction: ● Drone market growth from 2 billion USD in 2016 to 22.5 billion USD in 2020. ● Increase in research on drone autonomy driven by deep learning and computer vision. ● Two-fold purpose: common vocabulary for drone autonomy levels and analysis of research works. Approach: ● Defines six levels of autonomy based on the Society of Automation Engineers (SAE) standard. ● Three autonomy feature groups: Awareness, Basic Navigation, and Expanded Navigation. ● Citations used as a basic indicator of research attention. ● Evaluation criteria include accuracy, F1 score, efficiency (processing time),

	and engineering features. Results: ● Subset of research pool categorized into Awareness, Basic Navigation, Expanded Navigation, and Engineering features. ● Detailed features under each category include Spatial Evaluation, Obstacle Detection, Collision Avoidance, Path Generation, On-Board Processing, etc. ● Focus on most cited entries per year for each feature category. Discussion: ● Identifies areas of concentrated research effort and common learning models (VGG-16, YoloV3, ResNet, DroNet). ● Three common deep learning models discussed: VGG-16, ResNet, and DroNet. ● Areas of concentrated research effort include DNN-based autonomous movement with quad rotor drones. ● Highlights underdeveloped areas in research for potential future exploration. Conclusion: ● Provides a detailed analysis of research efforts in autonomous drone navigation. ● Identifies common learning models and areas of concentrated research. ● Indicates potential areas for future research and development in drone autonomy.
Research Question/Problem/ Need	There are many ventures into autonomous flight control in UAVs, and a lack of concrete and collated progress.

Important Figures	 Flowchart used to distinguish branches of features. Generalized based on most used and researched topics.
VOCAB: (w/definition)	Taxonomy of drone navigation autonomy: A system for classifying different levels of drone autonomy based on their capabilities. Vehicular autonomy levels: A set of standards defined by the Society of Automation Engineers (SAE) that classify the level of automation in vehicles. Autonomy feature groups: Three main categories of features that contribute to drone navigation autonomy. Awareness: The ability of the drone to perceive its surroundings and understand its environment. Basic Navigation: The ability of the drone to follow a pre-programmed path or

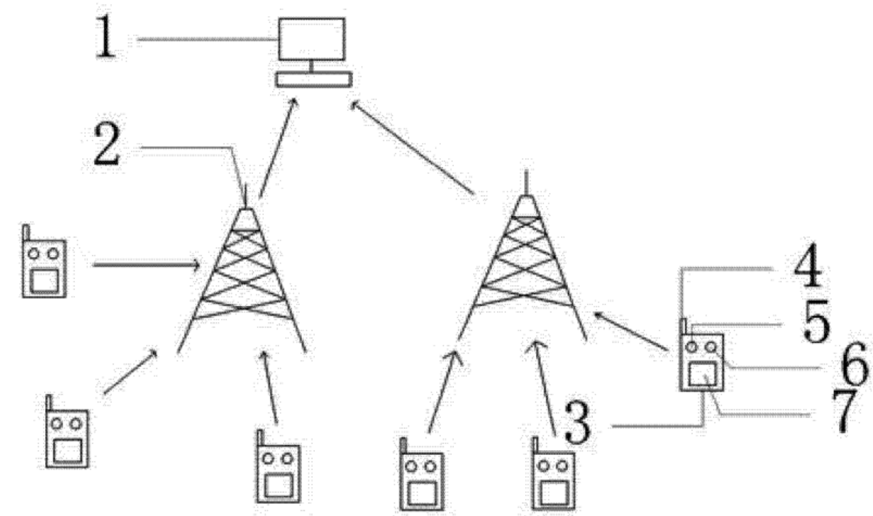
	navigate to a specific location. Expanded Navigation: The ability of the drone to plan and execute complex maneuvers, including obstacle avoidance and path planning. F1 score: A measure of the accuracy of a machine learning model that takes into account both precision and recall. Spatial Evaluation: The ability of the drone to understand its position and orientation in its environment. Obstacle Detection: The ability of the drone to identify and avoid obstacles in its path. Collision Avoidance: The ability of the drone to take evasive action to avoid colliding with obstacles. Path Generation: The ability of the drone to plan a safe and efficient route to its destination. On-Board Processing: The ability of the drone to process information and make decisions on-board, without relying on a ground station. DNN-based autonomous movement: Autonomous drone movement controlled by deep neural networks.
Cited references to follow up on	Zeggada, A.; Melgani, F.; Bazi, Y. A Deep Learning Approach to UAV Image Multilabeling. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 694–698.
Follow up Questions	What are the main differences between object detection algorithm developed purposely for UAVs and traditional object detection algorithms?

Patent #1 Notes: Forest Fire Monitoring System

Article notes should be on separate sheets

Source Title	Forest Fire Monitoring System
Source citation (APA Format)	王一为. (2015). *Forest fire monitoring system* (China Patent CN104658156A). https://patents.google.com/patent/CN104658156A/en
Original URL	https://patents.google.com/patent/CN104658156A/en
Source type	Patent
Keywords	Fire, system, m
#Tags	fire
Summary of key points + notes (include methodology)	Abstract: The patent describes a forest fire monitoring system that includes multiple sensors, base stations, and a monitoring center. The sensors are equipped with wireless communication modules, smoke sensors, thermal pyroelectric sensors, processors, and batteries. The wireless communication module of the sensors connects to the base stations, and the base stations are wirelessly connected to the monitoring center. The system detects forest fires through logical operations and judgments on data from the sensors and promptly locates the fire's position. Claims: ● The forest fire monitoring system includes sensors, base stations, and a monitoring center. The sensors have wireless communication modules, smoke sensors, thermal pyroelectric sensors, processors, and batteries. The wireless communication module of the sensors is connected to the base stations, which are wirelessly connected to the monitoring center. ● The processor is specified to be a single-chip microcomputer. ● The base stations are specified to be wirelessly connected to the monitoring center through GPRS/CDMA/3G. ● The system includes one base station with 5 to 10 sensors evenly distributed within a radius of 1000 meters around the base station. ● The batteries are rechargeable, and the sensors are equipped with solar panels connected to the sensors' batteries. Technical Field: The invention falls within the technical field of fire monitoring and positioning devices, specifically focusing on a forest fire monitoring system.

	Background: Forests are essential ecosystems for human survival and development, but they are prone to fires, causing severe damage and ecological imbalance. Invention Content: The patent introduces a forest fire monitoring system designed to detect and locate forest fires promptly. Detailed Description: ● Structure of the System: ○ Multiple sensors are installed in the forest. ○ Multiple base stations are located at the centers of several sensors. ○ A monitoring center oversees the entire system. ○ Within a radius of 1000 meters around each base station, 5 to 10 sensors are evenly distributed. ● Sensor Components: ○ Sensors include a wireless communication module, smoke sensor, thermal pyroelectric sensor, processor, and battery. ○ Smoke sensors detect smoke concentration effectively. ○ Thermal pyroelectric sensors detect the occurrence of fires. ○ Processor performs logical operations and judgments on sensor data. ● Wireless Connectivity: ○ Wireless communication modules of the sensors connect to the base stations. ○ Base stations are wirelessly connected to the monitoring center through GPRS/CDMA/3G. ● Power and Energy Efficiency: ○ Sensors are equipped with rechargeable batteries. ○ Sensors also have solar panels connected to their batteries, enhancing energy efficiency and extending the sensors' lifespan. ● Advantages: ○ The forest fire monitoring system can promptly detect and locate forest fires, transmitting signals from sensors to base stations and then to the monitoring center. ○ The base stations play a crucial role in locating the fire's position promptly.
Research Question/Problem/ Need	Forest fires are not rapidly detected when they manifest, and there needs to be a warning system.

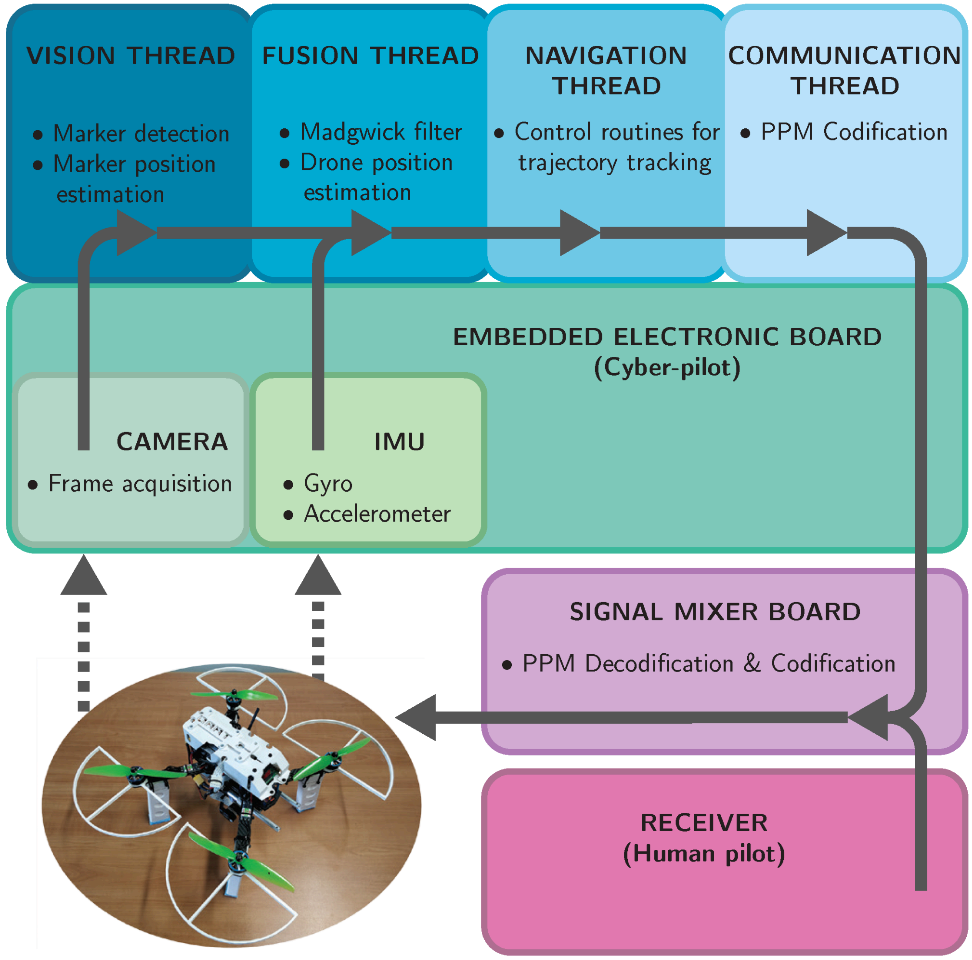
Important Figures	 Systems diagram of the system, including base stations and sensor input.
VOCAB: (w/definition)	Wireless communication modules: Enable sensors to communicate with base stations and vice versa. Thermal pyroelectric sensors: Detect temperature changes caused by fire, enabling early detection. GPRS/CDMA/3G: Technologies used for wireless communication between base stations and the monitoring center.
Cited references to follow up on	N/A
Follow up Questions	Is wireless communication reliable within conditions of a nearby fire?

Article #13 Notes: Development of Non Expensive Technologies for Precise Maneuvering of Completely Autonomous Unmanned Aerial Vehicles

Article notes should be on separate sheets

Source Title	Development of Non Expensive Technologies for Precise Maneuvering of Completely Autonomous Unmanned Aerial Vehicles
Source citation (APA Format)	Bigazzi, L., Gherardini, S., Innocenti, G., & Basso, M. (2021). Development of Non Expensive Technologies for Precise Maneuvering of Completely Autonomous Unmanned Aerial Vehicles. *Sensors*, *21*(2), Article 2. https://doi.org/10.3390/s21020391
Original URL	https://www.mdpi.com/1424-8220/21/2/391
Source type	Research article
Keywords	Drone, uav, autonomy
#Tags	drone
Summary of key points + notes (include methodology)	Introduction: ● Multi-rotor Unmanned Aerial Vehicles (UAVs) have gained interest due to versatility, low-cost, and diverse applications. ● Technological advances in mechatronic servo-systems, microelectronics, and sensors have improved UAV performance. ● Applications include precision agriculture, monitoring, patrolling, vision-based navigation, and aerial shooting. Vision-Based Navigation (VBN) in UAVs: ● VBN algorithms enhance positioning accuracy in various applications. ● Film makers use large drones with heavy cameras for aerial shooting, relying on pilot skills for navigation. ● Limitations in outdoor autonomous UAV precision are tied to standard GNSS devices, restricting novel applications. Autonomous UAV Challenges: ● Current technologies limit the autonomy of UAVs, and sensor fusion techniques are being explored to address challenges. ● Complete autonomy is difficult due to precision limitations, and environmental setup represents costs and delays.

	Project "Dart" Overview: ● Dart aims to create a completely autonomous UAV with centimetric precision using mass-market technologies. ● The Dart prototype features a high-precision vision-based positioning system, including a camera, gimbal, embedded board, and computer vision library. ● The drone aims for complete autonomy without ground assistance, relying on on-board systems. Drone Architecture: ● Dart's architecture separates low-level attitude stabilization tasks from high-level navigation tasks. ● The cyber-pilot concept substitutes the human pilot, and the drone features a modular hardware architecture. ● The on-board navigation system uses a Raspberry PI, camera, and IMU for position estimation and trajectory following. Hardware Configuration: ● Dart's hardware includes a carbon fiber frame, 6-DOF IMU, Raspicam camera, Raspberry PI, and a custom signal mixer board for hybrid autonomous/manual flight modes. ● The mixer board allows safe switching between autonomous and manual modes. ● IMU and camera are critical for position estimation. Gimbal Suspension: ● Dart employs 2-DOF and 3-DOF gimbal suspensions for stabilizing the Raspicam camera. ● Suspensions use brushless motors, dedicated IMU, and a micro-controller to freeze the camera attitude. Software Modules: ● Low-level module (CC3D-Revo board with LibrePilot firmware) stabilizes drone attitude based on set-points. ● High-level module includes computer vision, multi-PID controller, and a Madgwick sensor fusion filter for autonomous navigation. ● Navigation system generates set-points for attitude and motors thrust, allowing the drone to follow a desired trajectory.
Research Question/Problem/ Need	UAVs have become increasingly expensive, and a cost-efficient autonomous system would fill a much-needed niche.

Important Figures	 General control and process scheme of the developed system.
VOCAB: (w/definition)	Mechatronic servo-systems: Combined mechanical and electronic systems for precise control of UAVs. Microelectronics: Miniaturized electronic components used in UAVs, reducing size and cost. Vision-Based Navigation (VBN): Using computer vision algorithms for UAV positioning and navigation. Global Navigation Satellite System (GNSS): Satellite-based navigation system (e.g., GPS) with limited accuracy for UAVs. Centimetric precision: Highly accurate positioning within a few centimeters, crucial for autonomous navigation. Sensor fusion: Combining data from multiple sensors (e.g., cameras, IMU) into a single, reliable representation.

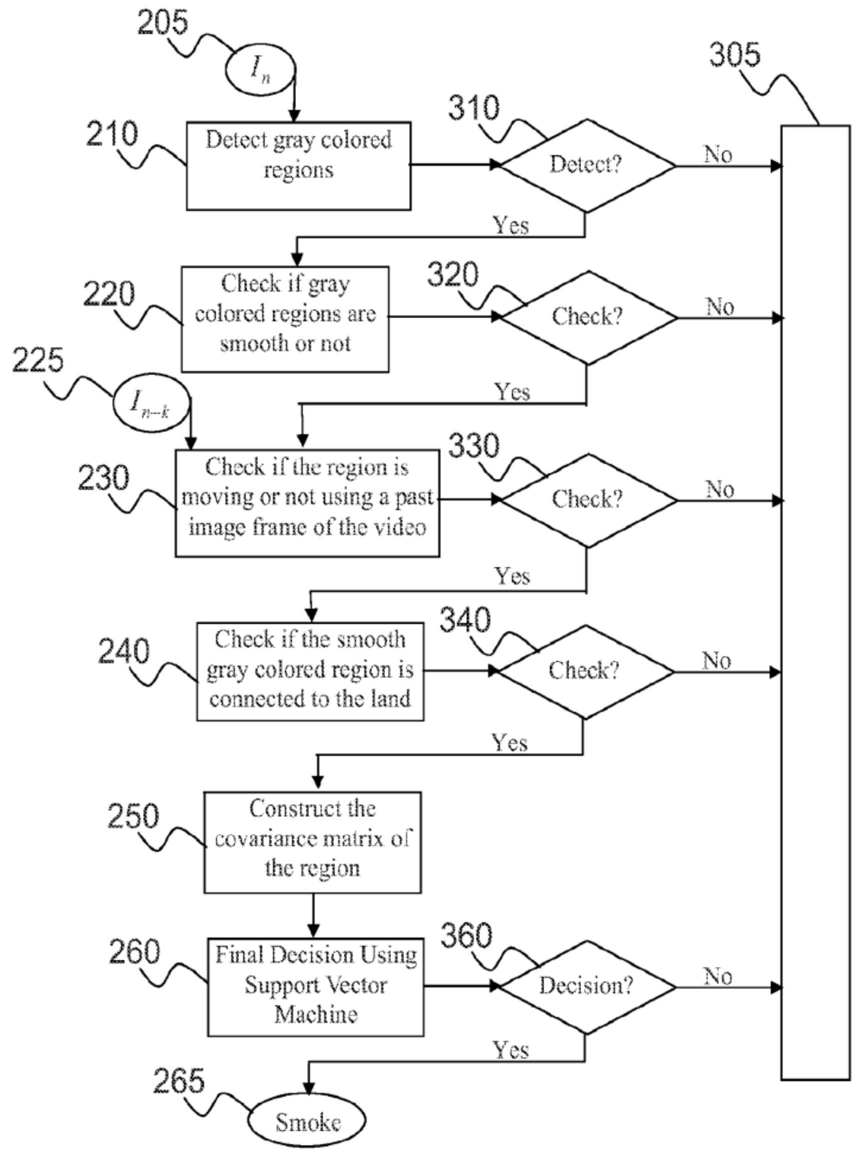
	Complete autonomy: Removing the need for human intervention in UAV operation. Low-level attitude stabilization: Maintaining the drone's balance and orientation. Madgwick sensor fusion filter: Combines IMU and camera data for accurate position estimation.
Cited references to follow up on	Dinesh, M.A.; Kumar, S.S.; Sanath, J.; Akarsh, K.N.; Gowda, K.M.M. Development of an Autonomous Drone for Surveillance Application. *Proc. Int. Res. J. Eng. Technol. IRJET* **2018**, *5*, 331–333.
Follow up Questions	Was carbon fiber really the most cost-effective choice?

Patent #2 Notes: Method and system for wildfire detection using a visible range camera

Article notes should be on separate sheets

Source Title	Method and system for wildfire detection using a visible range camera
Source citation (APA Format)	Cetin, A. E., & Gunay, O. (2015). *Method and system for wildfire detection using a visible range camera* (United States Patent US9047515B2). https://patents.google.com/patent/US9047515B2/en
Original URL	https://patents.google.com/patent/US9047515B2/en
Source type	Patent
Keywords	Wildfire, detection, wildfire detection
#Tags	fire
Summary of key points + notes (include methodology)	Introduction: ● Objective: The patent outlines a method and system for early detection of wildfires using a visible range camera. ● Advantage: The system aims to identify wildfires before the flames become visible, thereby facilitating timely intervention to prevent their spread and potential damage. Method Overview: ● Image Generation: The system employs a video camera to generate sequential images of a designated subject area. ● Color and Motion Analysis: It analyzes the images to identify gray colored regions that exhibit smooth and slow-moving characteristics. Key Steps in the Method: ● Step 1: Video Image Generation: The system captures sequential video images of the subject area. ● Step 2: Gray Region Detection: It identifies gray colored regions within the video images. ● Step 3: Smoothness Determination: The system assesses if a detected gray region is smooth in appearance. ● Step 4: Motion Analysis: It determines if the smooth gray region is slow-moving by comparing it to a previous video frame. ● Step 5: Connectivity Check: The system verifies if the slow-moving gray region is connected to a land portion of the subject area. ● Step 6: Covariance Matrix Construction: If connected, a covariance matrix

	of the land-connected slow-moving gray region is constructed. ● Step 7: Machine Learning Application: A trained support vector machine is applied to the covariance matrix to ascertain if the region signifies smoke from a wildfire. ● Alarm Trigger: If smoke is detected, an alarm is triggered. Early Detection and Prevention: ● The system's ability to identify wildfires at an early stage is emphasized, contributing to preventive measures against their rapid spread and resultant damage. Cost-Effective Nature of the System: ● The system is highlighted as cost-effective since it utilizes a visible range camera, eliminating the need for more expensive sensors such as infrared cameras or radar. Additional System Details: ● Camera Flexibility: The system can integrate with a pan-tilt-zoom camera, enhancing its adaptability to different surveillance scenarios. ● Image Segmentation: It can segment video images into distinct sky and land portions for more precise analysis. ● Edge Detection: The system employs a Sobel operator for edge detection, contributing to the identification of relevant features in the images. ● Support Vector Machine Training: The system can be coupled with a support vector machine trained specifically on smoke data, enhancing its accuracy in identifying wildfire-related patterns.
Research Question/Problem/ Need	Wildfire detection with a camera has not yet been implemented.

Important Figures	 Control scheme and logic of system
VOCAB: (w/definition)	Sobel operator: The Sobel operator hunts for edges in images by measuring how quickly pixel brightness changes in different directions. Support Vector Machine Training: SVM training finds the perfect line in high-dimensional space that maximally separates data points by grabbing onto "support vectors." Covariance matrix: A covariance matrix is a matrix capturing the joint variability of a random vector, quantifying how much each element "co-varies" with its associated elements.

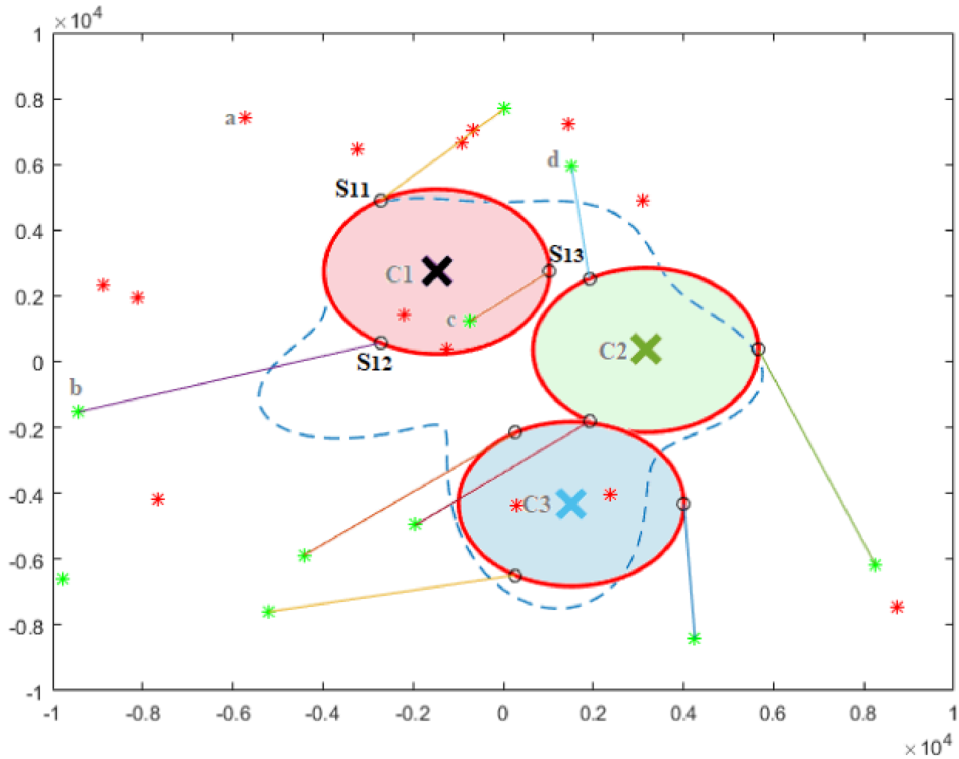
Cited references to follow up on	N/A
Follow up Questions	Do support vector machines learn from past decisions?

Article #14 Notes: Wildfire Monitoring in Remote Areas using Autonomous Unmanned Aerial Vehicles

Article notes should be on separate sheets

Source Title	Wildfire Monitoring in Remote Areas using Autonomous Unmanned Aerial Vehicles
Source citation (APA Format)	Afghah, F., Razi, A., Chakareski, J., & Ashdown, J. (2019). *Wildfire Monitoring in Remote Areas using Autonomous Unmanned Aerial Vehicles* (arXiv:1905.00492). arXiv. http://arxiv.org/abs/1905.00492
Original URL	https://arxiv.org/pdf/1905.00492.pdf
Source type	Research article
Keywords	Wildfire, uav
#Tags	Uav, fire
Summary of key points + notes (include methodology)	Introduction: ● Wildfires are severe natural disasters causing extensive damage and loss. ● Current methods for wildfire detection and monitoring are not fast and reliable. ● Cost of wildfire management is substantial, and the risk to human personnel is high. ● Proposed solution: Drone-based wildfire monitoring using autonomous UAVs for remote and hard-to-reach areas. Objectives of the Proposed System: ● Utilize autonomous UAVs for on-demand monitoring faster than current approaches. ● Minimize human intervention in risky wildfire zones. ● Develop a fully autonomous system with a distributed leader-follower coalition formation model. ● Cover the entire fire zone with minimum drones. ● Minimize energy consumption and latency of drones. Challenges and Drawbacks of Current Technologies: ● Delayed fire detection for small fires. ● Time lag for satellites to overpass the field. ● Infeasibility of deploying sensors with limited sensing distance ranges. ● Ground-based personnel and aircraft pilots at risk. Previous Attempts and Limitations: ● Previous drone-based monitoring used single remotely-controlled UAVs.

	● Limitations: Low spatial/temporal resolution, limited flight time, human intervention risks. ● COMETS project focused on using a fleet of heterogeneous drones but still controlled by humans. Proposed Framework: ● Framework for fire monitoring using heterogeneous autonomous drones in inaccessible regions. ● Decentralized leader-follower coalition formation for full coverage of fire zones. ● Differentiated UAVs: Fixed-wing UAVs for initial recognition, Rotary UAVs as observer drones. ● Event-triggered fire monitoring system initiated based on primary information. Leader-Follower Coalition Formation: ● Objective: Optimal UAV coalitions for full coverage in remote regions. ● Sectorized approach: Leader UAVs initiate coalition formation, recruit follower UAVs. ● Leader UAVs take greedy displacement actions to create intersection and separation conditions. ● Observer UAVs (followers) hover in circular paths, avoiding collisions, and collect imagery information. Coalition Formation Model: ● Each leader UAV broadcasts a proposal to potential follower UAVs in close proximity. ● Proposal includes needed sensor/camera types, mission duration, and fire region coordinates. ● Follower UAVs respond with their properties, available resources, and current position. ● Leader evaluates responses, considering resources, battery, and location. ● Formed coalitions satisfy properties and resource requirements. Simulation Results: ● Performance of the proposed system approaches that of a centrally-optimized system. ● Fully distributed solution with low complexity and close-to-optimal performance.
Research Question/Problem/ Need	Wildfires in remote areas are hard for humans to detect efficiently and consistently.

Important Figures	 Graph of overlapping and optimal search boundaries for evidence of fire area
VOCAB: (w/definition)	Coalition formation: Grouping of UAVs for coordinated tasks. Spatial/temporal resolution: Detail and frequency of data collection. Sectorized approach: Surveillance area divided into smaller sections for efficient monitoring. Greedy displacement: Leader UAVs adjust positions to optimize coverage. Coalition proposal: Information shared by leader UAVs to recruit followers. Centrally-optimized: System controlled and coordinated from a central hub.
Cited references to follow up on	H. Cruz, M. Eckert, J. Meneses, and J. Martnez, “Efficient forest fire detection index for application in unmanned aerial systems (UASs),” Sensors, vol. 16, no. 6, p. E893, 2016.
Follow up Questions	Is a coalition formation or drone swarm necessary for detection of wildfires?

Article #15 Notes: CompDrone: Towards Integrated Computational Model and Social Drone Based Wildfire Monitoring

Article notes should be on separate sheets

Source Title	CompDrone: Towards Integrated Computational Model and Social Drone Based Wildfire Monitoring
Source citation (APA Format)	Rashid, M. T., Zhang, Y., Zhang, D., & Wang, D. (2020). CompDrone: Towards Integrated Computational Model and Social Drone Based Wildfire Monitoring. *2020 16th International Conference on Distributed Computing in Sensor Systems (DCOSS)*, 43–50. https://doi.org/10.1109/DCOSS49796.2020.00020
Original URL	https://ieeexplore.ieee.org/abstract/document/9183707
Source type	Research article
Keywords	Drone, wildfire, model
#Tags	Drone fire
Summary of key points + notes (include methodology)	Problem Statement: ● Forest fires cause significant global ecological and economic damage annually. ● Detection of fire propagation is crucial for effective wildfire control. ● Computational wildfire models and social-media-driven drone sensing (SDS) are two approaches for monitoring wildfires. ● Computational models rely on real-time meteorological data, while SDS uses social media signals to drive drones for real-world observations. ● Both methods have limitations: computational models require constant real-time data, and SDS may underperform in remote regions or during large-scale fires. CompDrone Framework: ● Objective: ○ Develop a wildfire monitoring framework that integrates computational modeling and SDS for more reliable monitoring. ○ Address challenges: limited social media data in fire regions and

	identifying regions for drone dispatch. ● Challenges: ○ Limited social media data in fire regions due to data sparsity. ○ Identifying probable fire regions for efficient drone dispatch. ● Solution: ○ CompDrone leverages cellular automata, constrained optimization, and game theory. ○ Uses a trigger mechanism for social media signals in neighboring regions to drive a computational wildfire detection model based on cellular automata. ○ Enhances the model by explicitly considering humidity and air quality for more accurate predictions. ○ Employs a game-theoretic task allocation policy to assign drones to probable fire locations. ● Evaluation: ○ CompDrone outperforms state-of-the-art schemes in predicting wildfire propagation. ○ Real-world wildfire dataset evaluation shows significant performance gains. Comparison with Existing Approaches: ● Computational Models: ○ Require constant real-time meteorological data. ○ Limited by slow update intervals of weather satellites. ● SDS: ○ Relies on social media feeds for real-world observations. ○ Underperforms in remote regions or during large-scale wildfires. ● CompDrone: ○ Integrates computational modeling and SDS. ○ Addresses challenges of limited social media data and efficient drone dispatch. ○ Achieves significant performance gains over existing schemes. Technical Challenges and Solutions: ● Limited Social Media Data: ○ Challenge: Data sparsity in forest fire regions. ○ Solution: CompDrone utilizes social media signals from neighboring regions and employs a trigger mechanism. ● Identifying Probable Fire Regions: ○ Challenge: Efficiently dispatching drones to the right locations. ○ Solution: CompDrone employs game theory for task allocation, prioritizing locations with high chances of fire. CompDrone Modules: ● Social Signal Distillation (SSD) Module: ○ Analyzes uncertain social media posts to identify reliable event reports. ○ Uses a truth discovery mechanism to obtain reliable signals from noisy social media data. ● Wildfire Propagation Prediction (WPP) Module:

	○ Determines probable fire regions using reports from the SSD module as triggers. ○ Incorporates a cellular automata-based computational wildfire propagation model. ○ Considers dynamic factors like wind conditions, vegetation conditions, land topography, humidity, and air quality. ● Drone Task Assignment (DTA) Module: ○ Assigns drones to investigate probable fire regions obtained from the WPP module. ○ Uses a game-theoretic task allocation policy to enhance efficiency. ● Parameter Optimization (Po) Module: ○ Utilizes measurements obtained by dispatched drones to augment the wildfire prediction model. Evaluation and Significance: ● Evaluation Results: ○ CompDrone outperforms state-of-the-art wildfire monitoring approaches. ● Significance: ○ First endeavor to combine computational modeling with SDS for integrated wildfire monitoring. ○ Addresses challenges in existing approaches and achieves significant performance gains. Conclusion: ● CompDrone presents an innovative framework for wildfire monitoring. ● Successfully integrates computational modeling and SDS to overcome limitations of individual approaches. ● Demonstrates superior performance in predicting wildfire propagation based on real-world dataset evaluation.
Research Question/Problem/ Need	Forest fires cause great damage and and not reliably detected by humans.
Important Figures	
VOCAB: (w/definition)	Social-media-driven drone sensing (SDS): Highlights a novel approach using social media data. Cellular automata: A complex mathematical model simulating fire propagation. Constrained optimization: A technique for finding the best solution within defined limitations. Game theory: A mathematical framework for analyzing strategic decision-making in competitive situations. Task allocation policy: A rule-based system for assigning tasks (drone dispatch) to optimize performance.

	Social Signal Distillation (SSD): A technical process for extracting reliable information from social media. Truth discovery mechanism: A specific technique for identifying true reports from noisy data. Wildfire Propagation Prediction (WPP): A module responsible for predicting fire spread based on triggers and model simulations. Drone Task Assignment (DTA): A module responsible for efficient drone dispatch using game theory. Parameter Optimization (Po): A process for continuously improving the model based on real-world data.
Cited references to follow up on	A. Gaszczak, T. P Breckon and J. Han, "Real-time people and vehicle detection from uav imagery", *Intelligent Robots and Computer Vision XXVIII: Algorithms and Techniques*, vol. 7878, pp. 78780B, 2011.
Follow up Questions	How often are parameters updated, and what data sources are used for this process? Are there any specific challenges or limitations to consider when implementing it in wildfire-prone areas?

Article #16 Notes: Use of Fire-Extinguishing Balls for a Conceptual System of Drone-Assisted Wildfire Fighting

Article notes should be on separate sheets

Source Title	Use of Fire-Extinguishing Balls for a Conceptual System of Drone-Assisted Wildfire Fighting
Source citation (APA Format)	Aydin, B., Selvi, E., Tao, J., & Starek, M. J. (2019). Use of Fire-Extinguishing Balls for a Conceptual System of Drone-Assisted Wildfire Fighting. *Drones*, *3*(1), Article 1. https://doi.org/10.3390/drones3010017
Original URL	https://www.mdpi.com/2504-446X/3/1/17
Source type	Research article
Keywords	Fire, drone, wildfire
#Tags	Drone fire
Summary of key points + notes (include methodology)	Introduction: ● Roles of Forests: ○ Cleanse water, stabilize soil, cycle nutrients, control climate, absorb CO2, produce oxygen. ○ Habitats for wildlife, essential for economic wealth. ● Forest Fires: ○ Two types: wildfires and prescribed fires. ○ Causes: human (90%), nature (lightning, etc. - 10%). ○ Impact: severe hazards to wildlife and society. ○ Statistics (2017): 56,186 wildfires, 9.2 million acres lost, $5.1 billion loss, 4.5 million homes at risk. ● Challenges in Fire Suppression: ○ Terrain difficulty, wind impact, hard-to-reach areas. ○ Wildfire fuels: understory foliage, branches, forest floor, treetop residues. ○ Classification: surface fuels (on/above ground), aerial fuels (not in direct contact with the ground). ● Wildfire Behavior Descriptors: ○ Rate of spread (chains/hour), heat per unit area (Btu/ft2), flame length (feet), fireline intensity (Btu/ft/s).

	○ Suppression interpretations based on flame length and fireline intensity. ● Conceptual Design for Wildfire Fighting: ○ Utilizes small unmanned aircraft system (UAS). ○ Proposes fire extinguishing balls released from UAS. ○ Effective for short grass, timber litter, short needle litter, and chaparral vegetations. ● Fire Extinguishing Balls: ○ Sphere-shaped, Styrofoam filled with non-toxic chemical powders. ○ Activates within 3 seconds, explodes, releases extinguishing agents. ○ Brands: Elide (Thailand) and AFO (China). ○ Effective against Class A (solid burning), Class B (flammable liquids and gases), Class C (energized electrical equipment). Background: ● Use of Drones in Firefighting: ○ UAS used for search and rescue, situational awareness in firefighting. ○ Time crucial in suppressing forest fires. ○ UAS roles: monitoring, detection, diagnosis, prognosis. ○ Scientific research: technical and non-technical perspectives. ● Non-Technical Aspects: ○ Public perception of drones varies by application. ○ Firefighting drone applications well-supported. ○ Economic feasibility studied. ● Technical Aspects: ○ UAS-based remote sensing with computer vision. ○ Infrared sensors, visual cameras, LIDAR used for fire detection. ○ Simulation studies show promising results for UAS in monitoring, detecting, diagnosing, and prognosing wildfires. ○ Current research focuses on developing remote sensing for spot fires, fire head, and flanks' risk. Materials and Methods: ● Fire Extinguishing Ball Experiments: ○ Controlled experiments with local fire department in Commerce, TX. ○ Classes A and B fires ignited in an 8 × 8 feet fire demonstration cell. ○ AFO fire extinguishing ball (smallest size) used due to budget constraints. ○ Efficiency measured by 'time to activate.'
Research Question/Problem/ Need	Fire-extinguishing balls are already used for traditional fire mitigation, but drones are a more effective method to use.
Important Figures	No relevant figures

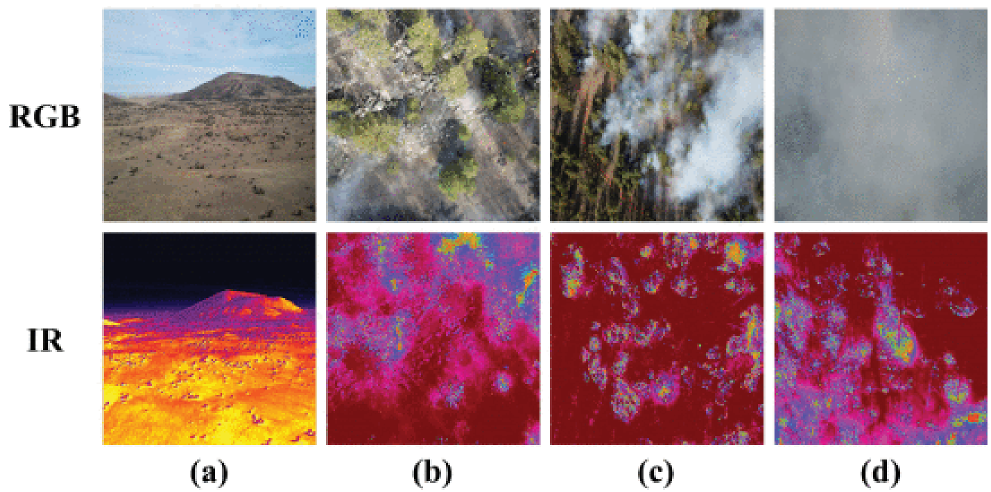
VOCAB: (w/definition)	Fireline intensity: Rate of energy release along the fire perimeter. Time factor: Critical importance of rapid response in wildfire suppression.
Cited references to follow up on	Yuan, C.; Liu, Z.; Zhang, Y. Aerial images–based forest fire detection for firefighting using optical remote sensing techniques and unmanned aerial vehicles. *J. Intell. Robot Syst.* **2017**, *88*, 635–654.
Follow up Questions	What are the challenges in ensuring reliable communication and data transmission between drones and ground control during firefighting operations? How are researchers addressing the issue of integrating different types of sensor data (infrared, visual, LIDAR) for more accurate fire assessment?

Article #17 Notes: Wildland Fire Detection and Monitoring Using a Drone-Collected RGB/IR Image Dataset

Article notes should be on separate sheets

Source Title	Wildland Fire Detection and Monitoring Using a Drone-Collected RGB/IR Image Dataset
Source citation (APA Format)	Chen, X., Hopkins, B., Wang, H., O'Neill, L., Afghah, F., Razi, A., Fulé, P., Coen, J., Rowell, E., & Watts, A. (2022). Wildland Fire Detection and Monitoring Using a Drone-Collected RGB/IR Image Dataset. *IEEE Access*, *10*, 121301–121317. https://doi.org/10.1109/ACCESS.2022.3222805
Original URL	https://ieeexplore.ieee.org/abstract/document/9953997
Source type	Research article
Keywords	Fire drone
#Tags	Dataset drone fire
Summary of key points + notes (include methodology)	Abstract: ● Forest Monitoring Technologies: Satellite, aircraft, and observation towers have uncertainties in monitoring wildfires, particularly in early growth stages. ● Drone Systems for Early Detection: Drones with 3D mobility, low flight altitude, and fast deployment are valuable for early detection of wildfires, especially in remote areas. ● Dataset Contribution: Presents a multi-modal UAV-collected dataset with RGB and thermal images of a prescribed fire. ● Detection Methodology: Uses a deep learning-based approach for fire and smoke pixel detection, achieving higher accuracy than single-channel video feeds. ● Dataset Context: Includes georeferenced pre-burn point cloud, RGB orthomosaic, weather information, burn plan, and other contextual information. ● Technology Advances: Discusses advances in TPUs, GPUs, communication technologies, and their role in on-the-fly detection and modeling of wildfires.

	Introduction: ● Wildfire Monitoring Challenges: Despite improvements, uncertainties remain in wildfire location, extent, and environmental conditions. ● Technological Gaps: Existing technologies face challenges in detecting low-intensity fires, early-stage fires, and fires through clouds, vegetation, or heavy smoke. ● Need for Rapid Identification: Identifying a fire's location, extent, and environment is crucial for effective intervention and management. ● Diverse Platforms: Various platforms, including satellites, aircraft, and drones, with different characteristics have been proposed to meet monitoring needs. Background and Related Works: ● Advances in Wildfire Response: Improved public reporting, satellite observations, and smoke-observing cameras have enhanced wildfire awareness. ● Spatial and Temporal Dynamics: Wildland fires' dynamic nature depends on factors like wind, terrain, and fuel, making their detection and mapping challenging. ● Technological Proliferation: UAVs offer high-resolution mapping, and new technologies like TPUs, GPUs, and communication technologies enhance onboard capabilities. ● Data-driven Models: Reliance on large-scale, multi-modal training datasets for data-driven onboard fire detection and modeling. Dataset Description (FLAME2): ● Dataset Features: FLAME2 provides dual RGB/IR drone videos and images of a prescribed burn, filling a gap in existing datasets. ● Supplemental Dataset: Includes georeferenced point clouds, weather and burn conditions, pre-burn aerial RGB videos, expanding applications beyond fire detection. Deep Learning-Based Wildfire Detection: ● Transfer Learning: Utilizes Transfer Learning for wildfire detection, fine-tuning pre-trained CNN models on large natural image datasets. ● Classification and Beyond: CNN models demonstrate outstanding performance in classification and can be extended to higher-level vision tasks like object detection and segmentation. ● Multi-Modality Learning: Integrates optical and thermal domains for fire detection, emphasizing feature fusion at different levels. Section V: Contributions: ● Dataset Contribution: FLAME2 dataset of side-by-side RGB/IR imagery, jointly labeled by human experts. ● Benchmarking and Analysis: Implements DL-based benchmarks with RGB-thermal fusion for fast fire classification, followed by a hybrid method for fire detection localization. ● Expected Impact: Anticipates contributions to fire detection, modeling, and management through methods developed using the FLAME2 dataset. Conclusion: ● Technological Advances: Acknowledges remarkable advances in fire

	detection technology and modeling systems. ● Remaining Challenges: Identifies discontinuities between instrument outputs and modeling system needs, emphasizing the need for further interdisciplinary research. ● Future Prospects: Anticipates ongoing technological proliferation, benefitting fire ignition and behavior measurements, and emphasizes the role of interdisciplinary teams in wildland fire applications.
Research Question/Problem/ Need	Infrared images can be used to detect fires, but are usually hard to obtain from a sufficient perspective.
Important Figures	 Rgb and ir pairs of images tak
VOCAB: (w/definition)	Multi-modal UAV-collected dataset: RGB and thermal images used for training and benchmarking. Georeferenced pre-burn point cloud, RGB orthomosaic, weather information, burn plan: Contextual data included in the dataset. TPUs, GPUs, communication technologies: Enabling on-the-fly detection and modeling. High-resolution mapping, onboard capabilities: Enhancements by UAVs and new technologies. Data-driven models: Reliance on large datasets for fire detection and modeling. Dual RGB/IR drone videos and images: Filling a gap in existing datasets.
Cited references to follow up on	F. Afghah, A. Razi, J. Chakareski and J. Ashdown, "Wildfire monitoring in remote areas using autonomous unmanned aerial vehicles", *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, pp. 835-840, Apr. 2019.
Follow up Questions	How was the FLAME2 dataset labeled for fire/smoke pixel detection, and what challenges were faced in ensuring accurate labeling?

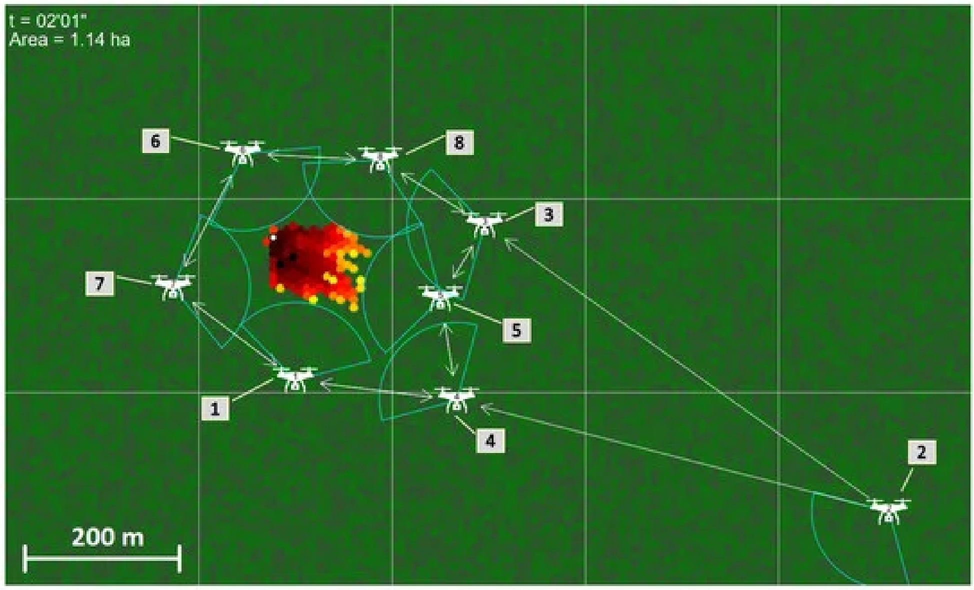
	How do communication technologies and bandwidth limitations impact real-time fire detection and data transmission from drones? How does the model account for the influence of weather conditions (wind, humidity) and varying terrain on fire behavior and detection?

Article #18 Notes: Monitoring and Cordoning Wildfires with an Autonomous Swarm of Unmanned Aerial Vehicles

Article notes should be on separate sheets

Source Title	Monitoring and Cordoning Wildfires with an Autonomous Swarm of Unmanned Aerial Vehicles
Source citation (APA Format)	Saffre, F., Hildmann, H., Karvonen, H., & Lind, T. (2022). Monitoring and Cordoning Wildfires with an Autonomous Swarm of Unmanned Aerial Vehicles. *Drones*, *6*(10), Article 10. https://doi.org/10.3390/drones6100301
Original URL	https://www.mdpi.com/2504-446X/6/10/301
Source type	Research article
Keywords	Drone, fire, autonomous
#Tags	Fire drone uav
Summary of key points + notes (include methodology)	Abstract: ● Unmanned aerial vehicles (drones) used in firefighting are typically remotely operated. ● Emphasis on potential of autonomous drone swarms for situational awareness in environmental protection. ● Monte Carlo simulation used to investigate the influence of key parameters on autonomous drone swarm performance. ● Goal: Locate and establish a continuous perimeter around a simulated fire event for real-time situational awareness to firefighters. ● Use of simple, robust, and realistically implementable distributed decision functions for swarm self-organization. ● Strong nonlinear effects observed in interaction between parameters, approximated using an empirical law. ● Findings could inform resource mobilization based on mission characteristics and odds of success. Introduction: ● Wildfires are a major global environmental issue linked to climate change. ● Forest fires release CO2, impact carbon sink, and contribute to ecological,

	social, and economic damages. ● Importance of early detection and monitoring in remote areas using sensing technologies. ● Unmanned and autonomous sensing platforms, especially drones, are valuable for wildfire prevention and surveillance. ● Current limitations in manual drone operation during wildfires. ● Future vision: Fully autonomous drone swarms for surveillance, reducing human involvement and environmental impact. ● Objective of the study: Evaluate the usability of drone swarms using simple autonomous features for fire surveillance. Scope and Contribution: ● Distinction between aspects of wildfire research: detection and fire spread modeling. ● Focus on monitoring and cordoning fires rather than prevention. ● Drones deployed for situational awareness, not involved in firefighting actions. ● Contribution: Advocacy for deploying autonomous UAV swarms against wildfires, supported by numerical experimentation. ● Three separate functions in the mission: Detection, Evasion, Encirclement. ● Systematic study of collective behavior and performance of a drone swarm using a decentralized decision-making algorithm. Modelling - The Wildfire Model: ● Swarm's ability to encircle a fire without prior knowledge of the fire's behavior or environment. ● Model focused on simulating realistically behaving fire for swarm encirclement. ● Limitations in developing detailed fire spread models due to environmental complexity. ● Evaluation against a class of scenarios defined by a simplified fire model. ● Model designed to provide a challenging stress test for swarm approach, not for precise fire spread prediction. ● Simple cellular automaton used based on principles of the "Prometheus" model. Environment Topology, Fuel, and Depletion of Fuel Due to Fire: ● Cellular automaton based on hexagonal grid with 6 equidistant neighbors. ● Simplified model for environment topology, fuel, and fuel depletion due to fire. ● Focus on providing a realistic simulation of a wildfire rather than precise prediction of fire spread. ● This summary provides a detailed overview of the key points in the provided text, covering the authors, affiliations, abstract, introduction, scope, contribution, and details about the wildfire model and its components.
Research Question/Problem/ Need	UAVs used for firefighting and detection purposes are not autonomous.

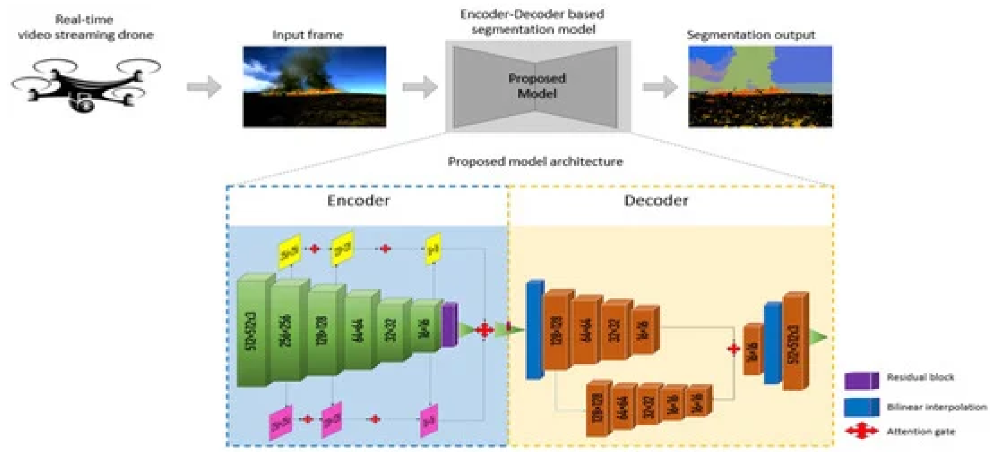
Important Figures	 Figure of simulation showing detected borders of fire and associated drone swarm.
VOCAB: (w/definition)	Monte Carlo simulation: A computational method used to analyze system behavior under uncertainty. Distributed decision functions: Rules governing individual drones' actions within the swarm. Numerical experimentation: Using simulations to evaluate the performance of drone swarms. Decentralized decision-making: Algorithms for coordinating drones without a central controller. Environment topology, fuel, and fuel depletion: Simulating the physical aspects of the fire and its surroundings.
Cited references to follow up on	Dufour, D.; Le Noc, L.; Tremblay, B.; Tremblay, M.N.; Généreux, F.; Terroux, M.; Vachon, C.; Wheatley, M.J.; Johnston, J.M.; Wotton, M.; et al. A Bi-Spectral Microbolometer Sensor for Wildfire Measurement. *Sensors* **2021**, *21*, 3690.
Follow up Questions	What are the limitations of using simple, robust decision functions instead of more complex algorithms in the swarm? How does the decentralized decision-making algorithm ensure efficient communication and coordination between drones in the swarm?

Article #19 Notes: Deep Encoder–Decoder Network-Based Wildfire Segmentation Using Drone Images in Real-Time

Article notes should be on separate sheets

Source Title	Deep Encoder–Decoder Network-Based Wildfire Segmentation Using Drone Images in Real-Time
Source citation (APA Format)	Muksimova, S., Mardieva, S., & Cho, Y.-I. (2022). Deep Encoder–Decoder Network-Based Wildfire Segmentation Using Drone Images in Real-Time. *Remote Sensing*, *14*(24), Article 24. https://doi.org/10.3390/rs14246302
Original URL	https://www.mdpi.com/2072-4292/14/24/6302
Source type	Research article
Keywords	Drone wildfire realtime
#Tags	Drone fire
Summary of key points + notes (include methodology)	Fire Incidences and Damage: ● In 2019, South Korea recorded 40,300 fire incidents, resulting in USD 688 million in losses, 2,219 injuries, and 284 deaths. ● In the US, 58,985 wildfires occurred in 2021, consuming approximately 7,125,643 acres, compared to 58,950 wildfires in 2020, consuming 10,122,336 acres. Use of UAVs for Wildfire Detection: ● UAVs (Unmanned Aerial Vehicles) with computer-vision-based remote sensing systems are gaining popularity for early wildfire detection. ● Drones are known for their mobility, speed, safety, and cost-effectiveness, providing spectral and spatial-temporal resolution. ● Computer-vision-based systems on UAVs offer extended range, gathering accurate information economically. Deep Learning for Wildfire Detection: ● Deep learning-based image processing techniques, including detection and segmentation, show improved performance in wildfire processing. ● DL algorithms efficiently study geometrical features, width, shape, angle, and height of wildfires, achieving promising results in segmentation and classification. Challenges and Drawbacks of DL Techniques:

	● DL techniques exhibit drawbacks like false detection of fire pixels and false alarms. ● Studies aim to explore the application of DL techniques for various challenges in forest fires, such as image degradation, background complexity, and small objects. Proposed Encoder-Decoder for Wildfire and Smoke Segmentation: ● The paper proposes an encoder-decoder framework for segmenting forest fires and smoke. ● The approach modifies EfficientNetv2 with a novel attention gate (AG)-based nested network for real-time segmentation. ● The network uses depth-wise convolutions for lightweight real-time application. ● Evaluation against state-of-the-art methods shows superior accuracy and speed. Key Aspects of the Proposed Study: ● Two-pathway architecture for real-time fire and smoke instance segmentation. ● Novel nested decoder with pre-activated residual blocks and AGs for improved segmentation accuracy. ● Lightweight network using depth-wise convolutions for efficient real-time processing. ● Satisfactory generalization of the dataset using a combination of datasets and encoder-decoder network. Attention Gate and Parallel Branches in Proposed Method: ● Attention Gate (AG) improves performance by focusing on relevant features, reducing responses to unnecessary information. ● Parallel branches in the decoder subnetworks, using AGs and pre-activated residual blocks, aim to aggregate features with different semantic scales. Feature Extraction Network Backbone: ● The proposed method uses EfficientNetv2 as an encoder, removing classification head and SE links for adaptability. ● Synchronized in-place activated batch normalization (iABN sync) replaces batch normalization layers for improved accuracy. Summary of Attention Gate and Parallel Branches: ● Attention Gate (AG) reduces reactions to unnecessary information, focusing on the region of interest (ROI). ● Parallel branches in the decoder subnetworks use AGs and up-sampling for efficient aggregation of features.
Research Question/Problem/ Need	

Important Figures	 Overview of architectures used for segmenting objects
VOCAB: (w/definition)	Spectral and spatial-temporal resolution: Ability to capture detailed information across space and time. Encoder-decoder architecture: Deep learning network structure for image segmentation. Attention gate (AG): Mechanism used to focus on relevant parts of an image. Depth-wise convolutions: Technique for reducing network complexity and computational cost. Residual blocks: Network components preserving information throughout the process. Two-pathway architecture: Processing fire and smoke data separately for improved accuracy. Pre-activated residual blocks: Enhanced residual blocks for better information flow. Satisfactory generalization: Ability of the model to perform well on unseen data.
Cited references to follow up on	Shamsoshoara, A.; Afghah, F.; Razi, A.; Zheng, L.; Peter; Fulé, Z.; Blasch, E. Aerial imagery pile burn detection using deep learning: FLAME Dataset. *Comput. Netw.* **2021**, *193*, 108001.
Follow up Questions	How well do existing deep learning algorithms generalize to different types of wildfires and environmental conditions? How well does the model deal with situations where fire and smoke overlap or appear alongside other confusing elements in the image?

Article #20 Notes: A review of machine learning applications in wildfire science and management

Article notes should be on separate sheets

Source Title	A review of machine learning applications in wildfire science and management
Source citation (APA Format)	Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews*, *28*(4), 478–505. https://doi.org/10.1139/er-2020-0019
Original URL	https://cdnsciencepub.com/doi/full/10.1139/er-2020-0019
Source type	Research article
Keywords	Machine learning wildfire
#Tags	fire
Summary of key points + notes (include methodology)	Introduction to Wildland Fire: ● Wildland fire is a global phenomenon occurring throughout the year, with significant environmental and human impacts. ● Over 90% of wildland fires are human-caused, with the remaining attributed to lightning. ● The occurrence and behavior of wildland fires are influenced by factors such as ignition source, fuel composition, weather, and topography. ● Wildfires result in direct impacts on human life, communities, and indirect effects through smoke exposure. ● Billions of dollars are spent annually on fire management activities to mitigate negative effects. Complexity of Wildland Fire: ● Wildland fire is a complex process influenced by various interrelated factors at different scales. ● Fire activity spans from small-scale ignition and combustion processes to larger-scale fire spread and growth. ● Current physics-based models have limitations in accuracy, regional bias, and resource requirements. ● Remote-sensing technologies have improved monitoring and observation, offering a data-centric approach to wildfire modeling. Rise of Machine Learning (ML) in Wildfire Science:

	● ML, a subset of artificial intelligence, is defined as algorithms detecting patterns in data to predict future outcomes. ● ML methods have gained popularity due to advancements, particularly in the environmental sciences. ● ML's data-centric approach makes it suitable for handling complex environmental variables in wildfire science. ● ML applications in the environmental sciences include geosciences, forest ecology, extreme weather prediction, and more. ML Methods Overview: ● ML methods can be categorized into supervised learning, unsupervised learning, and agent-based learning. ● Supervised learning involves mapping inputs to known outputs, while unsupervised learning extracts patterns without known outputs. ● Agent-based learning simulates behaviors and interactions, with reinforcement learning as a specific case. ● Common ML methods include decision trees, random forests, artificial neural networks, support vector machines, and genetic algorithms. ML Applications in Wildfire Science: ● A scoping review identified 300 relevant publications until 2019, highlighting common ML methods used. ● ML applications in wildfire science categorized into six domains: fuels characterization, fire detection and mapping, fire weather and climate change, fire occurrence and risk, fire behavior prediction, and fire effects and management. ● Advantages and limitations of ML approaches discussed, considering data size, computational requirements, generalizability, and interpretability. ● Opportunities for future ML advancements in wildfire science and management, especially involving large multivariate datasets. Conclusion: ● Emphasis on the active role of wildfire research and management communities in providing high-quality, freely available wildfire data for ML practitioners. ● Recognition of the need for expertise in wildfire science to ensure realistic modeling, especially with complex ML methods. ● Potential for applying more current ML methods, including deep learning and agent-based learning, in wildfire science. ● Overall, the review aims to guide researchers, practitioners, and ML specialists in the wildfire community, providing insights into the application of ML methods.
Research Question/Problem/ Need	Machine learning has become a large and widely studied subject, but there is a lack of cohesive and concrete information.

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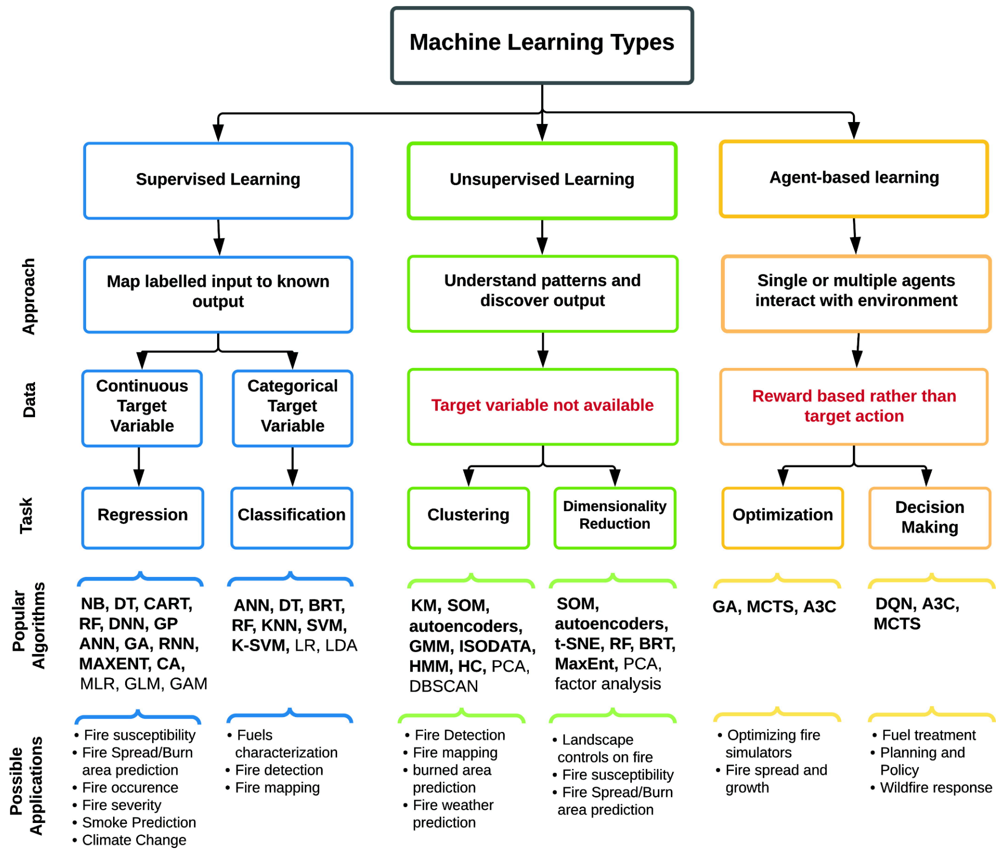
<td>Important Figures</td>
<td>


General diagram of branching topics reviewed in article, note listing of algorithms types.
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<td>VOCAB: (w/definition)</td>
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Data-centric approach: Remote sensing technologies provide data for improved monitoring and modeling.

Supervised learning: Maps known inputs to desired outputs.

Unsupervised learning: Identifies patterns in data without predefined outputs.

Agent-based learning: Simulates individual behaviors and interactions (including reinforcement learning).
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<tr>
<td>Cited references to follow up on</td>
<td>Zhao Y., Ma J., Li X., and Zhang J. 2018. Saliency detection and deep learning-based wildfire identification in UAV imagery. Sensors, 18(3): 712.</td>
</tr>
<tr>
<td>Follow up Questions</td>
<td>What challenges exist in interpreting and understanding the complex outputs of ML models applied to wildfire data?</td>
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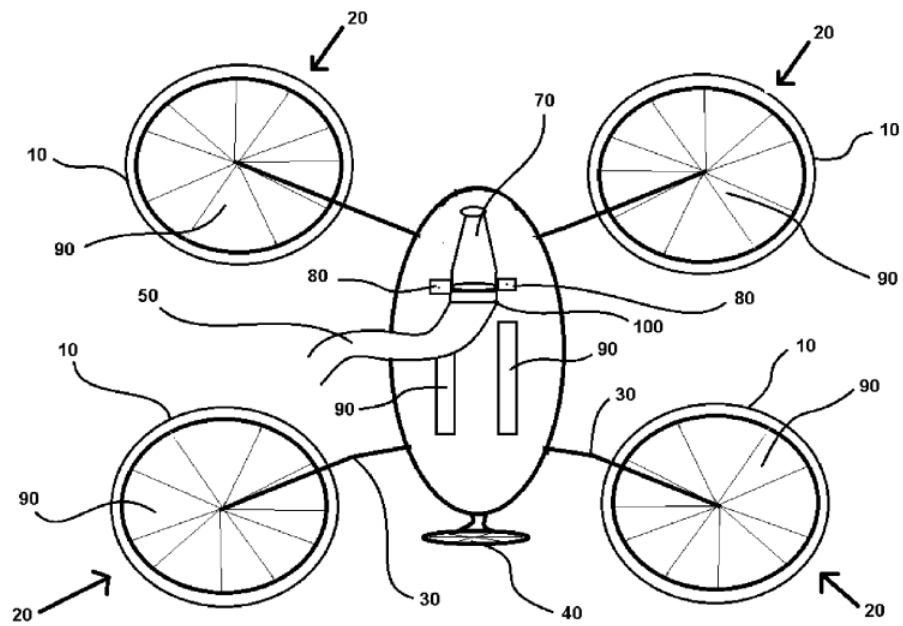
Patent #3 Notes: UAV Fire-fighting System

Article notes should be on separate sheets

Source Title	UAV Fire-fighting System
Source citation (APA Format)	Moore, J. (2013). *UAV Fire-fighting System* (United States Patent US20130134254A1). https://patents.google.com/patent/US20130134254A1/en
Original URL	https://patents.google.com/patent/US20130134254A1/en
Source type	Patent
Keywords	Uav, fire
#Tags	Uav system fire
Summary of key points + notes (include methodology)	Abstract: ● Unmanned Aerial Vehicle (UAV) designed for aerial firefighting while tethered to the ground via a tether system. ● Electrically powered UAV with stabilization using gyroscopes and electric motors to counteract recoil force from water escaping the nozzle. ● Ground-based command and control unit supplies electricity and water to the UAV through the tether. ● UAV stored within and launched from the command and control unit. Background: ● Conventional firefighting methods include fire hoses, trucks, helicopters, and UAVs with extinguishant tanks. ● Challenges in remote or hazardous areas where resupplying extinguishant is time-consuming. ● Existing UAV firefighting systems use onboard extinguishant tanks. Summary of the Invention: ● UAV designed to remain airborne while expelling water or fire-retardant chemicals from a nozzle. ● Stability maintained by gyroscopic stabilization and rotors opposing the nozzle's direction. ● Tether supplies electricity and water from the ground-based command and control unit. ● Gyroscopic stabilizer, rotors, and electric motors keep UAV aloft while countering water pressure. Key Features:

	● Gyroscopic stabilizer and rotors compensate for water pressure. ● Command and control unit houses UAV, provides launch point, and supplies water and electricity. ● Safety features include parachute, airbag, rotor covers, and emergency brake. ● Controller on the ground operates the UAV via remote sensors, cameras, and navigational controls. ● Multi-stage regulator system in the command and control unit regulates water pressure. ● Nozzle propels various extinguishant forms (water, foam, etc.) onto the fire. ● UAV equipped with backup battery for emergencies. Deployment and Operation: ● UAV tethered to the command and control unit. ● Tether provides electricity and water, enabling continuous firefighting without resupply. ● Launch point flexibility with multiple embodiments. Detailed UAV Structure: ● Primary rotors, gyroscope, and electric motors configured for stability. ● Rotor blades fixed or independently rotating for thrust adjustments. ● Command and control unit serves as a launching and docking point, equipped with launching bays. ● Water delivery system regulates pressure through a conventional fire hose connected to a hydrant.
Research Question/Problem/ Need	UAVs, as they are used for surveillance, have great potential in mitigation of wildfires.

Important Figures	 Diagram of system implementation on a single quad-rotor UAV
VOCAB: (w/definition)	Onboard extinguishant tanks: Existing UAV firefighting systems carrying limited amounts of fire-retardant chemicals. Gyroscopic stabilization: Mechanism using gyroscopes and counter-rotating rotors to maintain stability during water expulsion. Multi-stage regulator system: Precisely controls water pressure for efficient firefighting and UAV stability.
Cited references to follow up on	N/A
Follow up Questions	Compared to traditional and existing UAV firefighting methods, how does this tethered system perform in terms of fire suppression effectiveness, operational range, and resource consumption? How does the system's performance fare in different weather conditions (wind, rain) and challenging terrains (slopes, dense vegetation)? What are the estimated costs of implementing this system compared to other firefighting methods, and how feasible is its deployment in various regions and situations?