

Wildfire Detector

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Solution

In order to combat wildfires: Deploy autonomous drones with fire detection capabilities to enhance early identification and situational awareness.

Key Advantages:

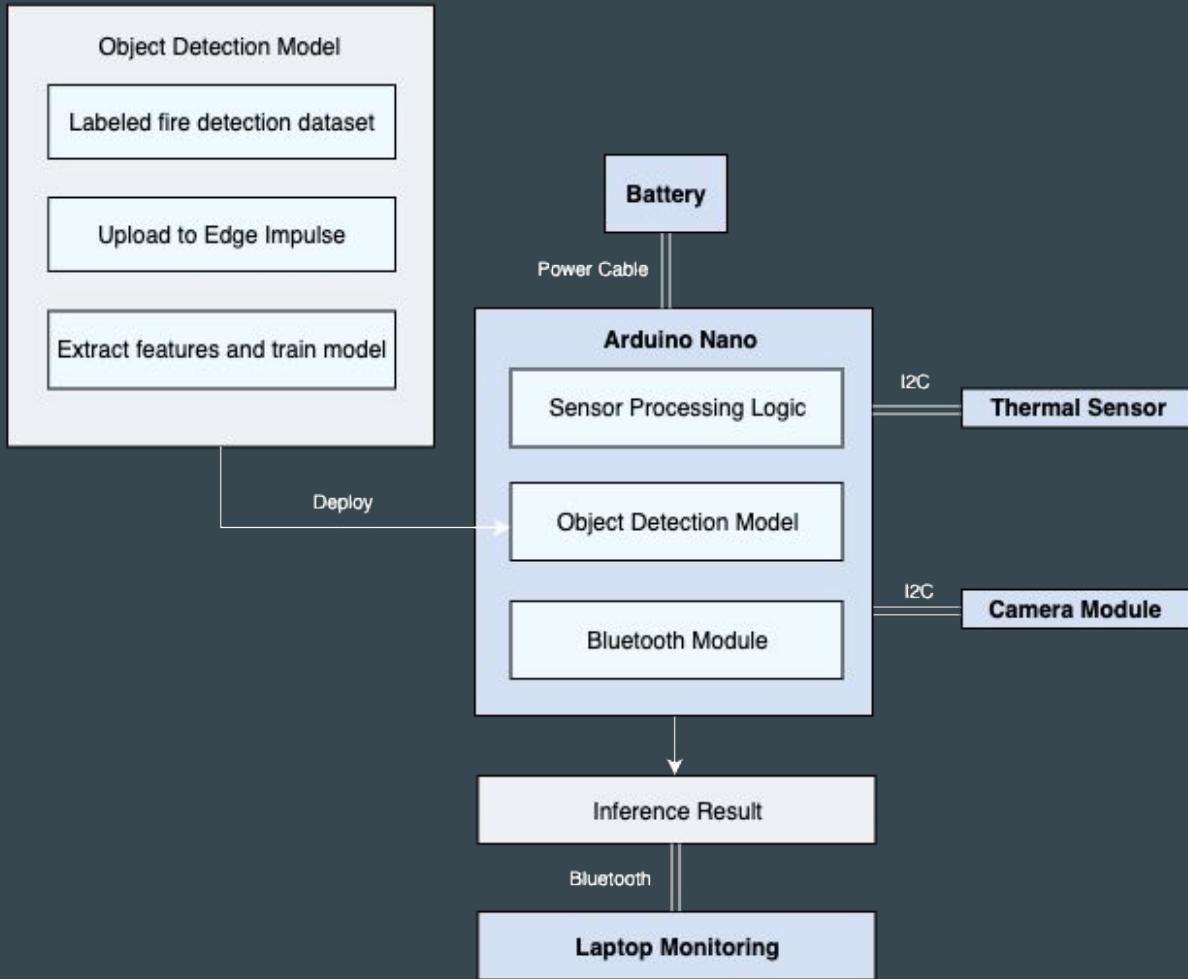
- **Overcome Terrain Barriers:** Drones can navigate rugged, inaccessible regions where ground sensors or cameras are ineffective.
- **Enhanced Detection Resolution:** Flying at lower altitudes provides higher-fidelity imagery for machine-learning-based fire recognition.
- **Smoke Adaptability:** Drones can operate beneath or around dense smoke plumes from active fires to identify new ignition points nearby.

Target Users

- Public Agencies such as:
 - National Interagency Fire Center
 - U.S. Forest Service
 - California Department of Forestry and Fire Protection (currently handling 7855 wildfires)
- Critical infrastructure operators such as:
 - Pacific Gas & Electric
- Large private landowners such as:
 - Owners of large vineyards/wineries
 - Owners of large ranches

BLERP - Why Use Embedded ML

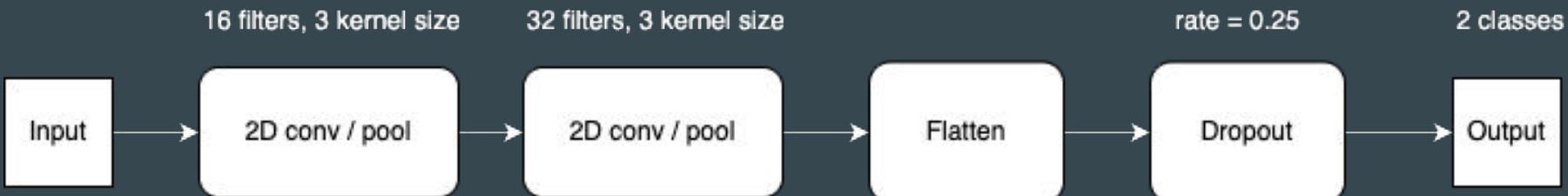
- **Bandwidth** - Using Embedded ML will decrease the amount of data that needs to be sent remotely, increasing effectiveness of network bandwidth.
- **Latency** - Doing inference on the drone itself decreases the latency of detecting fires.
- **Economics** - Operating locally also decreases costs of doing computation on the cloud.
- **Reliability** - Fire detection is not dependent on good network connection making local operations more reliable.
- **Privacy** - Local operation reduces exposure of data (photos) which should be private.



Components

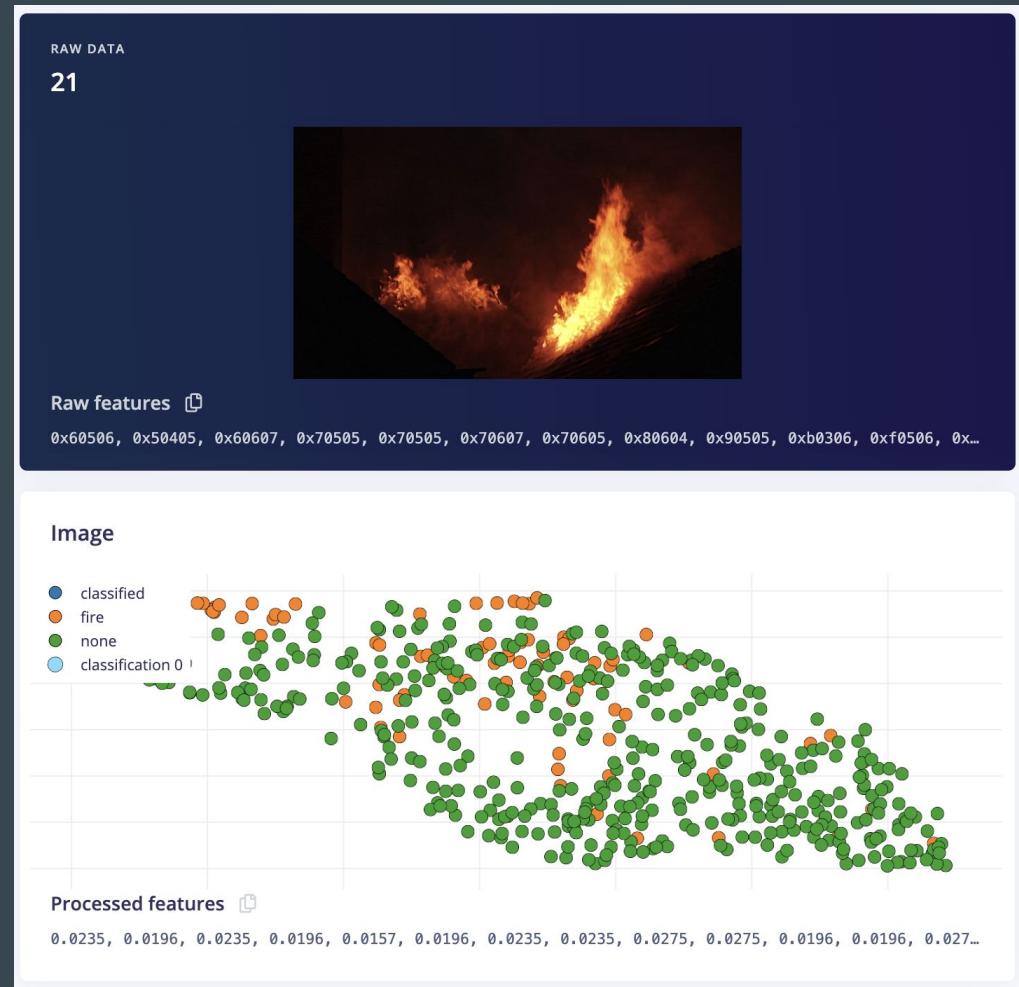
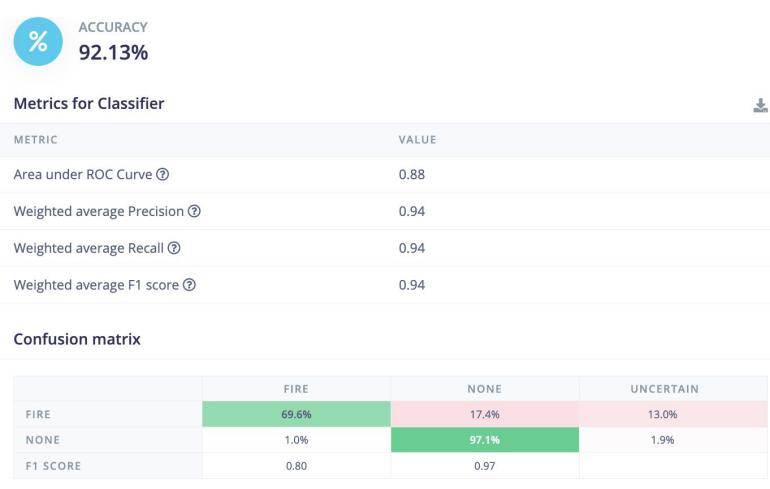
- Initial ML Model & Algorithm
 - Edge Impulse custom model (FOMO based CNN). Optimizations: int8 quantization, preprocessing data, pruning
- Dataset
 - Primary implementation includes a combination of Kaggle datasets.
- Feature extraction
 - Automatically learned from edge impulse; color features (RGB). Post MVP: texture, thermal gradients
- Hardware
 - Arduino Nicla Vision, STM32Lo, Thermal Imaging Camera.

Convolutional Neural Network Architecture

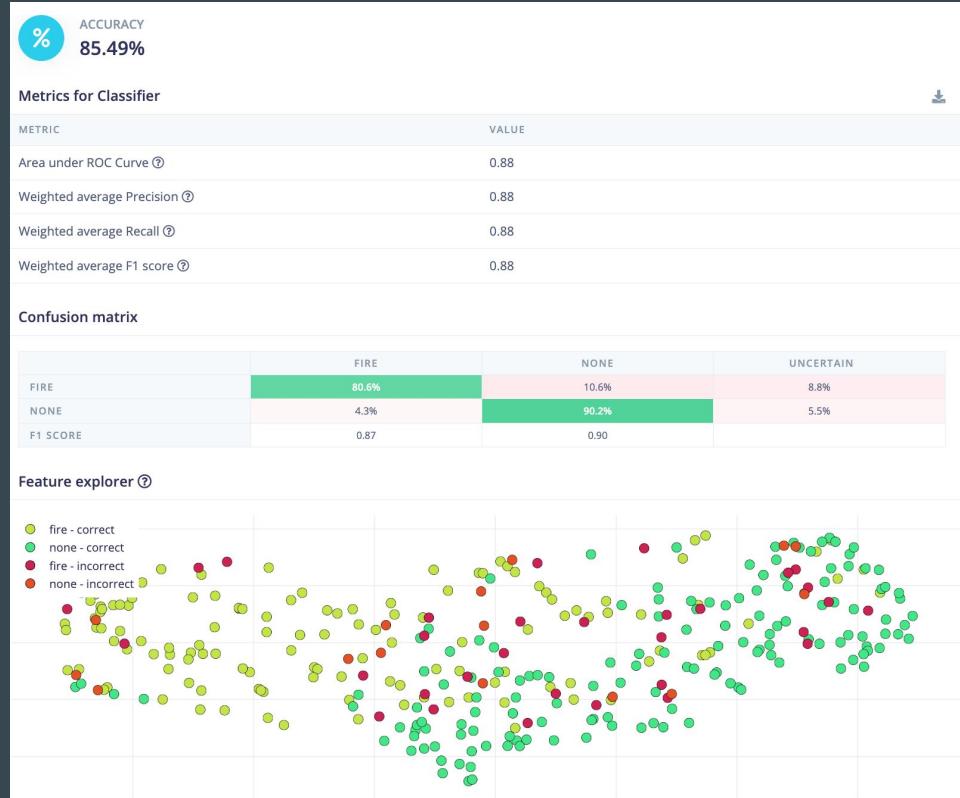
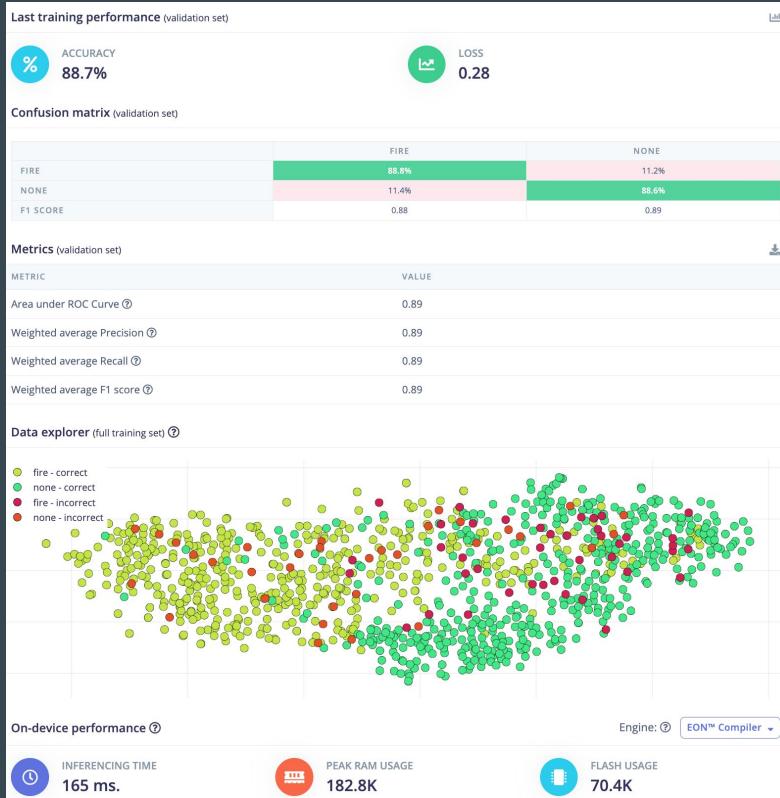


Classifier Metrics

- Model framework chosen:
Edge Impulse Classifier



Training and Test results



python3 Sun Nov 23 11:57PM

Arduino Nicla Vision

SKETCHBOOK

nicla_vision_camera.ino

```
216     float fire_score = 0.0f;
217     float none_score = 0.0f;
218
219     for (uint16_t i = 0; i < EI_CLASSIFIER_LABEL_COUNT; i++)
220         if (strcmp(ei_classifier_inference_categories[i], "fire") == 0)
221             fire_score = ei_classifier_inference_scores[i];
222
223     if (fire_score > none_score)
224         send_frame_over_serial();
225
226     ea_free(ei_camera_capture_out);
227     ei_camera_capture_out = NULL;
228 }
```

Nicla Vision Camera — python3 nicla_viewer.py — 80x25

(x=94, y=48) ~ R:80 G:108 B:128

parse

ire_sc

PRED fire 0.40234 none 0.59766
PRED fire 0.97266 none 0.02734
PRED fire 0.92578 none 0.07422
PRED fire 0.85938 none 0.14062
PRED fire 0.84375 none 0.15625
PRED fire 0.94531 none 0.05469
PRED fire 0.93359 none 0.06641
PRED fire 0.89453 none 0.18547
PRED fire 0.63672 none 0.36328
PRED fire 0.92969 none 0.07031
PRED fire 0.83594 none 0.16486
PRED fire 0.95312 none 0.04688
PRED fire 0.65234 none 0.34766
PRED fire 0.84375 none 0.15625
PRED fire 0.25391 none 0.74689
PRED fire 0.26562 none 0.73438
PRED fire 0.24689 none 0.75391
PRED fire 0.27734 none 0.72266
PRED fire 0.23438 none 0.76562
PRED fire 0.26562 none 0.73438
PRED fire 0.26562 none 0.73438
PRED fire 0.27734 none 0.72266
PRED fire 0.27734 none 0.72266
PRED fire 0.21484 none 0.78516

Output

```
Download [=====] 68% 155648 bytes
Download [=====] 72% 163840 bytes
Download [=====] 76% 172032 bytes
Download [=====] 81% 184320 bytes
Download [=====] 85% 192512 bytes
Download [=====] 88% 200704 bytes
Download [=====] 92% 208896 bytes
Download [=====] 96% 217088 bytes
Download [=====] 100% 225944 bytes
Download done.
File downloaded successfully
Transitioning to dfuMANIFEST state
```

NEW SKETCH

Ln 216, Col 5 Arduino Nicla Vision on /dev/cu.usbmodem141401 4

Thermal Camera Concept and Integration

If (thermal_max > 45°C) Then If (CNN fire_prob > 0.60) → TRUE FIRE

```
PRED fire 0.07422 none 0.92578
PRED fire 0.02734 none 0.97266
PRED fire 0.02344 none 0.97656
PRED fire 0.01172 none 0.98828
PRED fire 0.03125 none 0.96875
PRED fire 0.05859 none 0.94141
PRED fire 0.01953 none 0.98047
PRED fire 0.02344 none 0.97656
PRED fire 0.01953 none 0.98047
PRED fire 0.01953 none 0.98047
PRED fire 0.02344 none 0.97656
PRED fire 0.02734 none 0.97266
PRED fire 0.02734 none 0.97266
PRED fire 0.02344 none 0.97656
```

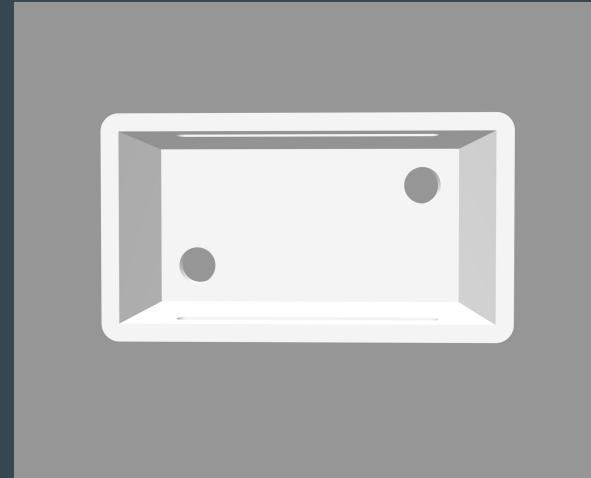
RGB + thermal double verification system

Thermal detects heat signature
CNN detects visual structure to confirm a fire

Payload Case

- 4 x 2 x 1.5 inch case
- Holes for thermal and rgb cameras
- Slits for strap to attach to drone

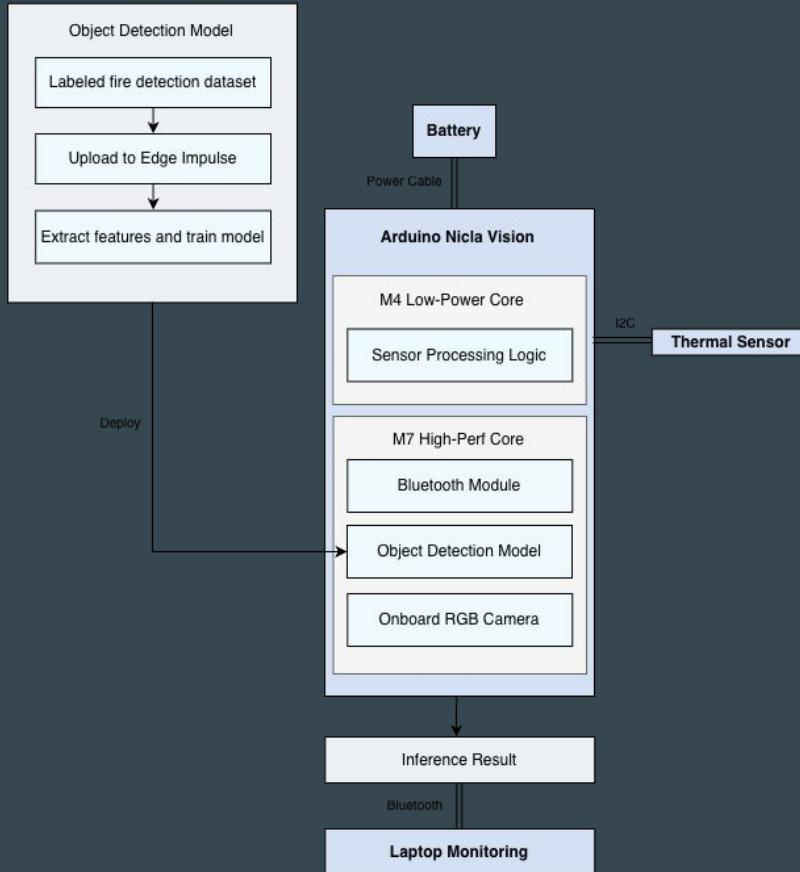
60% Accuracy
final product
interpretation
by GPT



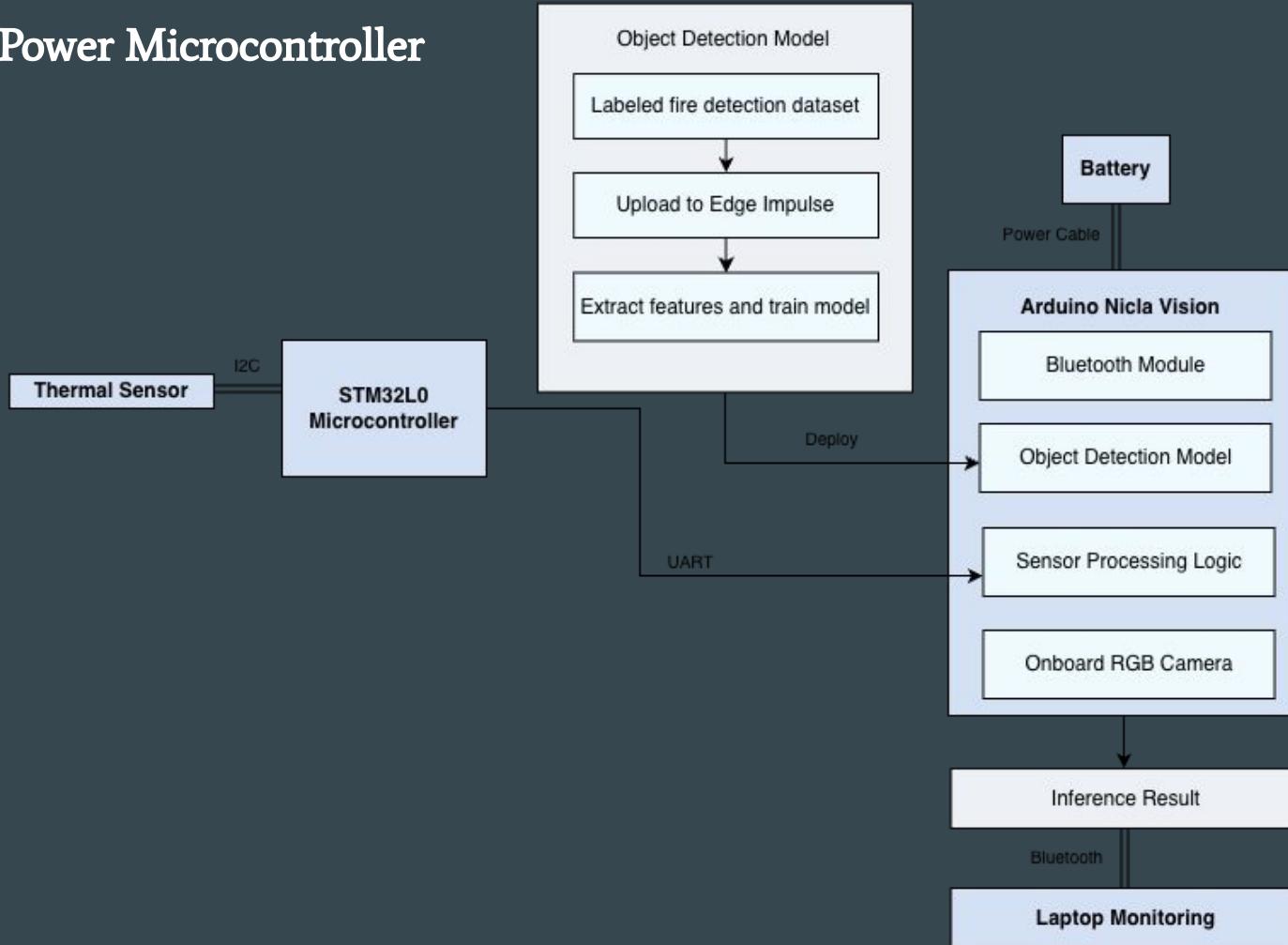
Alternate Designs Explored

- Dual Core approach
- Smaller lightweight microcontroller approach
- Object detection model
- Temperature sensor

Vision Dual Core



Low Power Microcontroller



Challenges

- Dual Core approach
 - M4 to M7 core's could not run simultaneously without manually editing binary file in region of memory
- Smaller lightweight microcontroller approach
 - MLX90640 is not supported on the STML031K6 because it requires 8KB of SRAM
- Communication between STM32 and Nicla Vision
 - UART Serial communication kept colliding with built in UART for USB
- Object detection model was too linear in results
 - Pivoted to classifier
- Temperature sensor
 - High enough reading to guarantee fire

