Developing a Machine Learning Equipped Drone for Early Detection of Wildfires in Forests around the Bay Area

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- Wildfires severely impact lives and livelihoods worldwide. In 2018, California's wildfires caused $148.5 billion in economic damage (Corry 20).

Introduction

Impact of Wildfires:

Displace individuals, destroy homes, jobs, buildings, and cherished possessions.

Devastate forests crucial for environmental balance.

Current Challenges:

Fire hazard warnings help raise awareness and aid emergency response.

Manual data collection by experts is too slow and inefficient for urgent wildfire threats.

Our Solution:

Machine Learning Model:

- Automates wildfire risk assessment in real-time using a drone.
- Provides a faster and more comprehensive solution compared to manual methods.

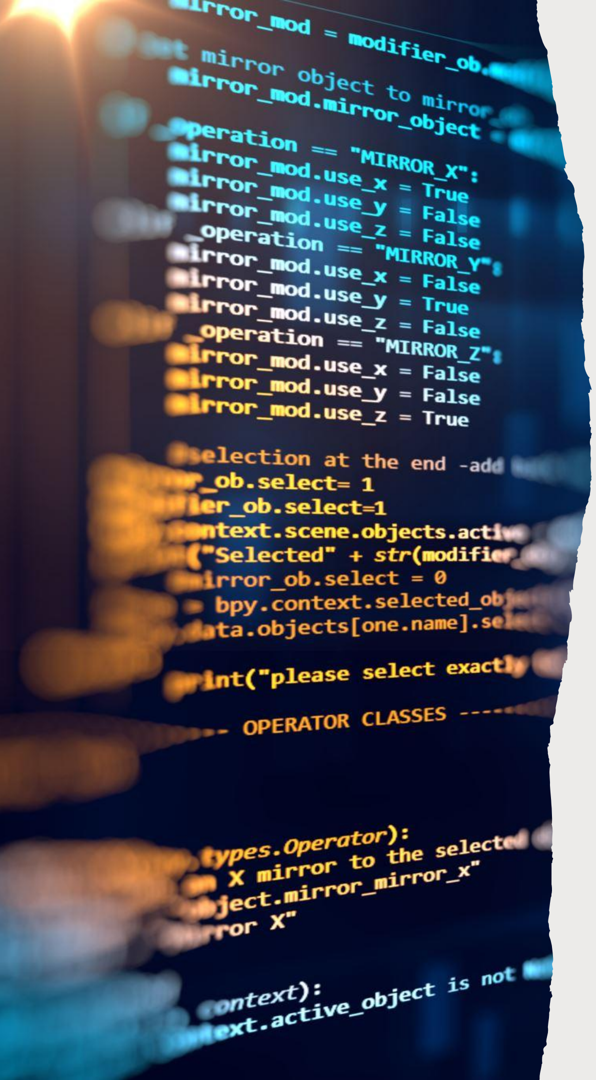
User-Friendly Website:

- Requires three inputs—temperature, humidity, and a satellite image—to quickly assess wildfire risk.
- Features include a map of wildfire risk zones around the Bay Area.

Benefits:

Empowers individuals to make informed safety decisions.

Provides accessible fire probability insights, urpassing the limitations of manual data collection.



Background

- **Existing Models:**
  - **Kondylatos et al. (2022):** Used machine learning and deep learning to predict wildfire-prone areas in the Mediterranean. Verified results with the 2020-2021 Greek wildfire season.
  - **US Department of Homeland Security:** Created a National Wildfire Risk Index Map using historical data, not machine learning or AI generated data.
- **Drones in Wildfire Detection:**
  - **SmokeD:** Drones equipped with cameras and optical sensors to spot early signs of fire and smoke.
  - **Sathishkumar et al. (2023):** Used Convolutional Neural Networks (CNN) to detect fires after they start.
- **Fire Spread Prediction:**
  - **Rubi et al. (2023):** Developed a machine learning model in Brazil to predict fire behavior and spread using multiple data sources (e.g., water sources, geography, vegetation, urbanization).

Our AI-powered Solution

Aims to detect wildfire risk before fires start using real-time data from drones and machine learning.

Our model leverages machine learning and AI to provide accessible and user-friendly wildfire risk assessment tools for everyone.

From local authorities to community members, anyone can utilize this technology to enhance safety and make informed decisions.

Engineering Goals

Goal:

Develop a specialized wildfire prediction model for the Bay Area's forests using temperature, relative humidity, and aerial images.

Method:

Data Collection: Utilize drone-captured imagery, temperature, and humidity data.

User-Friendly Interface: Model accessible via our website for individuals with basic drone skills.

Instant Assessment: Manual input of image, temperature, and humidity into the model on our website provides immediate wildfire risk assessment.

Benefits:

Diverse User Base: Local authorities and community members can monitor wildfire likelihood instantly.

Proactive Approach: Identifies the probability of wildfires occurring in specific locations before they start.

Accuracy Goal: Aim to predict fire risk with above 90% accuracy.

Website Features:

Map of fire risk zones around the Bay Area.

Display of wildfire likelihood for each area.

Methods – Data Collection

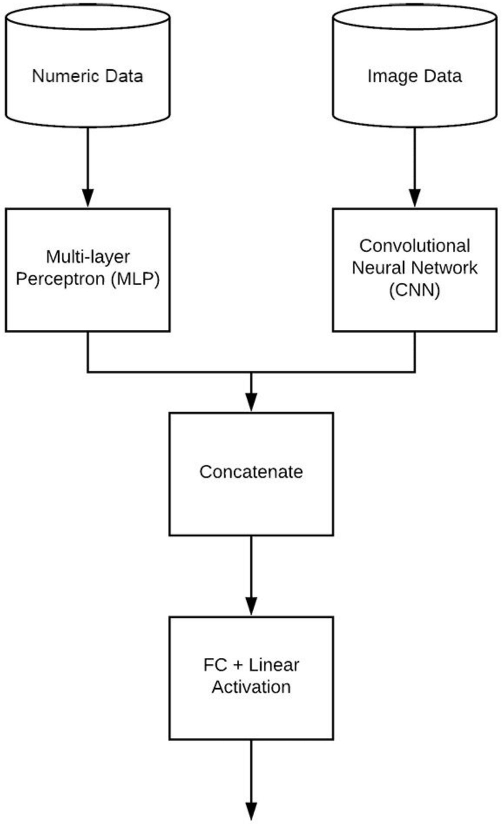
- **Dataset:**
  - 5750 entries of fire and non-fire data points.
  - Each entry includes a satellite image, highest daily temperature, and humidity at the time.
- **Data Sources:**
  - **Google Earth Pro:** Satellite images.
  - **Wikipedia:** Fire information.
  - **Timeanddate.com / Wunderground.com:** Temperature and humidity data.
- **Drone Usage:**
  - Cost: Drone $150, Sensor $50.
  - Equipped with a SensorPush sensor for temperature and humidity data.
  - Collects bird's-eye view images and sends them to our back-end servers.
- **Website Development:**
  - Allows user input of data to generate fire risk probability.
  - Features a Bay Area map with specific location fire risk assessments.

Methods – Machine Learning Modeling

Machine Learning Model Tools:

- Python's TensorFlow library for building and training models.

- **Model Structures:**
  - **Numeric Data:** Multi-layer Perceptron (MLP) model for temperature and humidity values, effective for recognizing patterns in small datasets.
  - **Image Data:** Convolutional Neural Network (CNN) model for analyzing satellite images of vegetation.
- **Process:**
  - Outputs of MLP and CNN models are concatenated.
  - Processed with a linear activation layer to produce the final wildfire risk index.



Methods – AI model Training

- **Dataset:**
  - 5750 data points (2875 fire, 2875 non-fire)
- **Training Process:**
  - Trained for 100 epochs
  - Batch size of 32
- **Optimization:**
  - Over 100 epochs led to overfitting (memorization of data, reduced validation accuracy)
  - Fewer than 100 epochs insufficient for full learning
- **Result:**
  - Achieved an accuracy of <u>91% to 92%</u>

```python
# create the MLP and CNN models
mlp = create_mlp(numlist.shape[1], regress=False)
cnn = create_cnn(256, 256, 3, regress=False)
# create the input to our final set of layers as the *output* of both
# the MLP and CNN
combinedInput = concatenate([mlp.output, cnn.output])
# our final FC layer head will have two dense layers, the final one
# being our regression head
x = Dense(4, activation="relu")(combinedInput)
x = Dense(1, activation="linear")(x)
# our final model will accept categorical/numerical data on the MLP
# input and images on the CNN input, outputting a single value (the
# predicted price of the house)
model = Model(inputs=[mlp.input, cnn.input], outputs=x)
```
[112]

```python
def create_cnn(width, height, depth, filters=(16, 64, 256), regress=False):
    # initialize the input shape and channel dimension, assuming
    # TensorFlow/channels-last ordering
    inputShape = (height, width, depth)
    chanDim = -1
    # define the model input
    inputs = Input(shape=inputShape)
    # loop over the number of filters
    for (i, f) in enumerate(filters):
        # if this is the first CONV layer then set the input
        # appropriately
        if i == 0:
            x = inputs
        # CONV => RELU => BN => POOL
        x = Conv2D(f, (3, 3), padding="same")(x)
        x = Activation("relu")(x)
        x = BatchNormalization(axis=chanDim)(x)
        x = MaxPooling2D(pool_size=(2, 2))(x)
        # flatten the volume, then FC => RELU => BN => DROPOUT
        x = Flatten()(x)
        x = Dense(16)(x)
        x = Activation("relu")(x)
        x = BatchNormalization(axis=chanDim)(x)
        x = Dropout(0.5)(x)
        # apply another FC layer, this one to match the number of nodes
        # coming out of the MLP
        x = Dense(4)(x)
        x = Activation("relu")(x)
        # check to see if the regression node should be added
        if regress:
            x = Dense(1, activation="linear")(x)
        # construct the CNN
        model = Model(inputs, x)
        # return the CNN
        return model
```

```python
def create_mlp(shape, regress=False):
    # define our MLP network
    model = Sequential()
    model.add(Dense(8, input_dim=shape, activation="relu"))
    model.add(Dense(4, activation="relu"))
    # check to see if the regression node should be added
    if regress:
        model.add(Dense(1, activation="linear"))
    # return our model
    return model
```
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Python code for the Sensorflow Model Structure

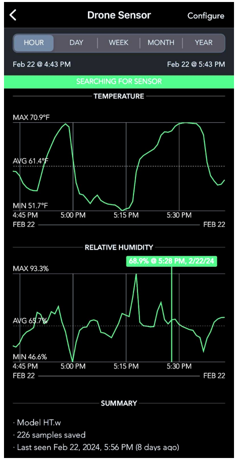
Methods – Software Tools

Ophelia Go

An app fit for drone control and aerial photography. We used/plan to use Ophelia Go to capture the aerial photos required for our machine learning model to predict the likelihood of a fire.

Sensorpush

is an app dedicated to give users environmental data. We used this device, and paired it with the Ophelia Go app to receive the temperature and relative humidity data.

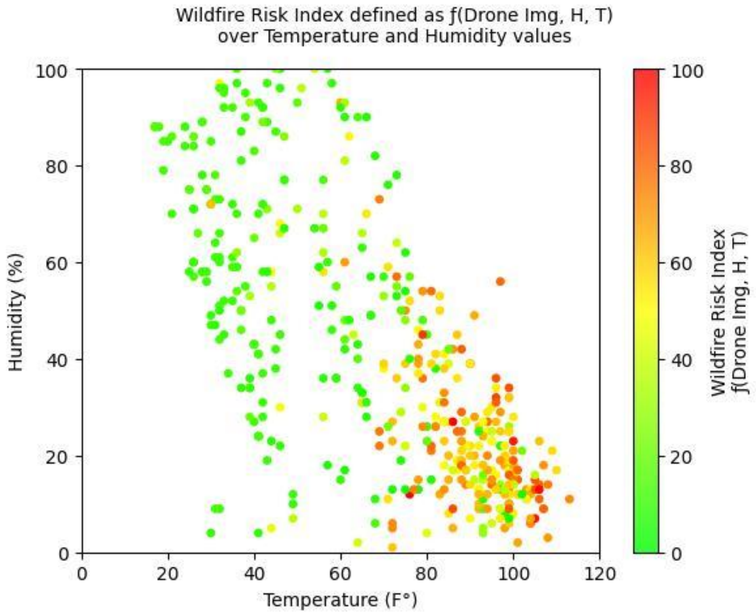


Temperature and humidity data from the SensorPush app.

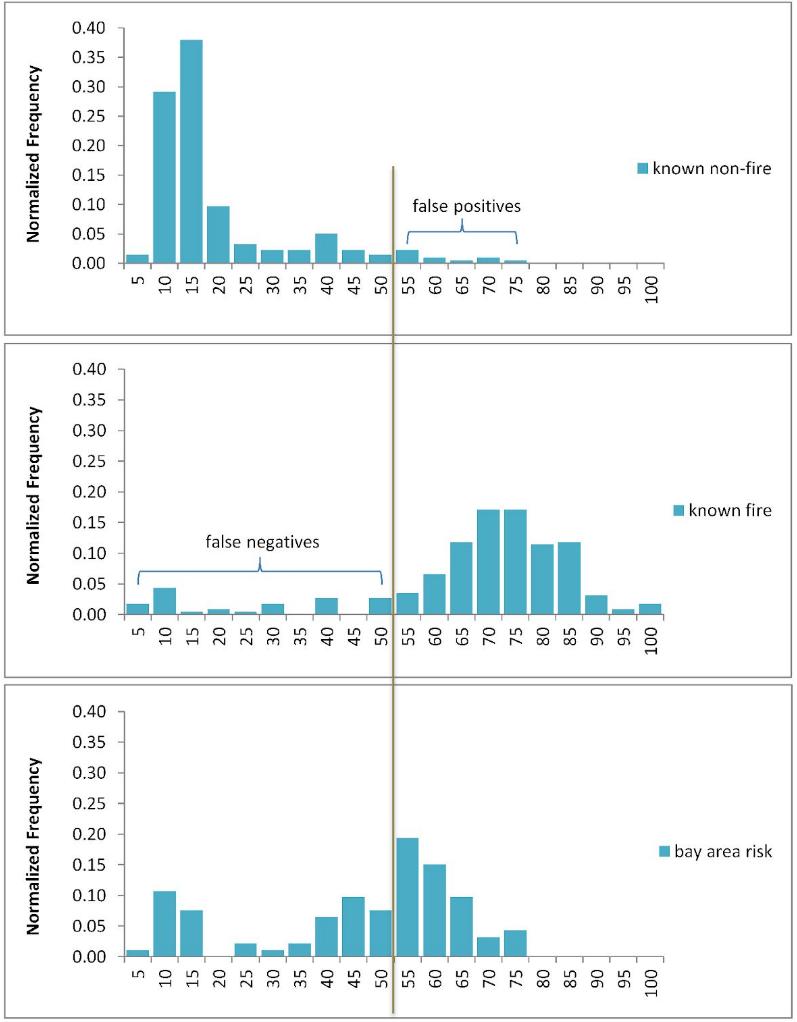
Results and Findings

Wildfire Risk Index over Various Temperature and Humidity Values

- **Data Collection:**
  - Collected 445 data points, each including an image of vegetation and temperature/humidity values.
- **Model Input and Analysis:**
  - Input data points into our AI model to obtain risk indexes.
  - The AI model uses Convolutional Neural Networks (CNN) to analyze vegetation images and Multi-layer Perceptron (MLP) for numerical data.
- **Findings:**
  - High temperatures and low humidity correlate with higher risk indexes.
  - Variations in risk indexes for similar temperature/humidity values indicate significant influence from vegetation images analyzed by AI.

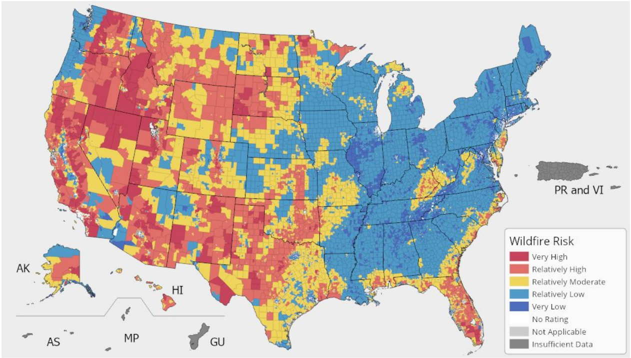


Validity/Accuracy



f(Drone Img, T, H) based Wildfire Risk Index

Methods: We used the National Wildfire Risk Index Map by the US Department of Homeland Security to validate the accuracy of our model. (https://hazards.fema.gov/nri/map)



Results: 92% Accuracy Rate

Will grow higher as we add more data points

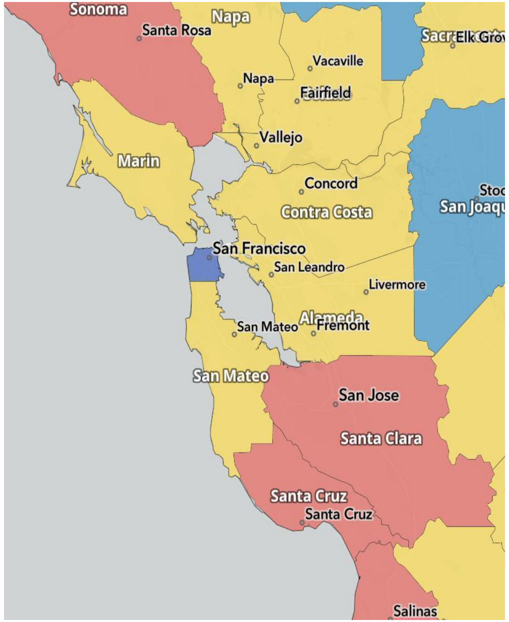
Outcomes – Wildfire Risk Index Map

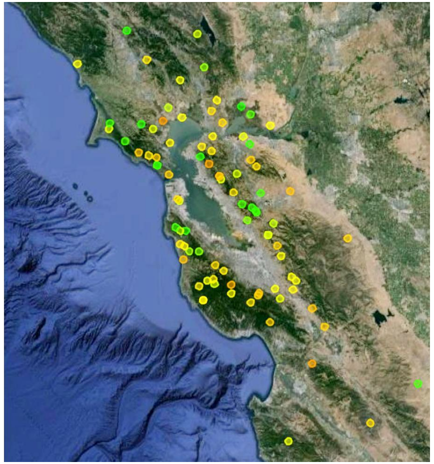
Risk Index Mapping:

- Collected 94 data points using a combination of drone and satellite images.
- Plotted the risk index on a map of the Bay Area.
- Overall, the wildfire risk of the Bay Area at this time seems to be moderate.
- Likely influenced by the current season, as wildfires are more common around August.

Comparison with USDHS Map:

- Our data is consistent with the USDHS's map.
- Forests in the northern Bay Area have a relatively low risk index compared to the southern Bay Area.





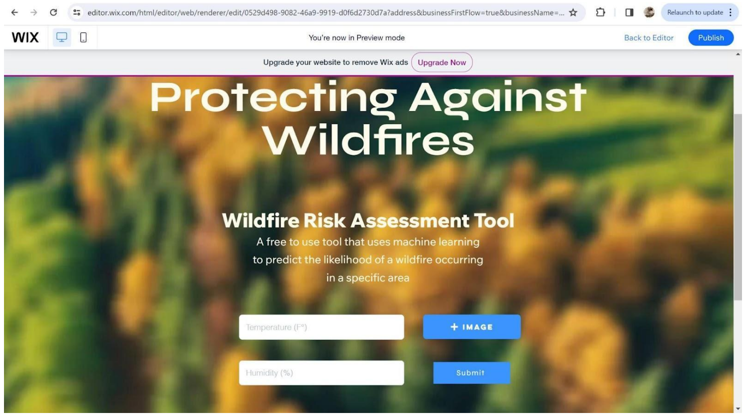
Bay Area Map

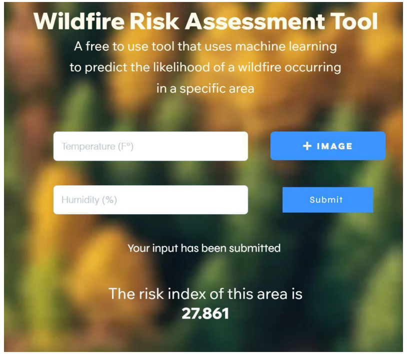
Outcomes - Website

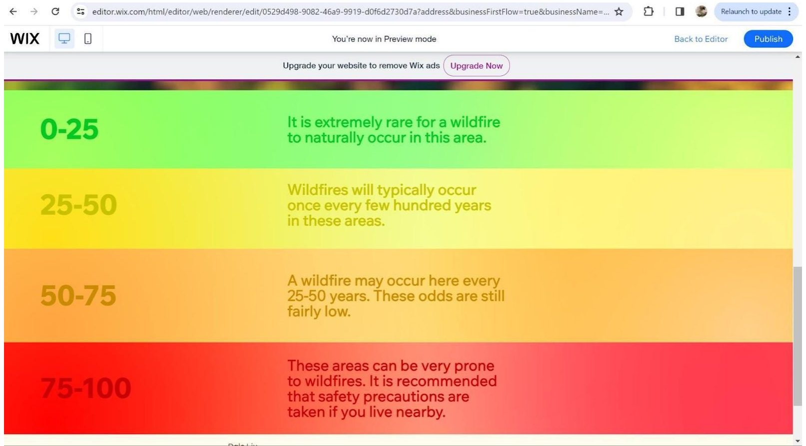
- **Platform:**
  - Created using Wix to provide global access to our tool.

- **Functionality:**
  - Users can input temperature and humidity values.
  - Aerial image automatically inputted

- **Risk Index:**
  - The website displays a risk index score ranging from 0-100 to evaluate wildfire risk.







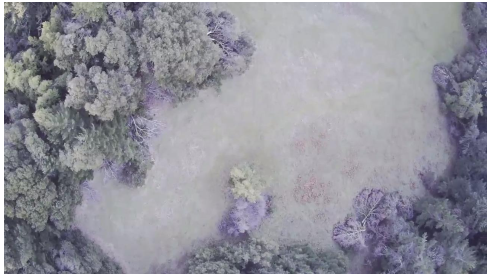
Examples – Real world data

Real World Data Examples

62 degrees Fahrenheit, 63% humidity
Risk Index: 46.502

50 degrees Fahrenheit, 70% humidity
Risk Index: 24.849

59 degrees Fahrenheit, 72% humidity
Risk Index: 52.117

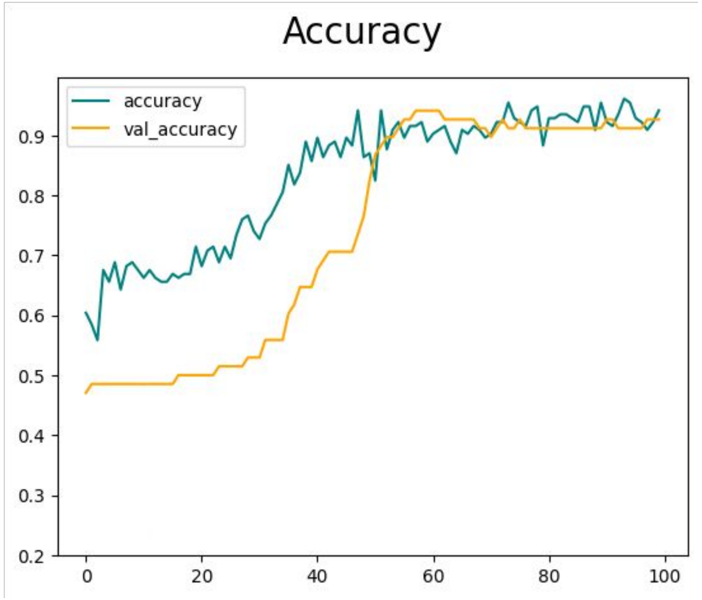


51 degrees Fahrenheit, 72% humidity
Risk Index: 44.715

Conclusion

AI Model Summary:

- Using the National Wildfire Risk Index Map from the US Department of Homeland Security, our analysis revealed an impressive 91-92% accuracy
- Demonstrated robust reliability.
- Expanding the dataset with additional data points improved accuracy as anticipated.
- Ultimately, the model maintained an accuracy of around 91-92%.



100 Data points - 5750 Data Points

Conclusion:

- The AI-driven model integrates image data and environmental variables to provide a comprehensive wildfire risk assessment.
- Highlights the power of AI in enhancing predictive accuracy.

Vision and Forward Looking Goals

Impact:

- The impact of our AI-powered fire-detecting drone enhances global safety by providing proactive and real-time wildfire risk assessments, eliminating reliance on traditional news sources or weather updates.
- Individuals can easily determine wildfire likelihood in their immediate surroundings.

Future Goals:

- **Real-Time Data Integration:** Automate temperature and humidity data transfer to backend servers, eliminating manual input and providing instant risk index during drone flights.
- **Improved Accuracy:** Currently at 91-92% accuracy. Aim to increase with more training data and model configuration.
- **Additional Features:** Incorporate elevation, wind speed, and fuel loading for more comprehensive assessments.

Vision:

- Create a seamlessly integrated AI system that sets a new standard for rapid and reliable fire risk

Acknowledgements

- A special appreciation to Mr. Lester Leung for his support and guidance, without which nothing would have been possible. His expertise and encouragement have been really important in shaping our success in building this machine learning model and drone.

- We would also like to thank our parents for taking the time to drive us around forests in the Bay Area so we could collect real world data.

- Overall, we are deeply grateful for the valuable contributions of everyone involved, making this project a reality.

Flying the drone
in Bay Area forests during Data Collection

Left to right: Pranav Saharan, Lucas Su, Dale Liu