# Classifying Aerial Objects Based on Risk: A Machine Learning Approach

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## ABSTRACT

The spy balloon that flew across the U.S. in February 2023 posed a serious security threat. US security officials have said this balloon tried to gather intelligence by monitoring sensitive military sites, and as a result, the U.S. government began more closely scrutinizing its airspace to better categorize aerial objects and detect threats. However, the airspace is filled with a myriad of aerial objects, making the problem of classifying and risk determination very challenging. We hypothesize that if we label aerial objects based on the risks they pose, then a Machine Learning algorithm can be made to learn and predict the risks of previously unknown or unseen aerial objects. Currently, there are no known single datasets that contain both old and newer aerial objects, such as drones, planes, etc., nor do datasets have labels to identify the risks associated with the objects. The goal of this research is twofold: 1) We create a new comprehensive dataset that contains traditional and newer aerial objects. We label the objects as high, medium, low, or no risk based on the threat markers on the aerial objects. 2) We use the MobileNetV2 CNN classification algorithm to validate the dataset and provide accurate results. Advancements in this space can potentially help intelligence agencies and security analysts quickly assess developing scenarios and provide a reliable risk assessment for observed aerial objects.

## Introduction

### Motivation

In early 2023, the U.S. Air Force targeted four airborne objects and shot them down with Sidewinder missiles. Out of the four aerial objects, one was the spy balloon, and the rest were most likely recreational or research objects and therefore benign [22]. The cost of each missile was around $400,000, thus costing a total of 1.6 million US taxpayer dollars [24]. One of the reasons to shoot down the other three aerial objects was because it was difficult to determine if the aerial objects were a threat or not. Therefore, it is important to determine the risks posed by aerial objects. The need to associate threats with aerial objects is also necessitated by the increasing incidents of Unidentified Aerial Phenomena (UAP) in recent years. The UAPs are defined by the U.S. Department of Defense as “anything in space, in the air, on land, in the sea, or under the sea that can't be identified and might pose a threat to U.S. military installations or operations” [22]. In 2022, the government of the United States, through the Office of the Director of National Intelligence (ODNI), released a report on 144 UAPs and said that UAPs are a potential threat to national security [21]. Assessment of the UAP’s threat is critical to determining what action to take on the UAPs by the intelligence community. Therefore, the problem of associating threats with aerial objects is of great importance.

### Deep Learning

In this paper, we try to solve the above problem using supervised deep learning. Deep learning trains computers so that the input data is processed just like the human brain. Deep learning models can help recognize very complex patterns in pictures, text, sounds, and other data. Deep learning is a type of supervised learning where the input data, referred to as the dataset, is first labeled, and then the data is used for training. After several rounds of training, the algorithm can predict and provide a label for previously unseen data [1]. Deep learning is widely used for object recognition. Object recognition encompasses two broad areas: image classification and object detection. Image classification refers to algorithms that assign a class label to an image. Object detection refers to algorithms that identify the location of one or more objects in an image and draw a bounding box around their extent. In this paper, we focus on image classification.

## Hypothesis

We hypothesize that if we create a dataset of different aerial objects labeled as high-risk, medium-risk, low-risk, or no-risk, then supervised machine learning can be made to learn and predict the risks of previously unseen aerial objects.

The key to the hypothesis above is the availability of a dataset that includes different aerial objects with proper risk labeling. Recent developments in computer vision and machine learning algorithms have led to the development of many datasets. Aerial image-specific datasets include CIFAR [3], ImageNet [11], MS-COCO [4], FGVC-Aircraft [7], Helicopter datasets [9, 10], Class 1, UAV [24], and USC-Drone [21]. However, there are three key drawbacks to the existing dataset and approaches.

1. There is no single dataset that has newer aerial objects like UAVs, drones, weather balloons, etc. and legacy aerial objects.
2. Existing datasets do not classify the aerial objects based on the risks of the aerial objects that determine if the object is a threat or not.
3. There is no machine learning algorithm that can use the existing datasets and derive a risk score for aerial objects.

## Contribution

We approach the above challenges by creating a new dataset that includes old and newer aerial objects and associated labels that help assign risk to the aerial objects. Grouping of the aerial images as high, medium, low, or no risk is achieved based on the presence or absence of risk markers. The markers are certain characteristics of the aerial object that determine its function and the threat that object could pose. Examples of these markers include the presence of a solar panel on a balloon, long-winded Unmanned Aerial Vehicles (UAV), high-resolution cameras mounted on a drone, drones that can carry a heavy payload, etc. We can then train a Convolutional Neural Network (CNN) based deep learning algorithm on the new dataset. Once trained, the algorithm will classify new, unseen aerial objects and provide the risk of the aerial object.

The contributions of this paper include: we construct, present, and publish a comprehensive aerial object dataset, called the Aerial Risk Dataset, based on the risk of the object. This new dataset is made available publicly as “Aerial Risk Dataset” on the Kaggle platform [2]. We provide an approach and a system for aerial object classification based on a new dataset. The remainder of this paper is organized as follows: In the background section, we provide a literature review of datasets related to aerial objects. Then, in the aerial risk dataset section, we present our proposed dataset, collection, and risk-based labeling approach. The model used, the reasoning behind choosing it, their architecture, their advantages and disadvantages, and their architecture are discussed in the models section. Our analysis of the results, metrics, and methodology for evaluation is discussed in the results section. Finally, we provide a summary, and future work and conclusions are drawn.

# Background

In this section, we review existing datasets and their challenges.

## Existing Datasets Challenges

The Canadian Institute for Advanced Research (CIFAR) dataset was created in 2009 and is one of the early datasets that includes aerial objects [2]. This includes 10 classes of real-world objects. This dataset, however, includes only two classes of aerial objects: airplanes and birds. The airplane class includes images of both commercial and military planes. The CIFAR-100 dataset contains 60,000 color images in 100 classes, with 600 images per class. The CIFAR-100 focuses on terrestrial objects, and only one aerial object, a rocket, is part of their dataset. The ImageNet 1000 dataset was created in 2009 and contains 1000 categories of images [3]. This dataset contains five different aerial categories: airlines, warplanes, airships, balloons, and space shuttles. The Microsoft COCO dataset was created in 2014 and contains images with context, like surroundings. It has 80 categories and a total of 330,000 images [4]. All the above datasets are useful for benchmarking image classification models and research. However, all the above datasets do not contain newer aerial objects like weather balloons, drones, UAVs, military helicopters, etc.

Recently, new datasets have been proposed for different aerial objects. The Fine-Grained Visual Classification of Aircraft is a benchmark dataset for the fine-grained visual categorization of aircraft [7]. This dataset contains 10,200 images of aircraft, with 100 images for each of 102 different aircraft model variants. There is also MTARSI, the first public aircraft remote-sensing image database [22]. It contains 9,385 remote-sensing images of 20 aircraft types. Both the FGVC-Aircraft dataset and the MTARSI dataset contain aircraft images only and not other aerial objects. Two helicopter datasets are widely referred to: single-rotor helicopters and dual-rotor helicopters [8, 9]. Both of these datasets are specific to helicopter images only. All the newer aerial datasets above are specific to a type of aerial object and do not have risk-based labeling. Therefore, we have to create a new dataset that includes all aerial objects and also has the ability to label them based on risks.

# Aerial Risk Dataset

## Images Sources

The aerial object images for this new dataset are collected from three primary sources. Manufacturers websites.Existing Dataset. Google Image Search. The manufacturer's website provided the most accurate images of various types of planes, helicopters, UAVs, and drones. They also have a rich photo gallery of new and future aerial objects. The following manufacturers were used to download images: Boeing, Lockheed Martin, Airbus, DJI, Raytheon, BAE Systems, Northrop Grumman, Thales, Ebit Systems, Israel Aerospace Industries Ltd., and Bell. We also used images from two existing datasets, which contained legacy airplanes and helicopters. They are the Fine-Grained Visual Classification of Aircraft [7] and Dual-Rotor helicopter datasets [8,9]. For the weather balloons, spy balloons, hot air balloons, and birds, images were downloaded from a Google Image search manually. A total of 31170 images were downloaded.

## Labeling Images

Four risk-based labels are used: high, medium, low, and none. Specific markers on the aerial objects are used to mark them with a particular label, as follows:

- High-Risk Label: Aerial objects intended for combat purposes are classified as high-risk. Example: fighter jets and combat drones. The markers for high-risk include drones that can carry large payloads, airplanes that can carry missiles, rockets, missiles, vertical takeoff and landing (VTOL) aircraft, and the presence of warheads or payloads.
- Medium-Risk Label: Aerial objects whose purpose is surveillance are classified as medium risk. Example: surveillance drones and spy balloons. Markers for medium risk include balloons with solar panels, drones equipped with sensors, long-wing-span long-range drones, high-resolution cameras, and the absence of warheads or payloads.
- Low-Risk Label: Aerial objects used for commercial or hobby purposes are classified as low-risk. Low-risk markers are passenger large, and small planes, commercial planes, drones used for hobby, drones for package delivery, gliders, and hot air balloons, and the absence of solar panels or sensors.
- The No-Risk label includes birds or trash.

Examples of high-risk, medium-risk, and low-risk aerial objects and their markers used for classification are shown in Figure 1 below. Figure 1A is high-risk as they have warheads and military-styled wings. Figure 1B and Figure 1C are both UAVs. Figure 1B is classified as high-risk due to the presence of warheads, and Figure 1C is medium-risk as it lacks a warhead but has long wings and sensors. Figure 1D and Figure 1E are both balloons but Figure 1D is classified as medium-risk due to the presence of solar panels and sensors, whereas Figure 1E, which is a weather balloon, is classified as low-risk due to the lack of sensors or solar panels. Lastly, Figure 1F is a hobby drone and labeled as low risk.

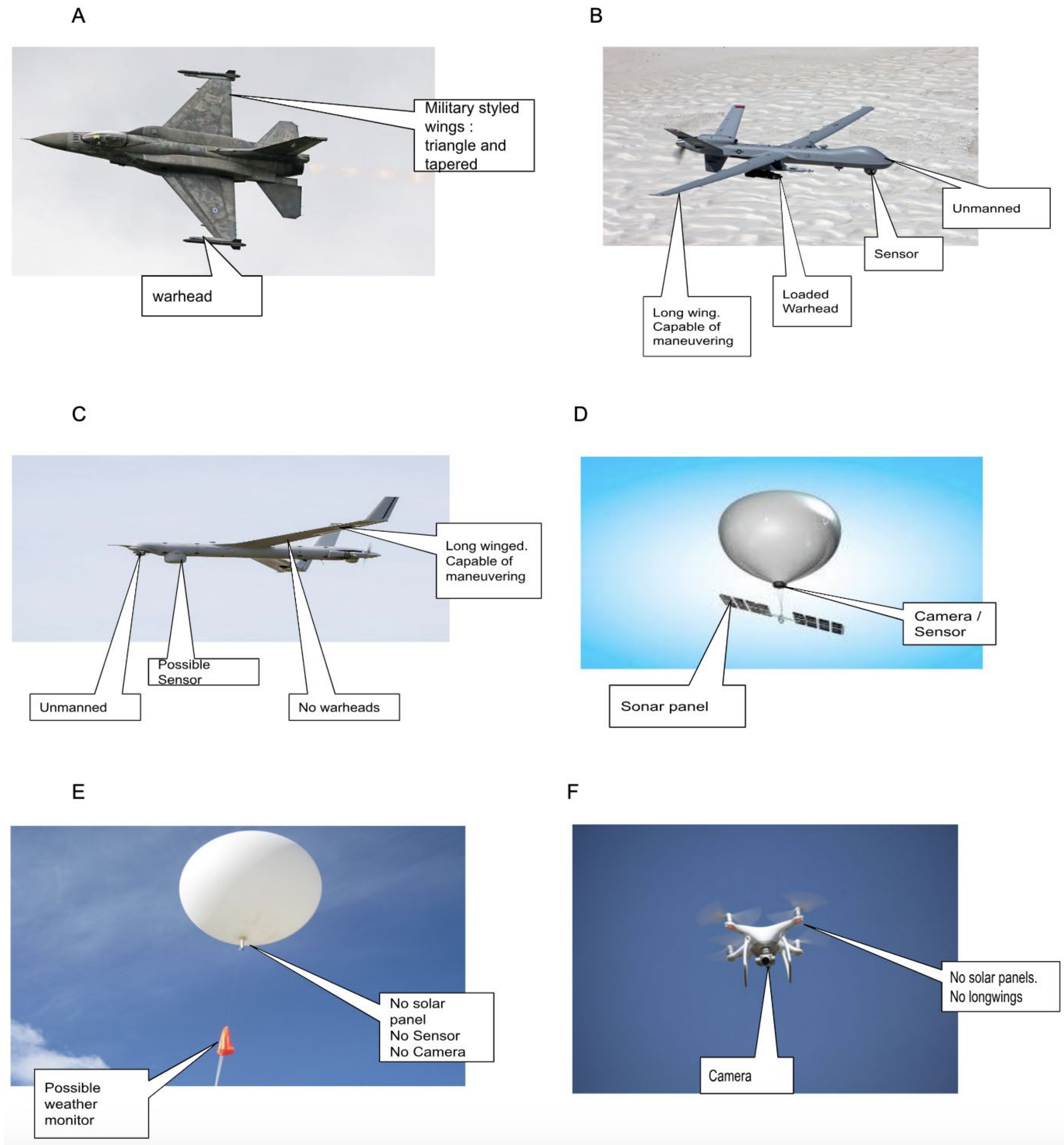


**Figure 1.** Aerial Object Labeling. (1A) is an image of a fighter jet, and (1B) is an armed drone image. Both are high risks. (1C) and (1D) are examples of medium risk surveillance drones and spy balloons, respectively. (1E) and (1F) represent spy balloon and hobby drones respectively, both are low risk examples. The markers that help classify them are noted in all the images.

Images are first labeled based on the presence and absence of the markers and added to the dataset directory containing that risk. Images that do not have significant markers are discarded. After discarding images with no proper markers, the number of images in the dataset was 14105. The dataset directory has four folders based on the risk (high,medium, low, or none). To further make the dataset organization easier, subfolders are created per risk label based on the category or type of the aerial object. The category of the aerial

Volume 13 Issue 2 (2024)

object can be further used to provide additional information on the object. This dataset directory organization is shown in Figure 2 below.

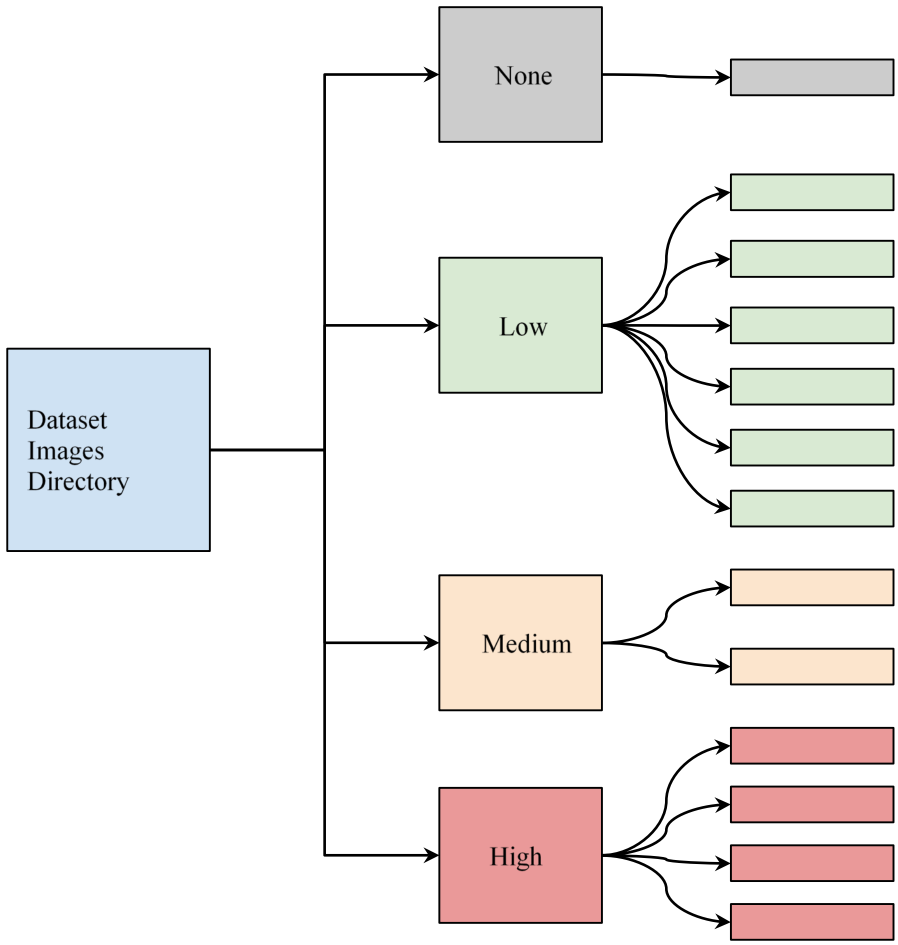


**Figure 2.** Dataset Sub-Folders. First-level folders are created based on the risk (high,medium, low, or none), and next-level folders are created based on the function or category of the aerial objects.

Our new dataset is made publicly available for research purposes on the Kaggle platform [2]. The entire dataset can be downloaded and used for research.

## Model Selection

There are two popular architectures for deep learning: convolutional neural networks (CNN) and recurrent neural networks (RNN). They each have different strengths: CNN is better at handling 2D images, while RNN is more effective at sequential signals such as speech [7]. We use the CNN architecture as it is most suitable for handling images. The CNN model is composed of an input layer, an output layer, and many hidden layers in between. These layers perform operations that alter the data with the intent of learning features specific to the data. There are several flavors of CNN architecture, like Faster R-CNN [19], Single Shot Detector (SSD) [14], YOLO (You Only Look Once) [18], and MobileNetV2 [14]. All the above image classifications can be designed to run on any dataset. The accuracy results vary based on the datasets and the tuning parameters.

When an aerial object or UAP enters an airspace, the intelligence community should quickly classify the aerial object as a threat or not, and they should do it with good accuracy. Also, they may have to run the algorithm on the devices, which have limited computing resources like CPUs and memory. One of the machine learning classification models that satisfies the above requirements is MobileNetV2. MobileNetV2 is a model proposed by Google and is designed specifically to run on mobile architectures like iPhones, etc. This model is widely used for image classification, requires fewer compute resources, and runs faster. In the next section, we provide literature on MobileNetV2 performance.

## Performance of MobileNetV2

In machine learning, the performance of a model is measured using latency and accuracy. The latency metric measures the amount of time the model takes to predict after learning. The accuracy metric refers to how accurately the model can predict.

The latency of a model is often measured using FLoating Point Operations (FLOPs), and this refers to the number of operations performed. FLOPs are calculated from actual instructions like add, subtract, multiply, divide, etc. that are used when running that model. Lower FLOPs values mean that the model is able to run faster as it needs fewer instructions. Luo, C. 2020 [15], performed benchmarking results on six popular models running on mobile devices and compared the results in terms of FLOPs. The results of this paper show that MobileNetV2 performed the fastest among the chosen models, with the least number of FLOPs (300 million).

The accuracy of the model is measured by comparing the different model predictions on existing, well-known datasets. The authors in [28] used different models, including MobileNetV2, on a public fruit dataset containing forty different types of fruits. Their results showed that MobileNetV2 achieved the highest accuracy with 89%. Similarly, authors in [16] proposed a modified MobileNetV2, called I_CBAM_MobileNetV2, which achieved 98.21% accuracy on seed classification. The authors used a total of 11 maize varieties, where each image was a single maize seed. MobileNetV2 was used on the Fashion-MNIST dataset [6] by authors in [5], and this model achieved up to 93% accuracy. The Fashion-MNIST dataset contains 60,000 training images and a testset of 10,000 images of fashion products from 10 categories.

As seen by past research, MobileNetV2 performs faster and with good accuracy on different datasets. Therefore, we chose MobileNetV2 as our classification model.

## MobileNetV2 Design

In our design, MobileNetV2 will get the input of aerial images with labels, extract the different features through multiple layers, and provide the final classification result as high-risk, medium-risk, low-risk, or no-risk. We create a fully connected layer that contains three sequential layers as part of the MobileNetV2 model design. The layers are : Input Layer, Dropout Layer and Output Dense Layer

The input layer takes in the shape of the images, and in our case of images, it is a three dimensional vector of height, width, and color channels. The Dropout Layer is a technique often used in CNN to help prevent overfitting, which occurs when a model learns deeply from the training data and performs well, but performs badly on unseen images. This layer helps generalize unseen images by randomly dropping a portion of input units during each training step. The output layer is a fully connected (dense) layer that uses a softmax activation function to give the output classification probability for each risk label. The final model classifier architecture is shown in Figure 3 below.

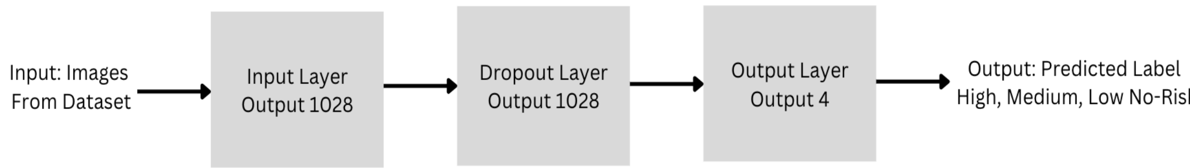


**Figure 3.** Architecture of our MobileNetv2 with input, dropout and output layers.

### *Implementation*

A popular deep learning framework called TensorFlow [20] was used for the modeling and implementation of image classification algorithms. Keras, a high-level programming tool, was chosen to implement MobileNetV2 [12]. Google Colaboratory was the programming environment, as it is freely available and runs directly on popular web browsers like Chrome. The entire dataset was first uploaded to Google Drive, and then the drive was mounted in the Google Colab environment for processing.

### *Preprocessing*

The aerial risk dataset we created has device images of different aerial objects with a total of 14105 images. This dataset was created from different sources, and the images have different resolutions and sizes. The pre-processing step is applied to all input images in the dataset to convert them into normalized attributes so that they can be fed to our MobileNetV2 model. The preprocessing steps are as follows: The images in the data set are divided into two sets: 80% for training and 20% for validation. Next, we resize images to 224x224 pixels. The images are then converted from BGR to RGB color channels, with the pixel intensity scaled in the range [−1, 1]. The final output array is then fed into the MobilenetV2 model.

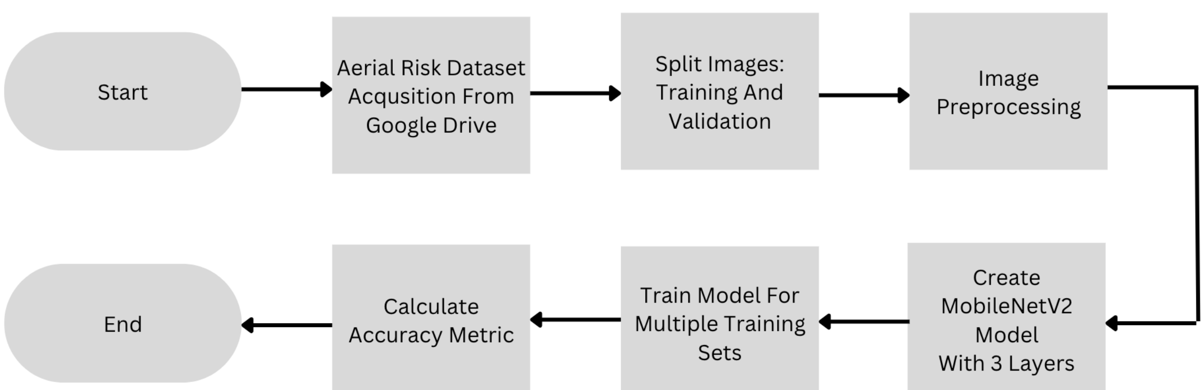


**Figure 4.** Implementation of MobileNetV2 model for Aerial Risk Dataset validation

### *Model Training*

The MobileNetV2 model, as described in the architecture section above, was created using the Keras-provided API. Keras provides a base MobilNetV2, and the default layers were overwritten by our own layers. The model created is compiled, and the model is trained using an aerial risk dataset. The training happens for multiple

HIGH SCHOOL EDITION
Journal of Student Research



datasets. The entire flow from data acquisition to preprocessing and training the model is shown in Figure 4 above.

## Results

The whole process of training our MobileNetV2 model with the aerial risk dataset took 2 hours and 8 minutes. The model was trained using the Nvidia A100. The epoch, or total training period, is set at 10. The batch size of images for each training period was set to 32 with a learning rate of 0.00001. These parameters are set after multiple rounds of testing to achieve the highest accuracy. Furthermore, the dropout layer to the model.

To evaluate the accuracy of the aerial object risk detection, we measured the model accuracy metric, loss metric and we also tested the risk detection of images using a test dataset that contained previously unseen aerial objects. The accuracy metric is the measurement of the model's accuracy in identifying patterns, where the model correctly predicts the actual risk of an aerial object. The accuracy of our model was 94.4%. The accuracy metric graph is shown in Figure 4A, with the epoch (training period) on the x-axis and the accuracy on the y-axis. The result shows that the accuracy increased after the first training period and remained consistent over the training periods. The reasons for the accuracy being close to 0.94 after the first training period is mostly due to marker based labeling of images in our dataset. These markers being strong attributes allows the machine learning to train and learn these markers of the images and thus allowing it to have higher accuracy. More experiments can be done to see if the accuracy increases as we increase the training period or by adding more dense layers to the model.

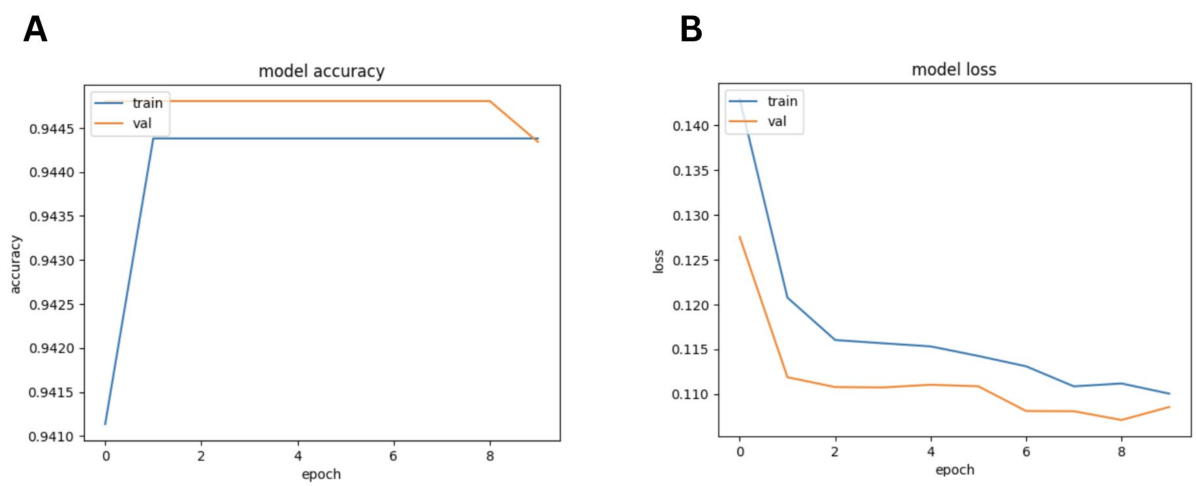


**Figure 5.** Model Accuracy and Model Loss Graph for training data and validation data for training period.

Loss is the measurement of the model's prediction and the value is between 0 and 1. If the model's prediction is perfect then the loss is zero, else the loss is greater than zero. The model loss for our dataset for validation and training is shown in Figure 5B below. The loss in our case reaches below 0.11 at the end of the training steps.

Both the model accuracy and model loss results show that our hypothesis is proven to be true. That is, a supervised machine learning model can learn about the risks of aerial objects and predict the risks of the objects. The aerial risk dataset can be used with a machine learning model to predict the risks of aerial objects with very high accuracy.

HIGH SCHOOL EDITION
Journal of Student Research
Volume 13 Issue 2 (2024)

## Model Testing

To test the model on real-world data, we created a new dataset of images not seen in the training dataset. This test dataset had a total of 10 images per risk category, for a total of 40 images. Sources of images for the test dataset are derived from manufacturer websites, existing datasets [7,8,9] and google image searches. These test images are pre-labeled so that the results can be verified. The model prediction was applied to the test dataset, and the results of the prediction are shown in Figure 5. It took one second for the model to complete the prediction. The predicted label is shown in the figure with green and red labels. The green label indicates that the image is predicted correctly, and the red label indicates that the prediction is incorrect.

Based on the results, out of 40 images in the test dataset, 36 were predicted correctly and 4 were predicted incorrectly. Therefore, for unseen images, the accuracy was 90%. The incorrect prediction could be due to images being too small. For example, a man jumping out of a parachute should be classified as low risk but it was classified as medium risk. Another reason for incorrect prediction is due to the markers in the object not clear. Example, a surveillance drone which is a medium risk is classified as high risk as the image has some for markers for high risk like a loaded weapon.

Both the model accuracy and test dataset results show that our hypothesis is proven to be true. That is, a supervised machine learning model can learn about the risks of aerial objects and predict the risks of the objects with a high accuracy.

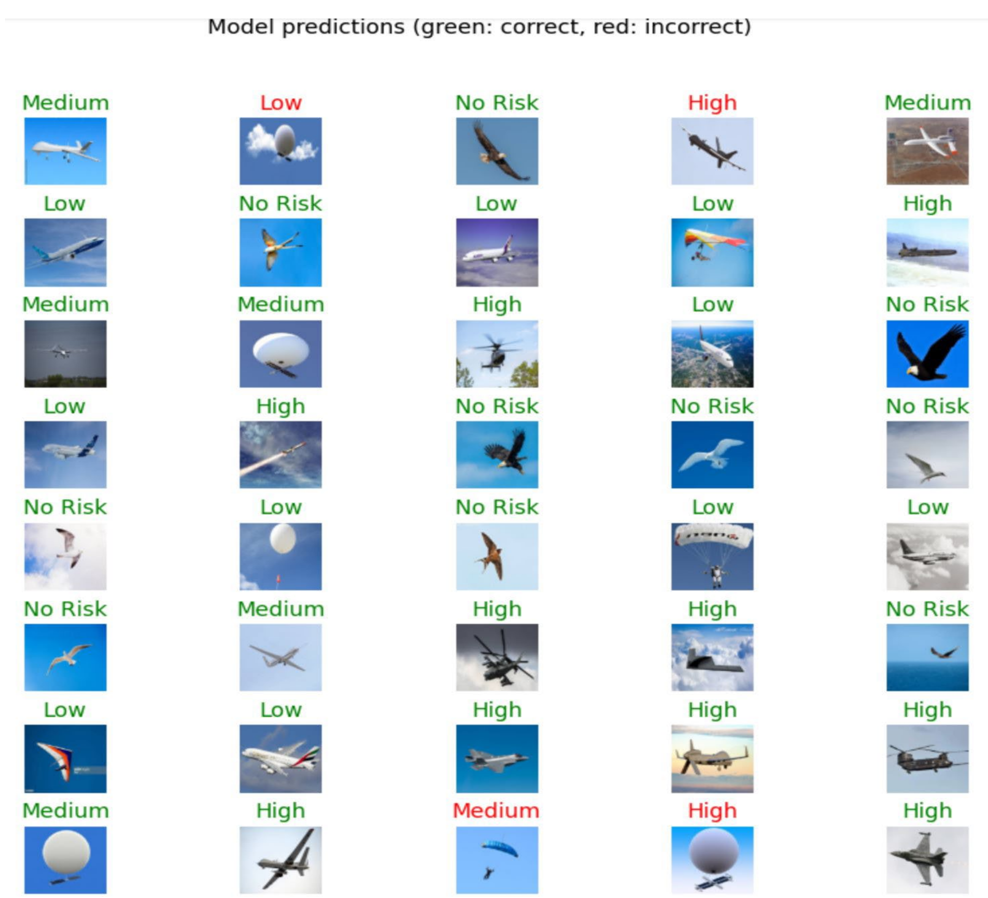


**Figure 6.** Test Dataset Results: Green predicted correctly and red incorrectly. Accuracy of 90% (36/40)

## Summary

With the increasing number of different types of aerial objects: drones, unmanned aerial vehicles, air taxis, agriculture drones, hobby drones, spy balloons, and weather balloons, it is an important problem to find the threat of aerial objects. We started with our hypothesis that a machine learning algorithm can be made to learn about the risks of aerial objects and can be made to predict the risks of future aerial objects. Currently, available datasets are ineffective in detecting threats from aerial objects. Therefore, a new dataset was created and labeled based on the risk markers present in the aerial objects. This dataset was made comprehensive by including older objects like passenger planes and fighter jets, as well as newer aerial objects like surveillance drones, unmanned combat aerial vehicles, etc. This resulted in a versatile dataset of over 12,000 images, with each image labeled as high, medium, low, or no risk. MobileNetV2, a Convolution Neural Network (CNN)-based deep learning model, was carefully chosen as the classification model. MobileNetV2 satisfied the requirement of being able to run with minimal resources, low latency, and high accuracy. Model accuracy metric and loss metric data show that our hypothesis is proven. Furthermore, a test dataset was used to validate real-world examples, and this resulted in an accuracy of 90%.

## Future Work

The model prediction algorithm can be combined with the GPS coordinates of the aerial object to determine further action on the aerial object. For example, the action to take can be different based on whether high-risk or low-risk aerial objects are flying over a densely populated area or a military installation. The input to our model prediction can include a parameter for the GPS coordinate. In the future, as newer aerial objects emerge, the aerial risk dataset can be easily extended by adding the newer objects. The markers on these new aerial objects can be used to put the correct label on them and retrain the model with an updated dataset.

Furthermore, classification algorithms can be enriched to provide more nuanced risk scores based on the sub-category (planes, drones, etc.) within the risk label. For example, a high-risk drone can have a different risk score than a high-risk fighter jet. Our dataset already contains sub-categories based on the function or type of the aerial object. Therefore, the machine learning model can be trained on the sub-category to provide a combined risk score based on the risk label and the function of the aerial object.

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