SATELLITE IMAGERY RECOGNITION

PROJECT II

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B.Tech
CSE (Artificial Intelligence and Machine Learning)

RELEVANCE

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OBJECTIVES

| RELEVANCE - RECENT EVENTS

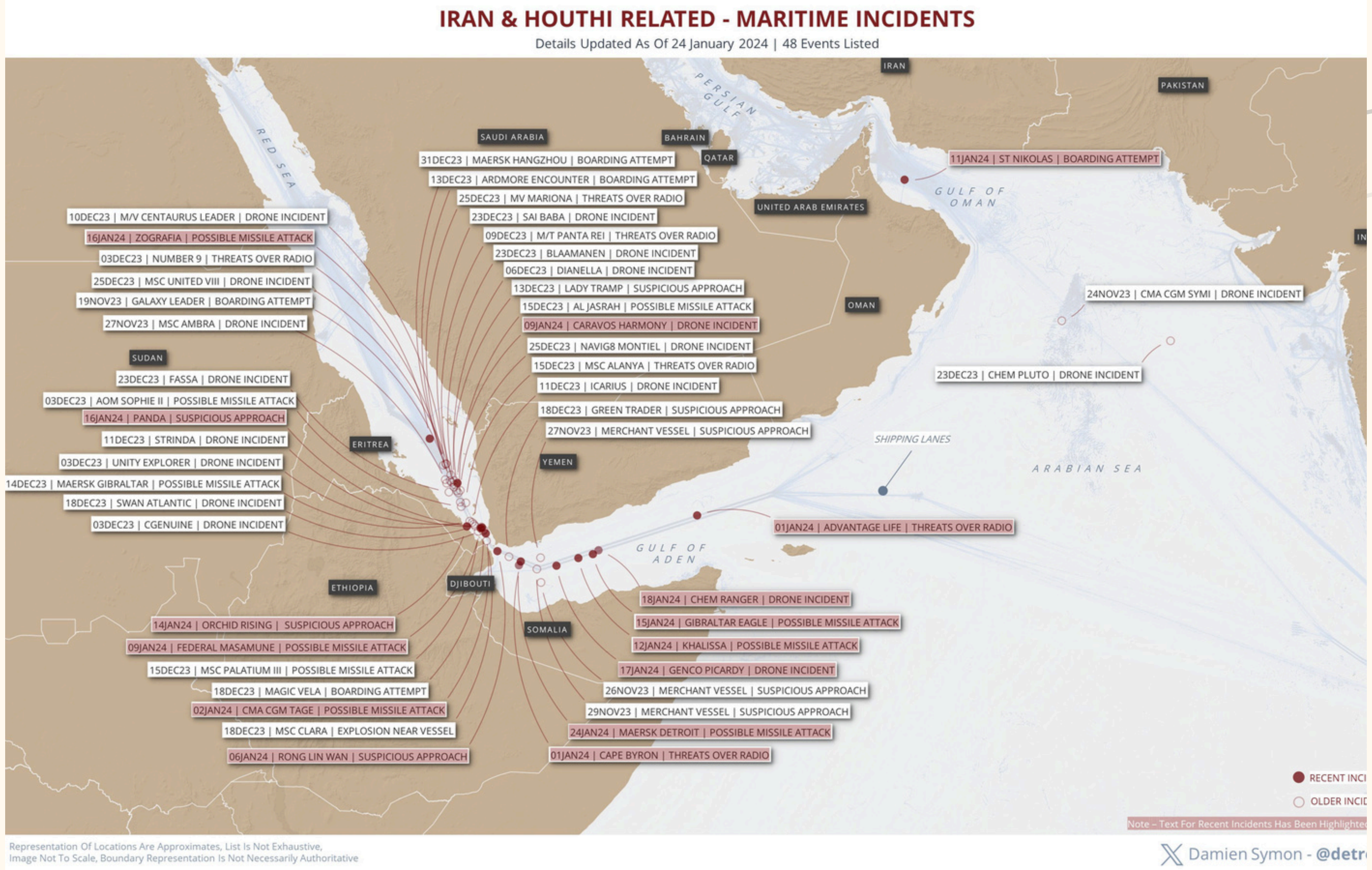
- **Prologue**: This project is a continuation of our previous work on Land-borne military vehicles.

- **Growing Importance**: Vital for military surveillance, the automated analysis of satellite imagery to detect and classify military assets

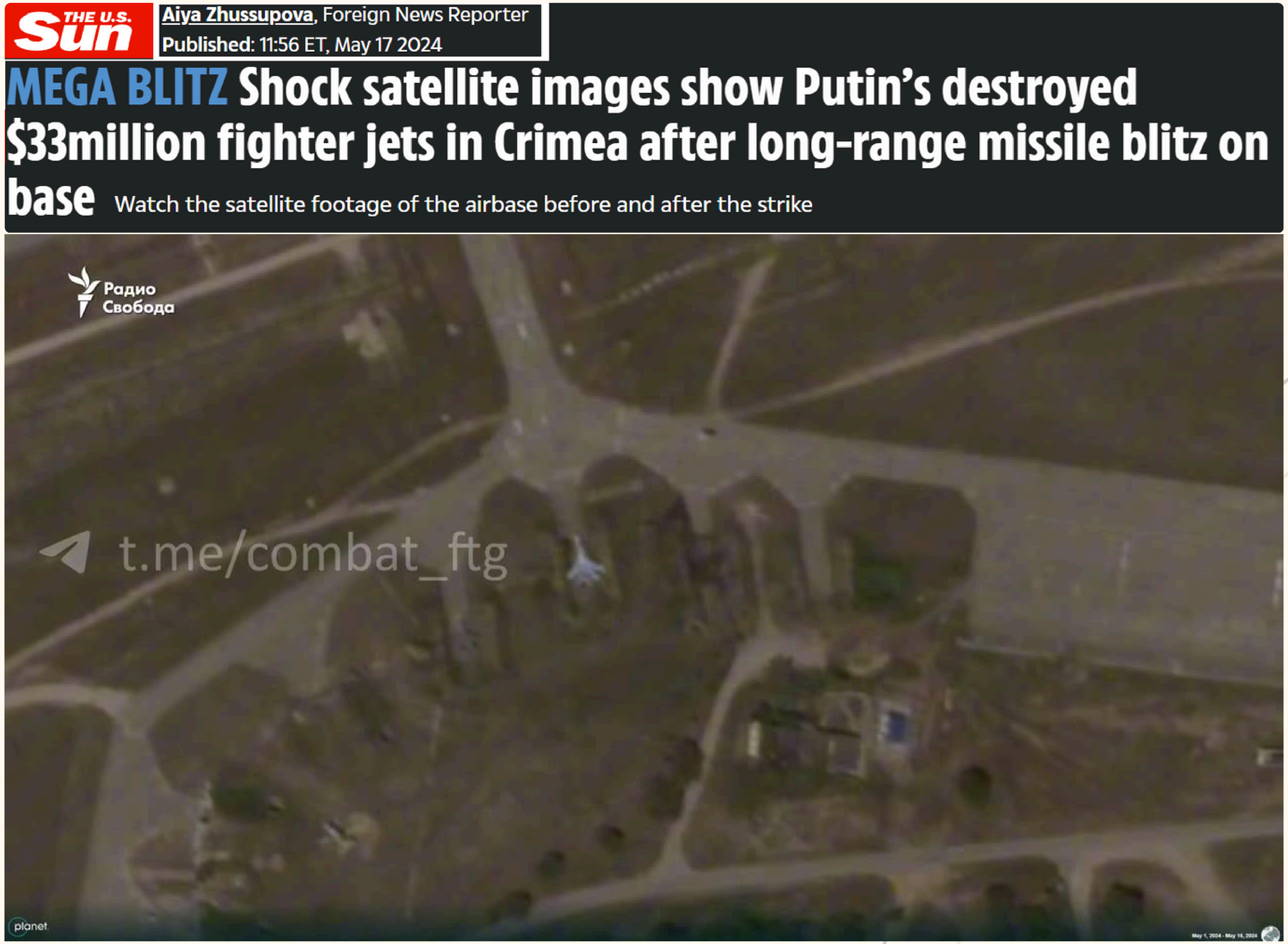
- RUSSO-UKRAINE WAR
- ARMENIA-AERBAIJAN CONFLICT
- ISRAEL-HAMAS CONFLICT
- PIRACY & ATTACKS IN RED SEA
- ISOUTH-CHINA SEA CONFLICT

| RELEVANCE - RECENT EVENTS

PIRACY & ATTACKS IN RED SEA



| RELEVANCE - RECENT EVENTS


THE U.S. Sun

Aiya Zhussupova, Foreign News Reporter

Published: 11:56 ET, May 17 2024

MEGA BLITZ Shock satellite images show Putin's destroyed $33million fighter jets in Crimea after long-range missile blitz on base

Watch the satellite footage of the airbase before and after the strike

PROBLEM ANALYSIS

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CHALLENGES

| PROBLEM ANALYSIS & CHALLENGES

- Effective Surveillance and Reconnaissance depend on the timely and precise detection of potential threats.

- **DataSet** :
  - **Sea-Borne**: Derived from Planet's **Open California dataset**
  - **Air-Borne**: Sourced Fine-Grained Visual Classification of Aircrafts **(FGVC Aircraft)**

- **Challenges**:
  - Limited Spatial Extent
  - Complete rotation invariance
  - Scarcity of Training Data (well-annotated)

| POTENTIALS

- The Datasets, Models and their Evaluations suggest that a machine capable of 23 programming itself has the potential to:
- Improve ***efficiency*** wrt development costs (software & hardware)
- Perform specific tasks at a ***superhuman level***
- Provide objective and ***fair decisions*** (against human psych bias)
- **Objective** : Overcome challenges for effective and accurate satellite imagery analytics and optimal vehicle identification in SAR images through iterative model evolution and strategic refinements.

LITERATURE REVIEW

| LITERATURE REVIEW

- Traditional approaches: ***sliding window*** method using SVMs, focus on ***non-military vehicle*** types.
- ***Liu et al.***(estimate their orientation and type).
- ***Tuermer et al.(***uses histograms of oriented features).
- Other works (color and edge features; used multiple descriptors).
- Employ non-maximum suppression to remove duplicate detections.

| LITERATURE REVIEW

Ross Girshick advanced object detection with:

- **R-CNN (2013)**: *Selective Search* for region proposals slow due to processing each proposal individually.
- **Fast R-CNN (2014)**: Processed the entire image and proposals together, speeding up training and testing with *RoI pooling*.
- **Faster R-CNN (2015)**: Intro of *Region Proposal Network* (RPN) for faster, integrated proposal generation, minus *Selective Search*.

FGVC-Aircraft dataset- Subhransu Maji el at. 10,000 images,100 distinct aircraft models (hierarchy)

DESIGN
&
METHODOLOGY

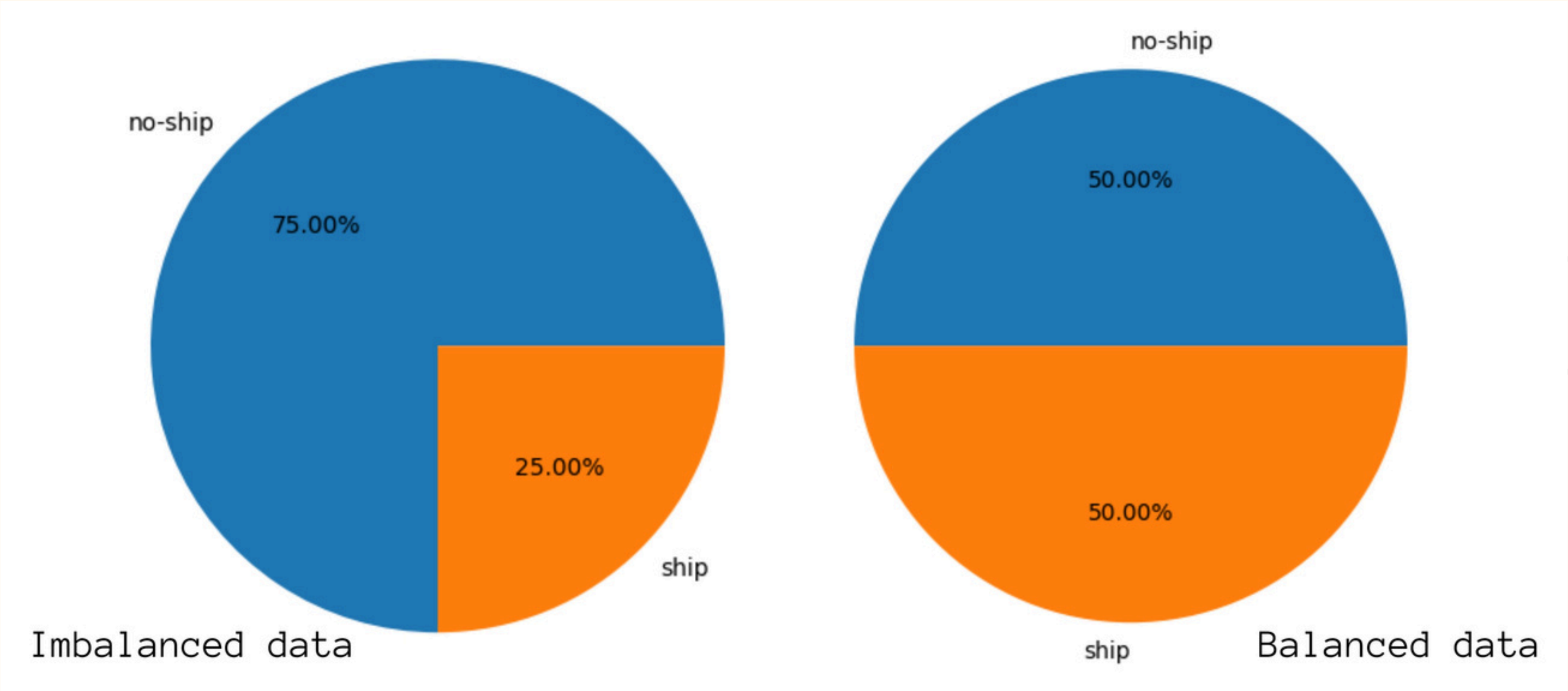
| DESIGN & METHODOLOGY

SEA-BORNE

Dataset

- Planet satellite imagery includes 4000 80x80 RGB images.

- **Label** : 1 - "ship" class - 1000 images
  0 - "no-ship" class - 3000 images



Data Preprocessing

- Augmenting Minority Class Images: **upsampling** to balance dataset
  Init class ratio- 1:3, two augmented images were generated per original ship image.

- Dataset is then split into the training, testing and validation sets .

| DESIGN & METHODOLOGY

SEA-BORNE

Class “Ship” →

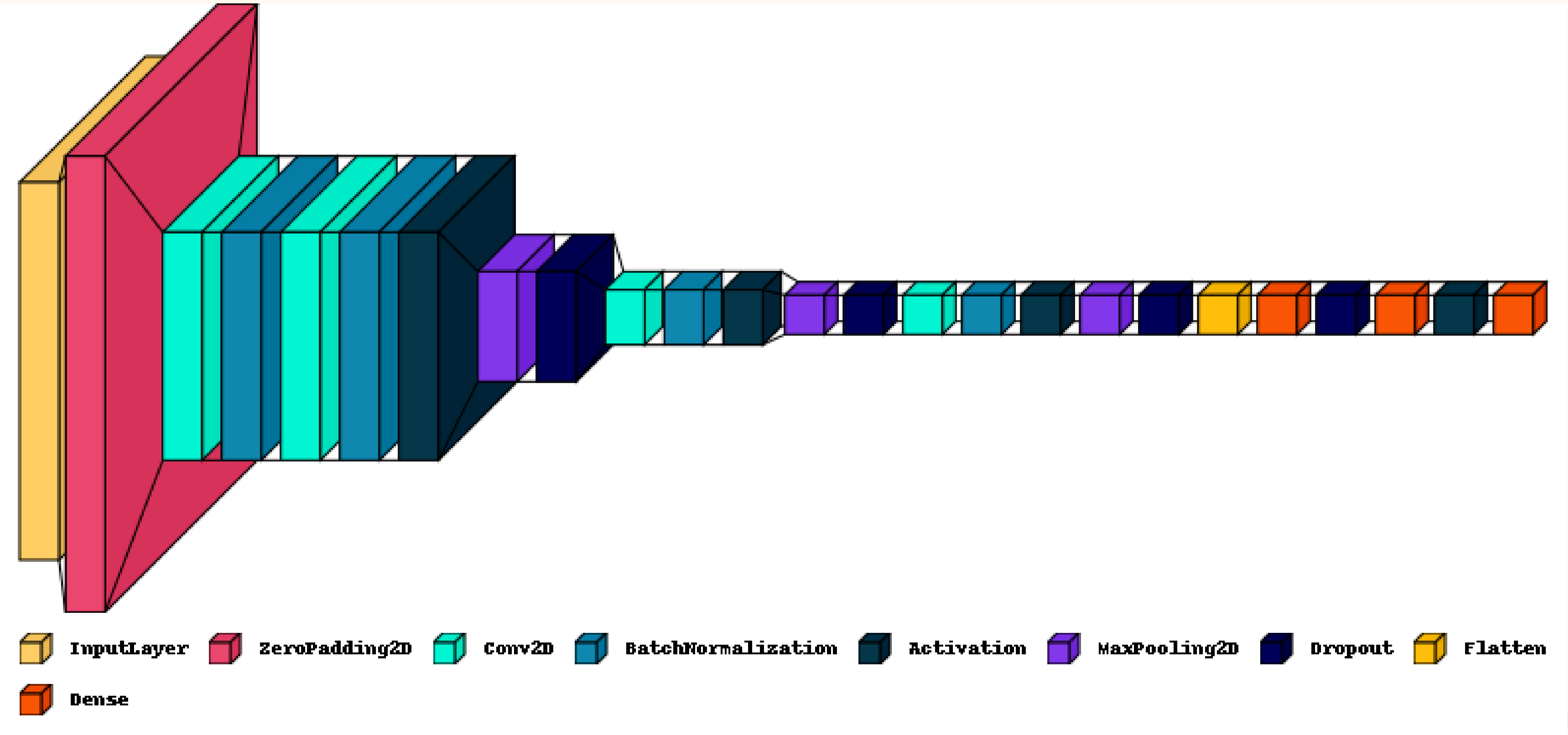
← Class “No-Ship”

| DESIGN & METHODOLOGY

SEA-BORNE

Architecture

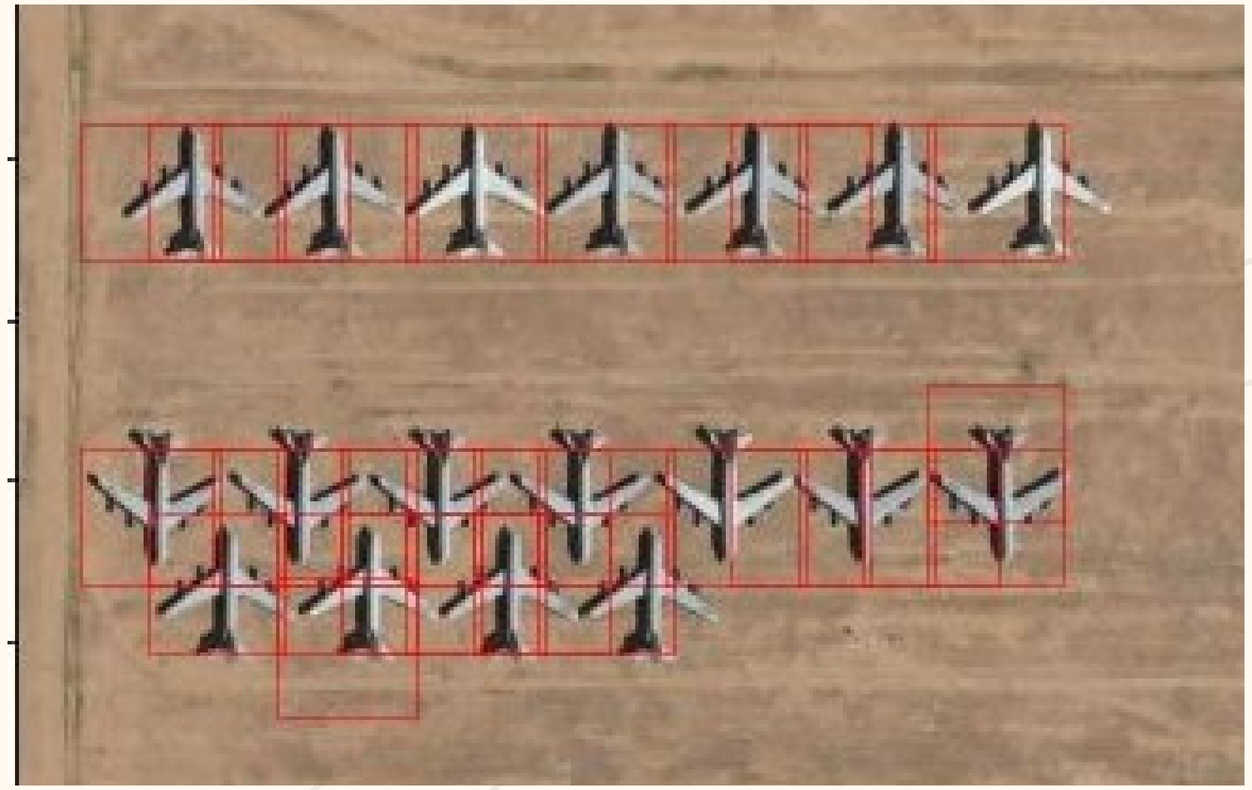
Feature map with Convolutional layers



- **Block 1**: Keras Input layer. ZeroPadding
- **Block 2**: First Conv Layer {16 filters, kernel size(3,3),strides (2,2)} Padding and Max-Pooling
- **Block 3-4**: Conv layer, Max-Pooling and Dropout layer
- **Output Block**:
  - Dense layer, sigmoid activation fn.

| DESIGN & METHODOLOGY

AIR-BORNE



Dataset

- 3,842 images, 20 types, with 22,341 instances
- Each image annotates the main aircraft with a **tight bounding box** and a hierarchical airplane **model label**.

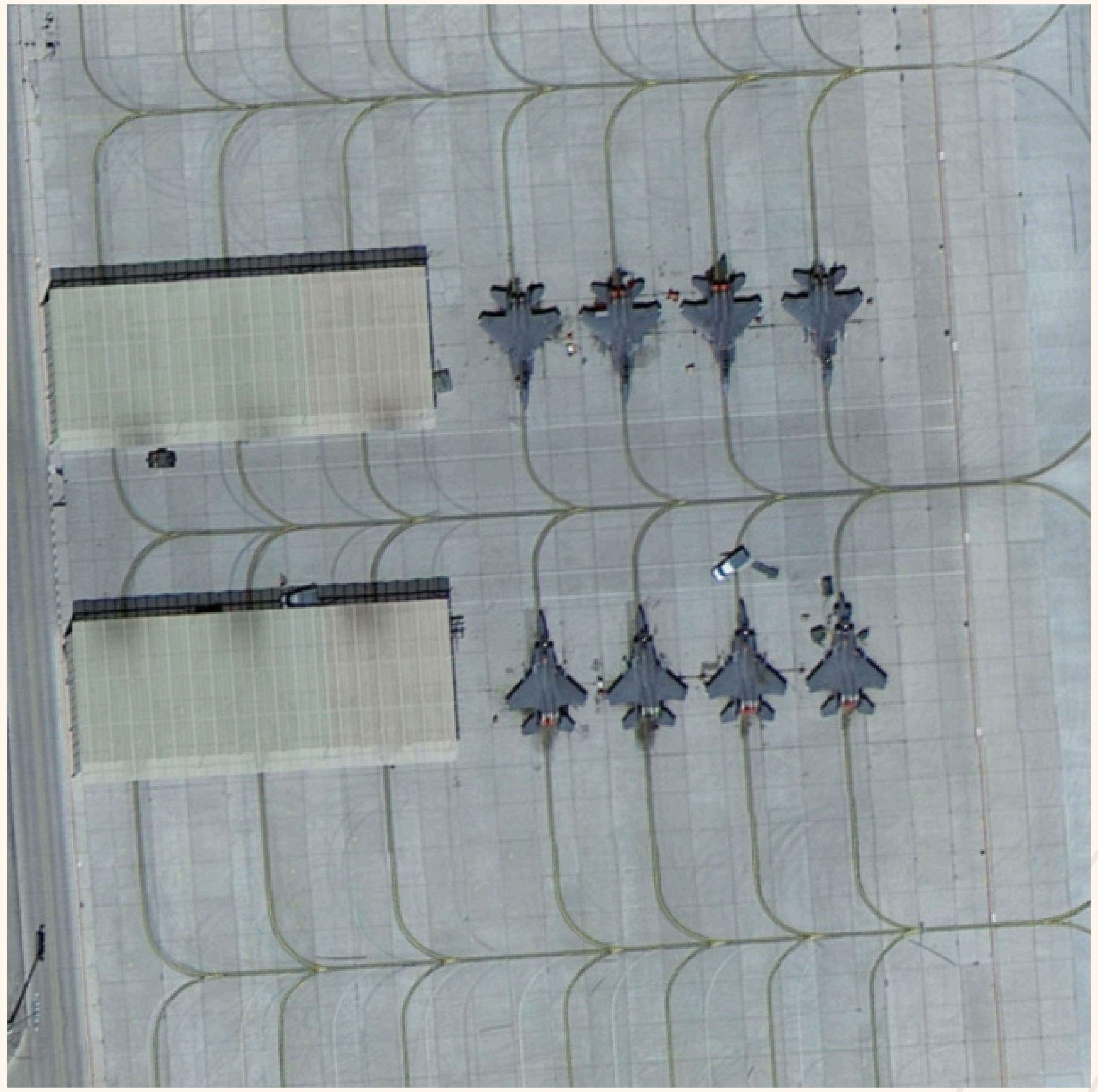
Data Preprocessing : function

- Images standardized to a consistent size- *pad_img(img)*
- Annotations(varying areas) result in non-uniform object sizes, ranging from small rectangles (24x24) to larger ones (111x140).- *extract_obj(img, annotations)*
- Dataset is then split into the training, testing and validation sets -*preprocessing(data)*

| DESIGN & METHODOLOGY

AIR-BORNE

A1 & A19 - Aircraft Type as Label



A13 -Aircraft Type as Label

A2 - Aircraft Type as Label

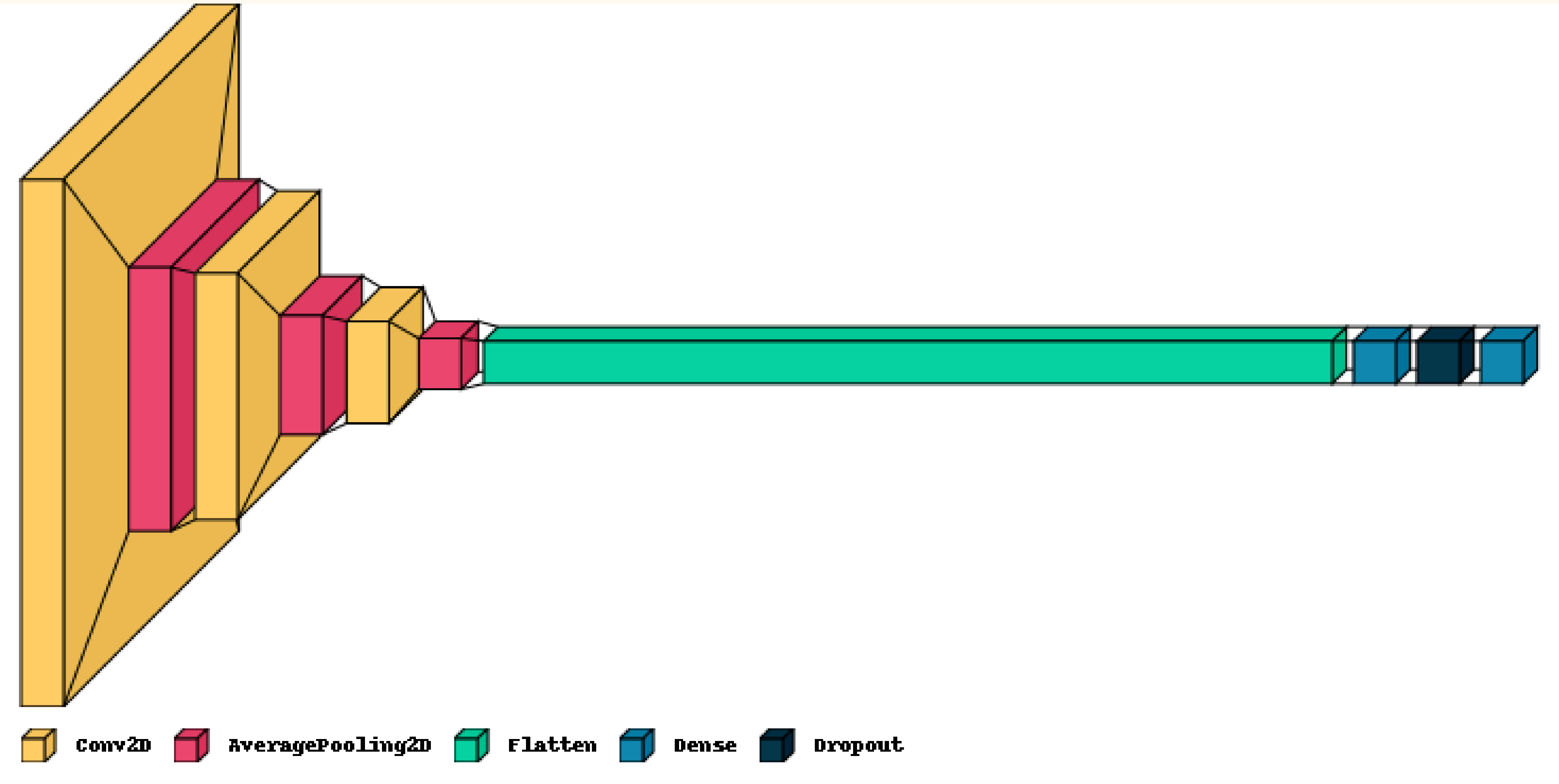
| DESIGN & METHODOLOGY

AIR-BORNE

Architecture

Faster R-CNN

- **The Keras Tuner** (Hyperband algo) to search for optimal hyperparameters.
- **Input Layer**: Conv Layer 32 filters, 3x3 kernel, ReLU activation. Input shape(64, 64, 3)



- **Average Pooling** Layer with a 2x2 pool size.
- **Flattening Layer**: Output from convo layers to flat vector.
- **Dense Layer** : Tunable (64 ,256; step:32), ReLU activation
- **Dropout Layer**: Tunable dropout rate (0.3,0.6; step:0.1)
- **Output Layer**: Dense layer , softmax activation.

RESULTS

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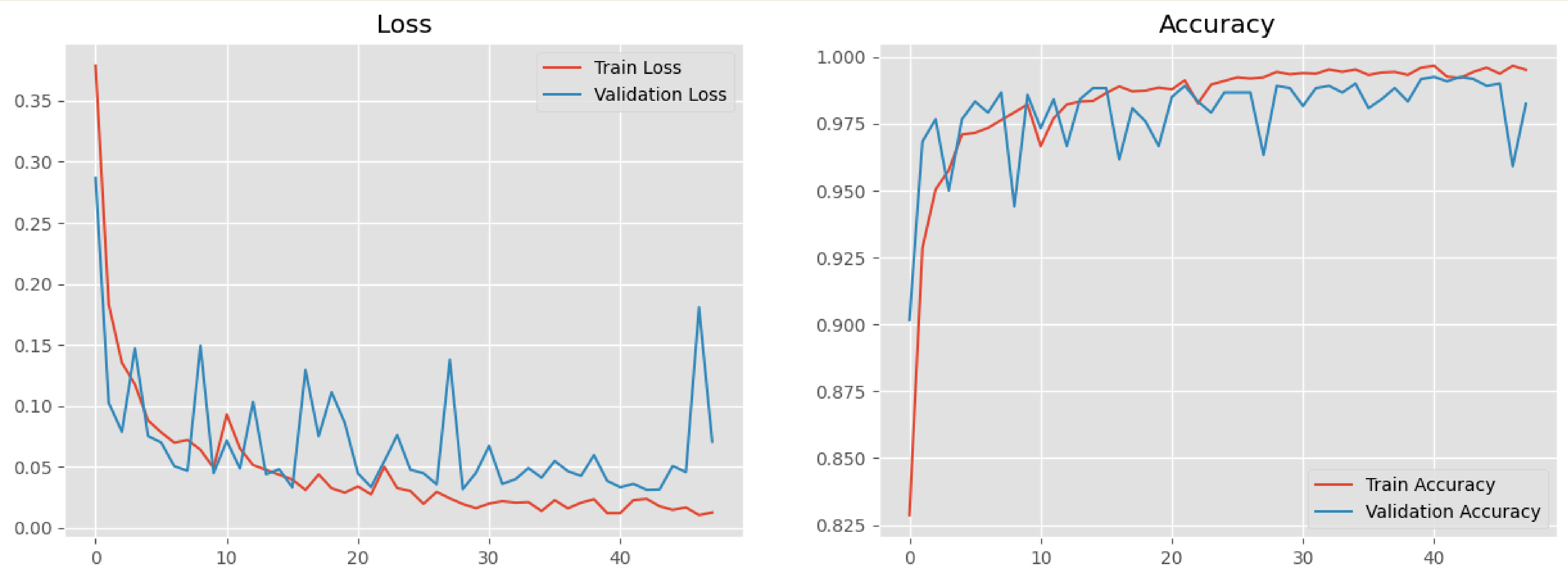
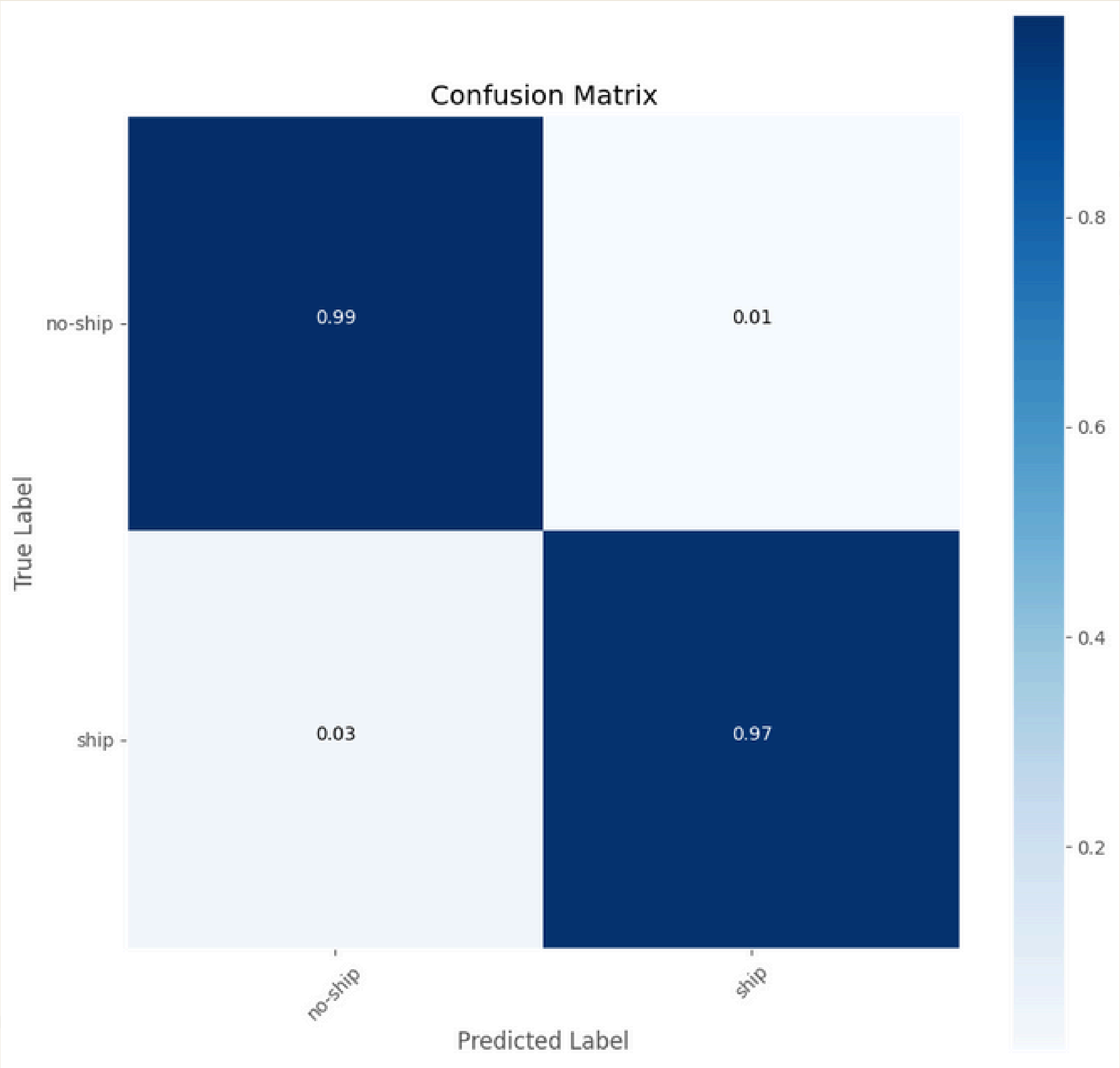
EVALUATION

| RESULTS & EVALUATION

SEA-BORNE



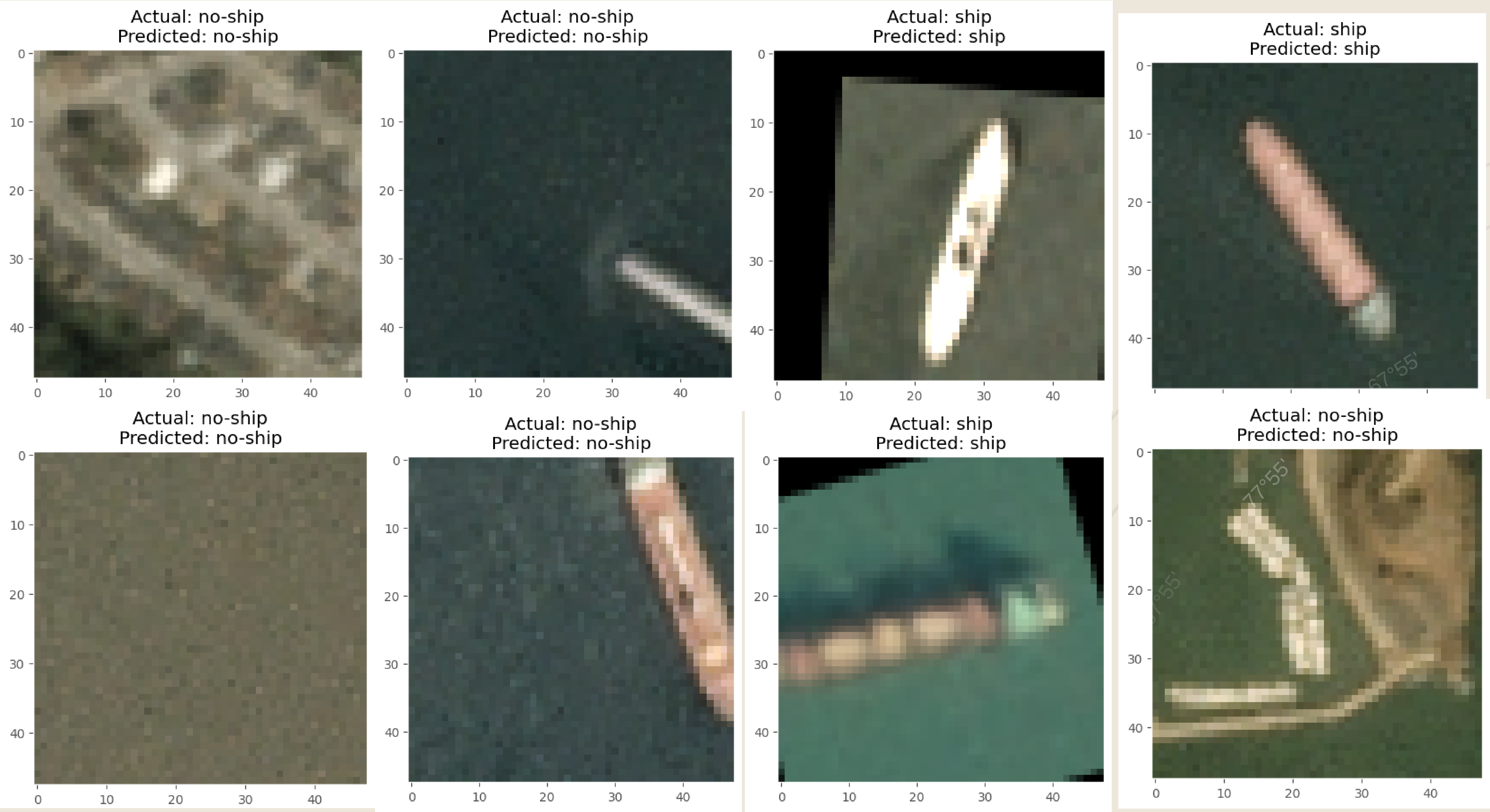


Confusion Matrix for Validation dataset

With Augmentation

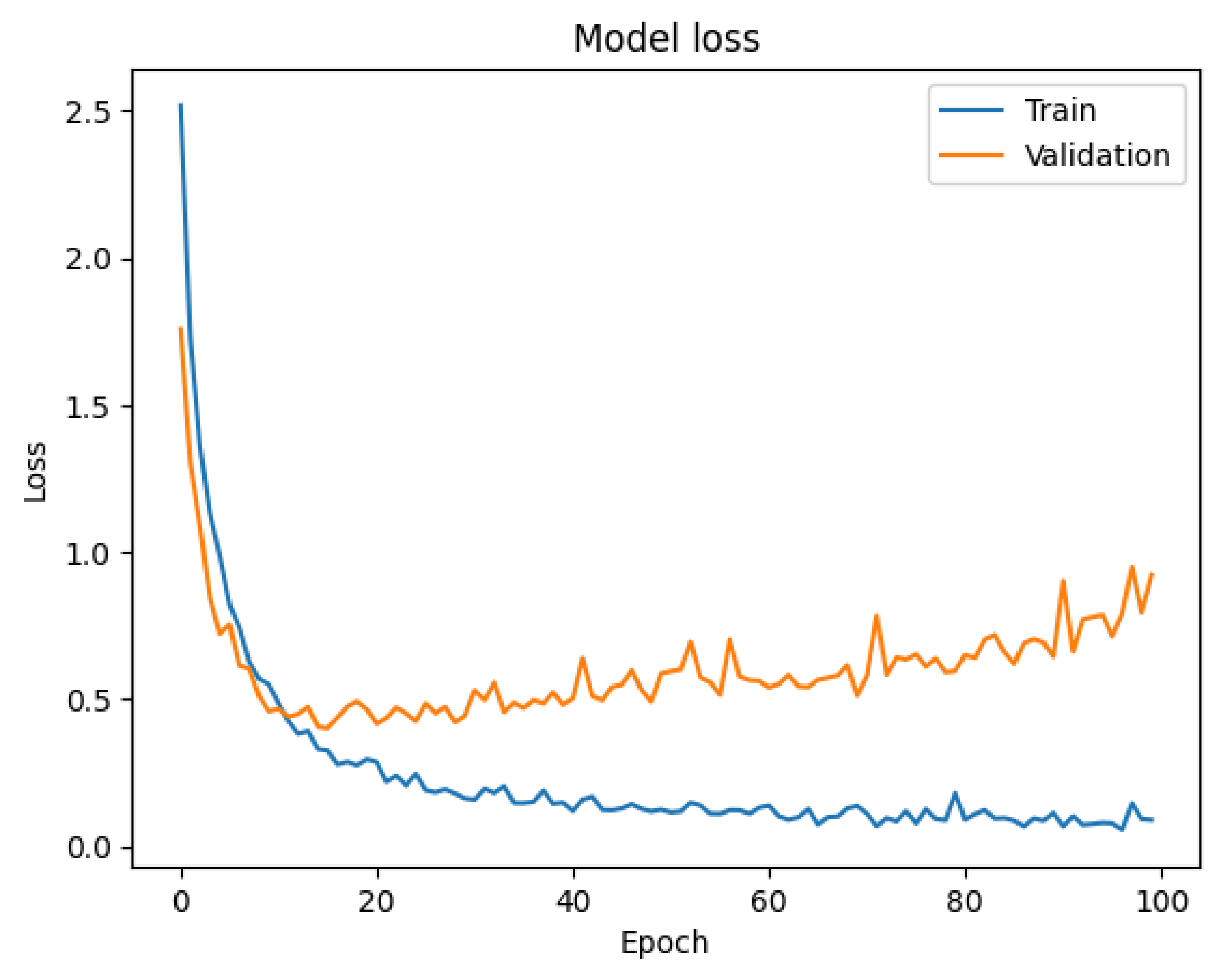
- Precision: no-ship : 0.942; ship : 0.989
- Recall: no-ship : 0.99; ship : 0.94

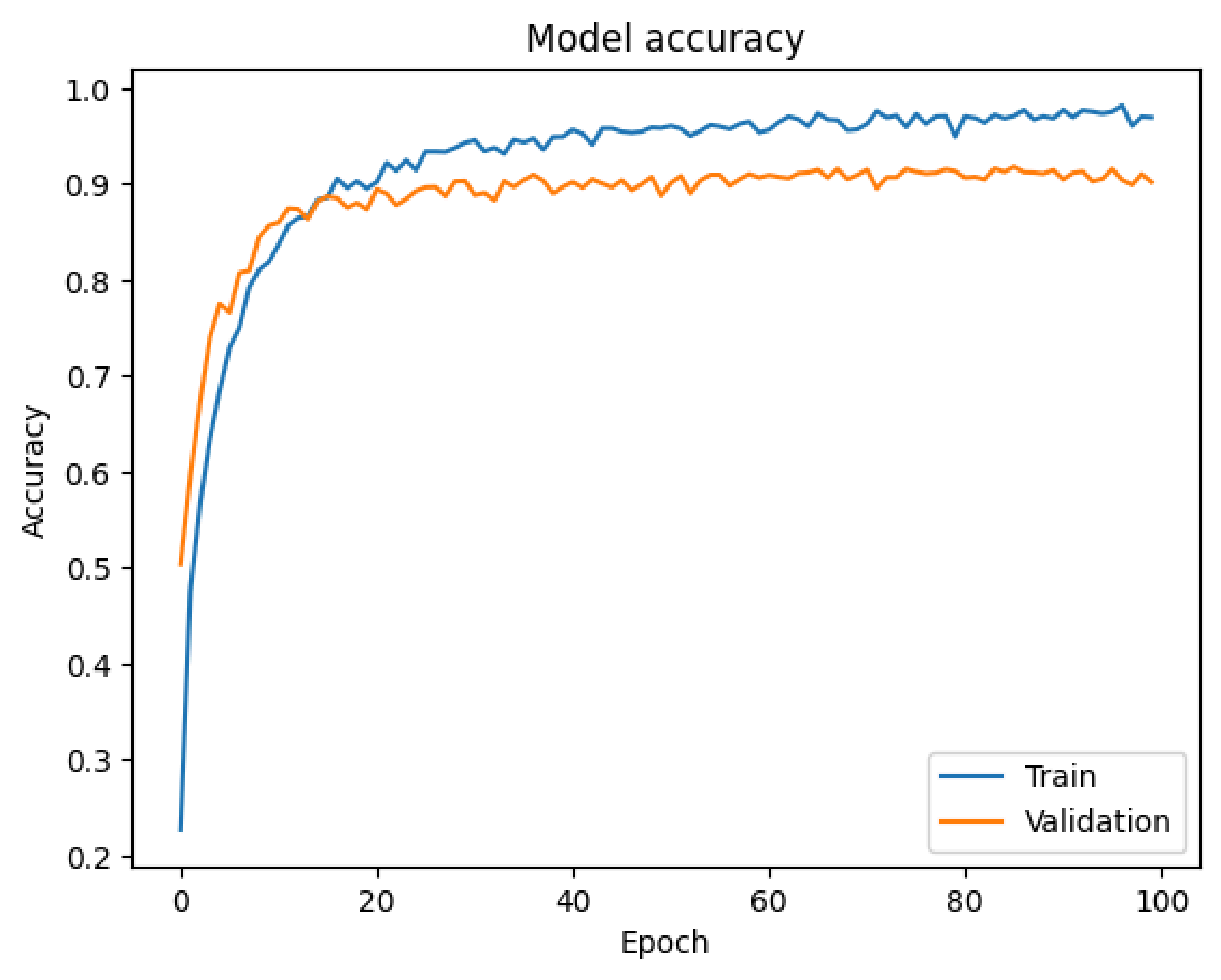
| RESULTS & EVALUATION



RESULTS & EVALUATION

AIR-BORNE





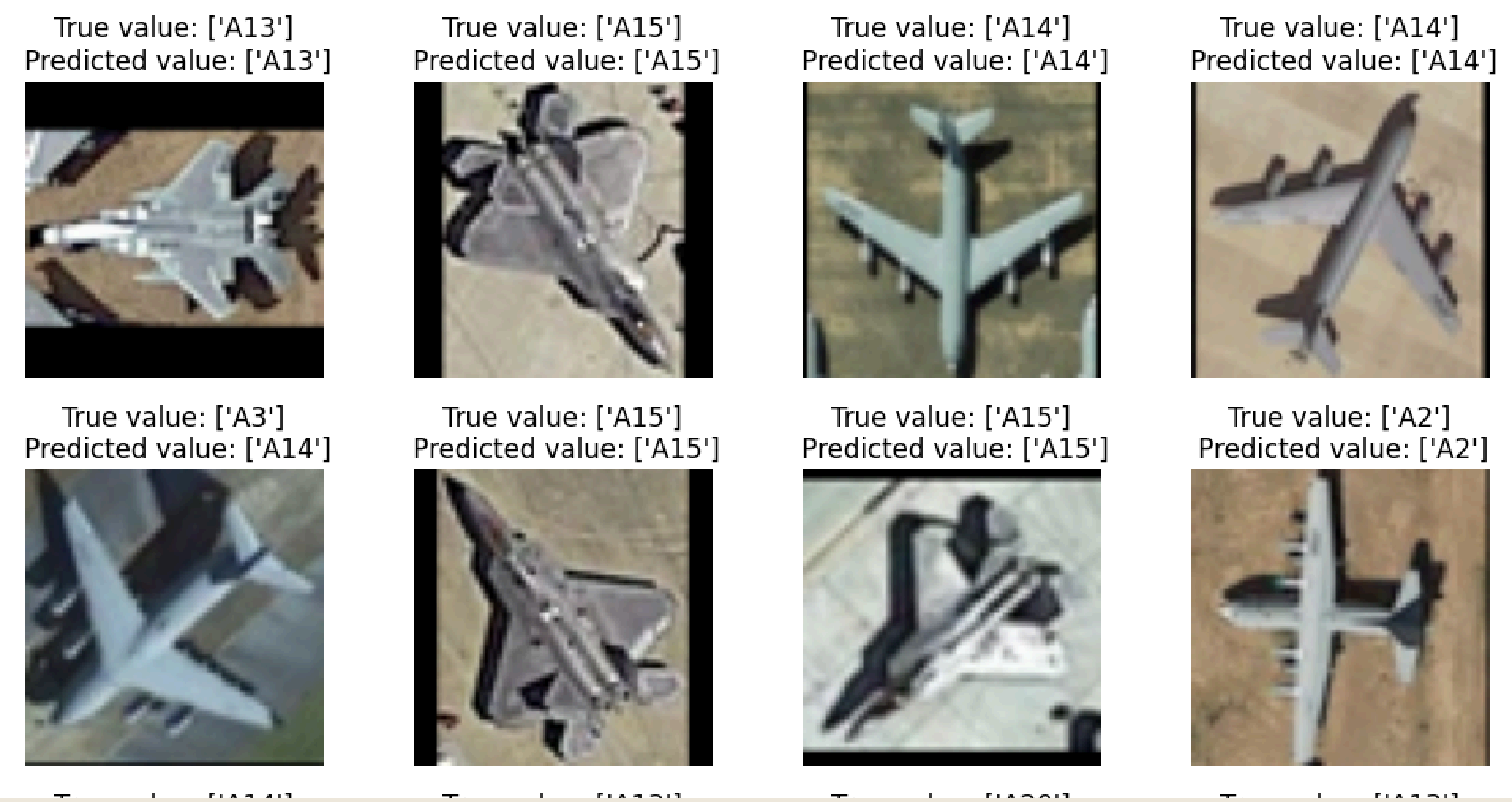
Build and train the model

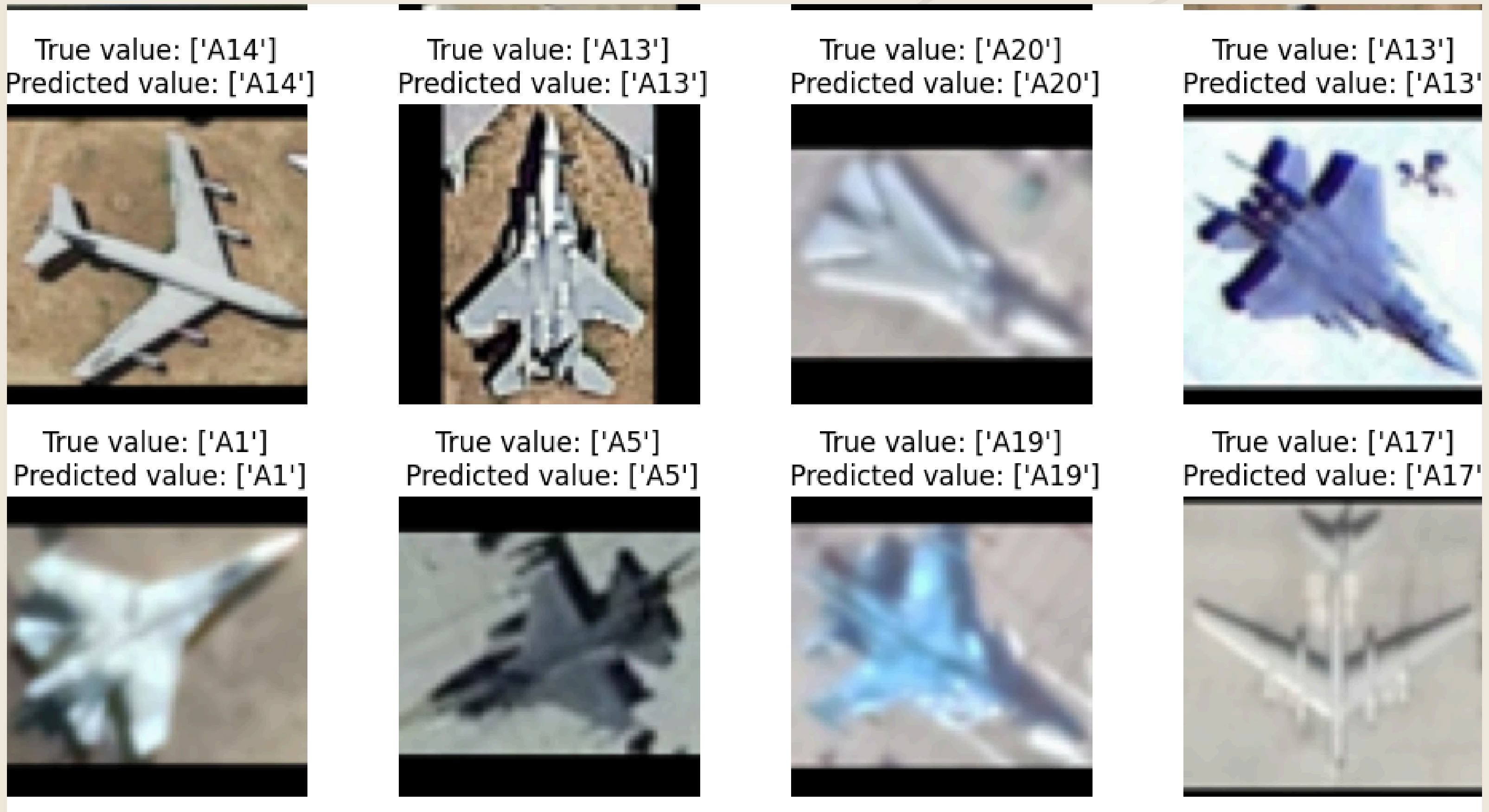
- loss: 0.0898
- accuracy: 0.9700
- val_loss: 0.9213
- val_accuracy: 0.9022

Test the model

- Test Loss: 0.9212860465049744
- Test Accuracy: 0.902249813079834

RESULTS & EVALUATION





Thank you!

TEAM 4

APPENDIX

| Benchmark MODels

Ross Girshick

advanced object detection with:

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	R-CNN	Fast R-CNN	Faster R-CNN
region proposals method	Selective search	Selective search	Region proposal network
Prediction timing	40-50 sec	2 seconds	0.2 seconds
computation	High computation time	High computation time	Low computation time
The mAP on Pascal VOC 2007 test dataset(%)	58.5	66.9 (when trained with VOC 2007 only) 70.0 (when trained with VOC 2007 and 2012 both)	69.9(when trained with VOC 2007 only)
The mAP on Pascal VOC 2012 test dataset (%)	53.3	65.7 (when trained with VOC 2012 only) 68.4 (when trained with VOC 2007 and 2012 both)	67.0(when trained with VOC 2012 only) 70.4 (when trained with VOC 2007 and 2012 both) 75.9(when trained with VOC 2007 and 2012 and COCO)

BEHIND THE SCENES

- Nature of Dataset: synthetic aperture radar (SAR) for cloud-penetrating vehicle identification.

- Models:
  - MLP-ANN Model: Initial exploration.
  - Simple & Deeper CNNs: Evolved for feature-rich SAR image analysis.
- Refinement:
  - Data Augmentation: Expand dataset artificially.
  - Dropout Layers: Prevent overfitting.
- Callbacks:
  - Early Stopping: Halts training at performance plateaus.
  - Learning Rate Reduction: Optimizes convergence.