ADS-B Data Engineering

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Acronyms I

- ABMS - Advanced Battle Management System
- ADS-B - Automatic Dependent Surveillance-Broadcast
- AIS - Automatic Identification System
- ANN - Artificial Neural Network
- ATC - Air Traffic Control
- BA-CNN - Bat Algorithm and Convolutional Neural Network
- CLNET - Cross-layer Convolutional Neural Network
- CNN - Convolutional Neural Network
- DAF - Department of the Air Force
- DCGS - Distributed Common Ground System
- DSDEC - Dual-Stage Deep Engine Classifier
- EASA - European Union Aviation Safety Agency

Acronyms II

- FCN - Fully Convolutional Network
- FGVC-Aircraft - Fine-Grained Visual Classification of Aircraft
- FNN - Feed-Forward Neural Network
- ICAO - International Civil Aviation Organization
- IoT - Internet of Things
- ISR - Intelligence, Surveillance and Reconnaissance
- JADC2 - Joint All-Domain Command and Control
- JSON - JavaScript Object Notation
- LSTM - Long Short-Term Memory
- LSTM-FCN - Long Short-Term Memory - Fully Convolutional Network
- MALSTM-FCN - Multivariate Attention Long Short-Term Memory - Fully Convolutional - Network

Acronyms III

- MFF - Multilayer Feature Fusion
- MLSTM-FCN - Multivariate Long Short-Term Memory - Fully Convolutional Network
- MSL - mean sea level
- NDAA - National Defense Authorization Act
- PAI - publicly available information
- PCB - Parallel Convolutional Block
- POL - pattern-of-life
- ResNet - Residual Network
- RF - Random Forest
- RNN - Recurrent Neural Network
- SSSNet - Separated Smooth Sampling Network
- SVM - Support Vector Machine
- WTC - Wake Turbulence Category

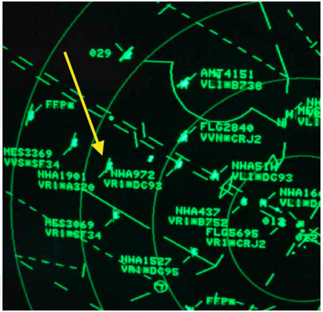
Motivation

- FY22 Posture Statement [1]
  - Translation and sharing of data to provide "real-time dissemination of actionable information" to provide "joint warfighting across all domains at a pace faster than our competitors"
  - Improve and optimize the ABMS
- AFRL/RYA tasked to improve military operations within the intel community by PoL modeling with machine learning
  - Use ground based and on-board aircraft sensors to predict aircraft characteristics

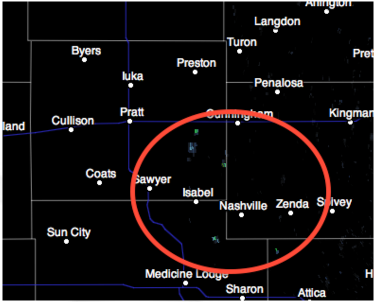
AFRL/RYA Mission Statement: Layered Sensing Exploitation Division Conducts basic research, exploratory and advanced development to provide efficient sensing exploitation for Air Force air, space, and C2 systems. Develops technology for target and threat detection, location, track, and identification using RF and EO sensors and other information sources. Develops performance driven sensing technology to determine sensor design goals and sensor deployment for layered sensing solutions in challenging environments, and projects layered sensing performance in relevant scenarios.

Problem

- ATC primary radar collects kinematic information only. Transponder is required for ID.
- During combat, hijacking and other hostilities, an enemy would turn their transponder off
- ADS-B can be used as surrogate data



ATC radar with transponder on [2]



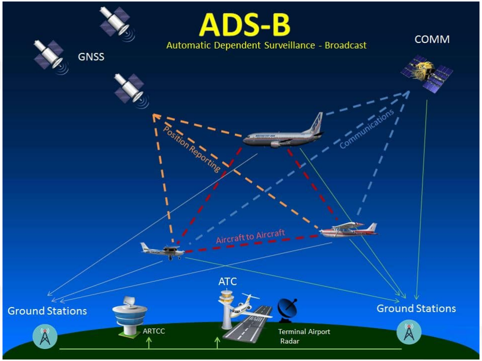
ATC radar with transponder off [2]

Research Objectives

- RQ-1: What is the minimum amount of data needed to effectively classify engine type within 10% accuracy of previous efforts?
- RQ-2: What is the smallest feature subset that predicts an aircraft's engine type with an accuracy within 5% accuracy of previous efforts?
- RQ-3: How does the identification of flight phase assist in aircraft prediction of description, designator and wake turbulence category (WTC)?
- RQ-4: Which phases and features work best to predict aircraft by their WTC, aircraft description and type designator (as listed in ICAO Doc 8643)?
- RQ-5: Does fusing weather and image data improve the predictive power of a model that uses ADS-B data to predict description, designator and WTC?
- RQ-6: Using pre- and/or post-classification fusion methods, how can a model be developed to predict description, designator and WTC using ADS-B, aircraft images and weather?

Automatic Dependent Surveillance-Broadcast (ADS-B)

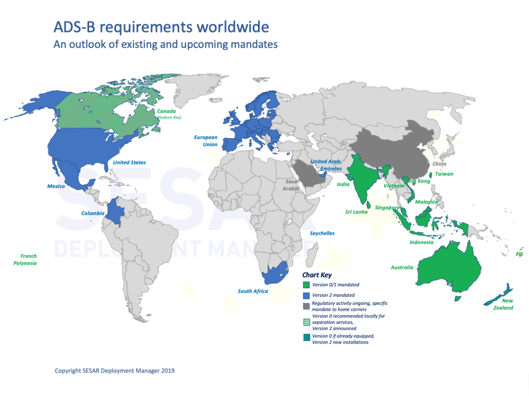
- 70 features: ICAO hex identifier, altitude, airspeed, vertical speed, directional heading, position time, latitude, longitude, and ground status
- Broadcast via ADS-B Out transponder @ 1090 and 978 MHz
- Saved in 2-5 second intervals as a JSON file



ADS-B High Level Operational Graphic [3]

Automatic Dependent Surveillance-Broadcast (ADS-B)

- Mandated use in US, Europe, Asia and Australia
- US mandates only in controlled airspace - above 10,000 feet MSL or near busy airports



Countries with ADS-B Mandate [4]

International Civil Aviation Organization (ICAO)

- Organization of United Nations
- 193 member states

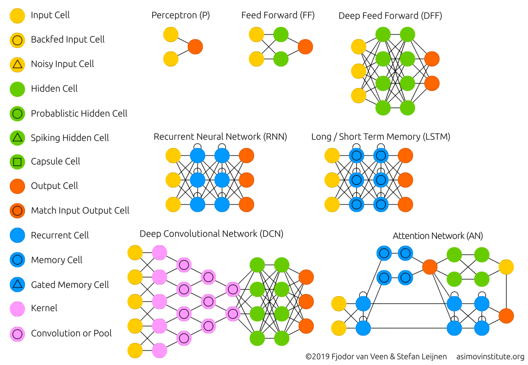
PART 2 — AIRCRAFT TYPE DESIGNATORS (DECODE)
PARTIE 2 — INDICATIFS DE TYPES D'AÉRONEF (DÉCODAGE)
PARTE 2 — DESIGNADORES DE TIPOS DE AERONAVE (DESCIFRADO)
ЧАСТЬ 2. УСЛОВНЫЕ ОБОЗНАЧЕНИЯ ТИПОВ ВОЗДУШНЫХ СУДОВ (ДЕКОДИРОВАНИЕ)

DESIGNATOR INDICATIF DESIGNADOR УСЛ. ОБОЗНАЧЕНИЕ	MANUFACTURER, MODEL CONSTRUCTEUR, MODÈLE FABRICANTE, MODELO ИЗГОТОВИТЕЛЬ, МОДЕЛЬ	DESCRIPTION DESCRIPTION DESCRIPCIÓN ВОЗДУШНОГО	WTC WTC WTC WTC
A1	DOUGLAS, Skyraider	L1P	M
	DOUGLAS, AD Skyraider	L1P	M
	DOUGLAS, EA-1 Skyraider	L1P	M
A2RT	KAZAN, Ansat 2RT	H2T	L
A3	DOUGLAS, NRA-3 Skywarrior	L2J	M
	DOUGLAS, ERA-3 Skywarrior	L2J	M
	DOUGLAS, A-3 Skywarrior	L2J	M
	DOUGLAS, Skywarrior	L2J	M
	DOUGLAS, TA-3 Skywarrior	L2J	M
	NORTH AMERICAN ROCKWELL, Quail Commander	L1P	L
	NORTH AMERICAN ROCKWELL, Sparrow Commander	L1P	L
	NORTH AMERICAN ROCKWELL, A-9 Sparrow Commander	L1P	L
	NORTH AMERICAN ROCKWELL, A-9 Quail Commander	L1P	L
A10	FAIRCHILD (1), OA-10 Thunderbolt 2	L2J	M
	FAIRCHILD (1), A-10 Thunderbolt 2	L2J	M
	FAIRCHILD (1), Thunderbolt 2	L2J	M
A16	AVIADESIGN, A-16 Sport Falcon	L1P	L

First Page of ICAO Doc 8643 Part 2 [5]

Deep Learning

- Classification of data
- RNN and LSTM: Time series data
  - LSTM - fixes gradient problem
- CNN - Grid-like topology data

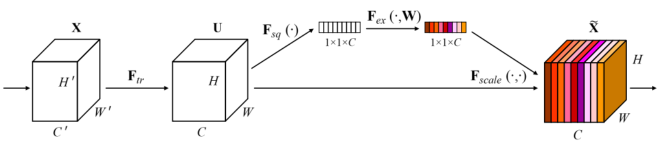


Neural Network [6]

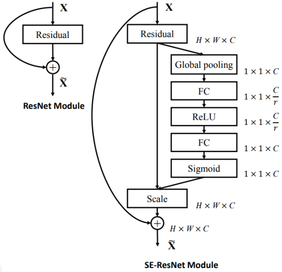
`https://www.asimovinstitute.org/neural-network-zoo/`

Squeeze and Excite Blocks

- Introduced by Jie Hu from MIT in 2018
- Built to model dependencies between channels
- Squeeze: Global average pooling creates $1 \times 1 \times C$ matrix
- Excitation: Multilayer ANN with C/r hidden layer. Output is multiplied element-wise with original input



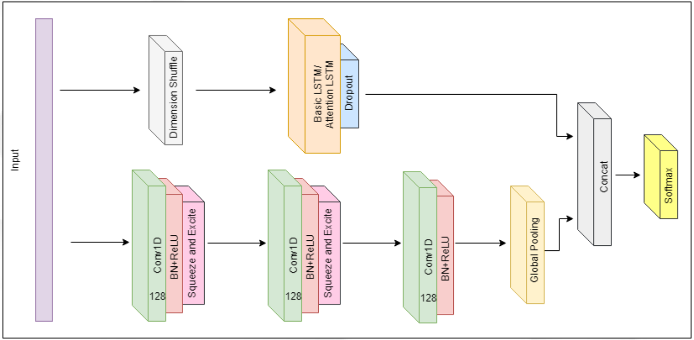
Squeeze-and-Excitation block [7]



The schema of the squeeze and excite model with a Residual Network [7]

Multivariate Long Short-Term Memory Fully Convolutional Network (MLSTM-FCN)

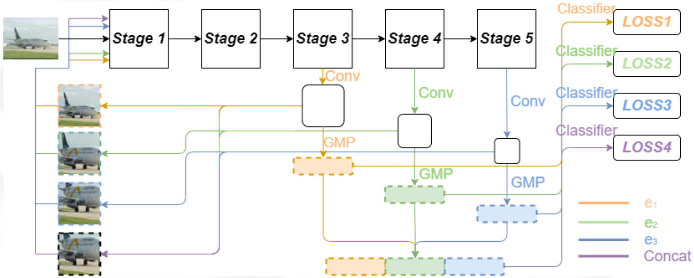
- Developed by Fazle Karim in 2019
- Uses Squeeze-and-excite blocks, LSTMs and FCNs for classification of time series data



MLSTM-FCN architecture [8]

Cross-Layer Mutual Attention Learning Network (CMAL-Net)

- Published by Liu et al in March 2023
- Uses a multi-stage CNN backbone (e.g. ResNet) with n experts.
- Each expert is trained separately, then concatenated:
  - Input: Feature map from a layer
  - Output: Categorical prediction with an attention region

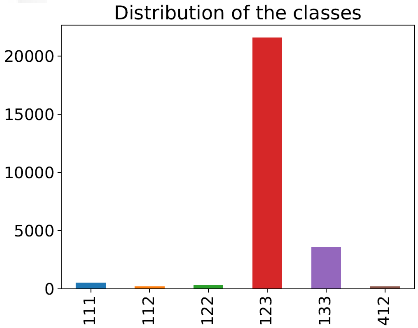


Example CMAL-Net architecture with 3 experts[9]

Statistical Features Extraction and Boosting

Ginoulhac et al. (2019) - Statistical Features Extraction and Boosting

- Researchers able to identify air and maritime traffic using kinematic data with an 87% and 86% success rate [10]
- Method allows real-time analysis since method is applied at each time step individually

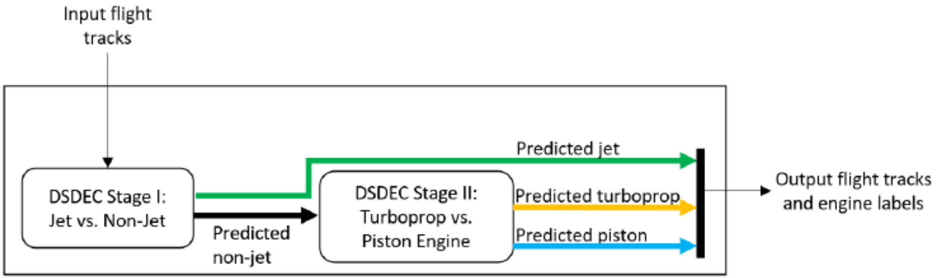


Distribution of training set [10]

Dual-Stage Deep Engine Classifier

Problem: Difficult to differentiate between piston and turboprop

- Two stage approach
- Researchers were able to identify jets with 98.4% accuracy, turboprop aircraft with 79.2% accuracy, and piston engine aircraft with 89.9% accuracy. Overall accuracy was 89.2%.



DSDEC architecture [11]

Image Classification

- Fine-Grained Visual Classification of Aircraft (FGVC-Aircraft) benchmark cited nearly 1,000 times
  - Contains 10,000 aircraft images identified by model, variant, family and manufacturer
- Top performing aircraft image classification studies use variations of CNN

Author	**Year**	**Method**	**Accuracy Achieved**
Maji et al. [12]	2013	Non-linear SVM	48.69%
Rong et al. [13]	2021	SSSNet	93.3%
Y Wang et al. [14]	2022	BA-CNN	89.2%
Lei Wang et al. [15]	2022	MFF net with PCB	91.4%
Liu et al. [16]	2023	CMAL-Net	94.7%

Flight Path Classification and Fuzzy Logic

- Type of mathematical logic with subjective truth values
- Flight phases can be determined from either a complete or partial flight path using Gaussian ($\mathcal{G}$), Z-shaped ($\mathcal{Z}$) or S-shaped ($\mathcal{S}$) membership functions
- H - altitude, V - velocity, RoC - Rate-of-climb

$$
\begin{array}{llll}
if & H_{gnd} \wedge V_{lo} \wedge RoC_0 & then & Ground \\
if & H_{lo} \wedge V_{mid} \wedge RoC_+ & then & Climb \\
if & H_{hi} \wedge V_{hi} \wedge RoC_0 & then & Cruise \\
if & H_{lo} \wedge V_{mid} \wedge RoC_- & then & Descent \\
if & H_{lo} \wedge V_{mid} \wedge RoC_0 & then & Level\ flight
\end{array}
$$

Fuzzy Relationships for Flight Phase [17]

Sensor Fusion

- Pre-classification - combines data prior to classification
- Post-classification - uses voting or some other scoring method to combine the classification results after classification
  - Post-classification is necessary when combining data types that are best classified using different models (i.e. images use CNNs, time series could use CNN or LSTM)

Study 1 - Feature Reduction and Data Minimization

- **Paper Title:** "ADS-B Classification Using Multivariate Long Short-Term Memory Fully Convolutional Networks and Data Reduction Techniques"
- **Venue**: Journal of Supercomputing
- **Research Questions**
  - RQ-1: What is the minimum amount of data needed to effectively classify engine type within 10% accuracy of previous efforts?
  - RQ-2: What is the smallest feature subset that predicts an aircraft's engine type with an accuracy within 5% accuracy of previous efforts?

Overview

- **Experiment 1:** Determine the effect of varying the number of training data observations.
- **Experiment 2:** Determine which subset of features have the highest overall accuracy when predicting engine type.

Methodology

- Data obtained from 16 November 2020 (evaluation) and 1 December 2020 (training)
- Data Processing Steps:
  1. Data converted from JSON to Pandas
  2. Irrelevant/incorrect data is removed
  3. Aircraft with fewer than 300 observations (10 min) removed
  4. Used lat/long to generate a 3-dimensional location
  5. Data balanced with undersampling technique
  6. Data formed into tensors (total: 4,110 tensors/1,233,000 observations)
- MLSTM-FCN used to train models (without DSDEC)
- k-fold method used to evaluate models ($k = 10$)

Experiment 1 - Minimum Data Amount

- 24 models: 3 feature sets $\times$ 2 learning rates $\times$ 4 data set sizes
  - Full data: 4,110 tensors (24-hours)
  - Half data: 2,055 tensors (12-hours)
  - Quarter data: 1,026 tensors (6-hours)
  - Eighth data: 513 tensors (3-hours)
- Trained for 200 epochs, learning rates: 0.01, 0.001

Feature Sets

Limited	Medium	Full
Altitude	Altitude	Altitude
Airspeed	Airspeed	Airspeed
Vertical Speed	Vertical Speed	Vertical Speed
Location (X,Y,Z)	Location (X,Y,Z)	Location (X,Y,Z)
	Barometric Pressure	Barometric Pressure
	Time	Time
	Track	Track
		Ground Altitude
		Lat/Long

Experiment 2 - Best Subset

- 255 models with all possible feature combinations except lat/long $(2^8 - 1)$
- Trained for 50 epochs (lr: 0.001)

Results

- Experiment 1 - Min Data
  - Limited feature set and 0.001 learning rate performed best for each data set size
  - Full: 89.4%; Half: 86.5%; Quarter: 83.9%; Eighth: 75.8%
- Experiment 2 - Best Subset
  - Airspeed, pressure and vertical airspeed trained most accurate model: 89.4%
  - Time produced worst performing models

Conclusion

Research Questions

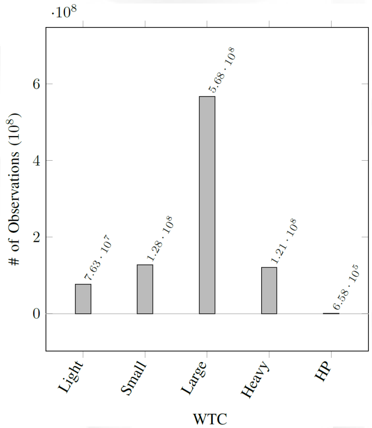
- RQ-1: What is the minimum amount of data needed to effectively classify engine type within 10% accuracy of previous efforts?
  - More is better, but quality of features is important
- RQ-2: What is the smallest feature subset that predicts an aircraft's engine type with an accuracy within 5% accuracy of previous efforts?
  - Airspeed, pressure and vertical speed for take-off phase

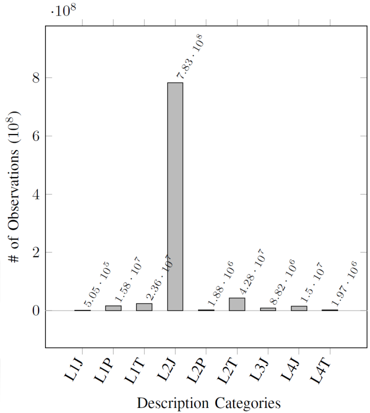
Study 2 - Aircraft Prediction

- **Paper Title:** "Aircraft Classification Using Flight Phase Identification"
- **Venue**: 2023 National Aerospace and Electronics Conference (NAECON)
- **Research Questions**
  - RQ-3: How does the identification of flight phase assist in aircraft prediction of description, designator and WTC?
  - RQ-4: Which phases work best to predict aircraft by their wake turbulence category (WTC), aircraft description and type designator (as listed in ICAO Doc 8643)?

Overview

- 3 Experiments to answer research questions:
  1. Compare 2 models to determine impact of flight phase
  2. Predict WTC, description and type designator using weighted classes
  3. Analyze and report accuracy per flight phase





Observations per class

Methodology

- ADS-B data from 1-31 October 2021 (training) and 1-2 November 2021 (evaluation) $\rightarrow$ 2,976,027 tensors (892,808,100 observations)
- Data processing steps similar to study 1, but undersampling technique is not used.
  - WTC and description obtained from Opensky Network Aircraft database [18] and double checked with ICAO Doc 8643 [5].
  - Feature generation: lat/long converted to 3-D, flight phase predicted using fuzzy logic, date features (generated, but not used)
- 130 most common aircraft are used to train model. 2,901,260 tensors (870,378,000 observations) remaining.
- MLSTM-FCN used to train model

Results - Experiment 1

Goal: Determine impact of flight phase prediction (imbalanced classes)

Flight Phase Results and Standard Deviations

Class	Phase	Loss	Precision	Recall	Accuracy
WTC	yes	.592 (.007)	.829 (.003)	.760 (.003)	.798 (.003)
	no	1.439 (.018)	.683 (.004)	.640 (.004)	.667 (.004)
Descr	yes	.252 (.006)	.935 (.006)	.925 (.007)	.929 (.007)
	no	.274 (.003)	.937 (.006)	.916 (.007)	.926 (.006)
Desig	yes	3.804 (.034)	.420 (.008)	.114 (.003)	.273 (.003)
	no	2.627 (.012)	.687 (.012)	.086 (.001)	.282 (.003)

Results - Experiment 2

Goal: Predict WTC, description and designator using weighted classes

- WTC - 5 classes
- Description - 9 classes
- Designator - 130 classes

Weighted Model Results and Standard Deviations

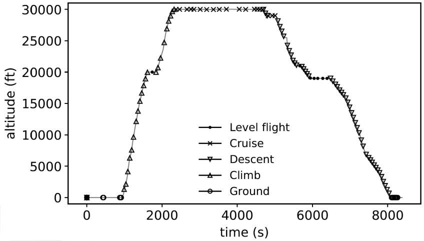
Class	Loss	Precision	Recall	Accuracy
WTC	.515 (.005)	.845 (.003)	.773 (.003)	.817 (.003)
Description	.743 (.008)	.781 (.005)	.620 (.006)	.722 (.004)
Designator	2.582 (.014)	.473 (.023)	.060 (.004)	.187 (.005)

Results - Experiment 3

Goal: Report accuracy per flight phase (i.e. which flight phase is most useful in predicting aircraft characteristics?)

Results per Phase

Class	Phase	Precision	Recall	Accuracy
WTC	Climb	0.82	0.89	0.92
	Cruise	0.75	0.75	0.82
	Descent	0.72	0.82	0.87
	Ground	0.60	0.74	0.73
	Level	0.71	0.78	0.79
	Unknown	0.81	0.84	0.87
Description	Climb	0.44	0.66	0.88
	Cruise	0.29	0.48	0.67
	Descent	0.34	0.56	0.80
	Ground	0.43	0.65	0.65
	Level	0.42	0.55	0.71
	Unknown	0.36	0.57	0.45
Designator	Climb	0.27	0.28	0.21
	Cruise	0.24	0.22	0.15
	Descent	0.25	0.24	0.14
	Ground	0.25	0.24	0.25
	Level	0.24	0.24	0.38
	Unknown	0.23	0.23	0.21



Fuzzy logic segmentation example [17]

Conclusion

Research Questions

- RQ-3: How does the identification of flight phase assist in aircraft prediction of description, designator and WTC?
  - WTC and description saw a benefit. Designator did not
- RQ-4: Which phases work best to predict aircraft by their wake turbulence category (WTC), aircraft description and type designator (as listed in ICAO Doc 8643)?
  - Climb for WTC and description. Level flight for designator.

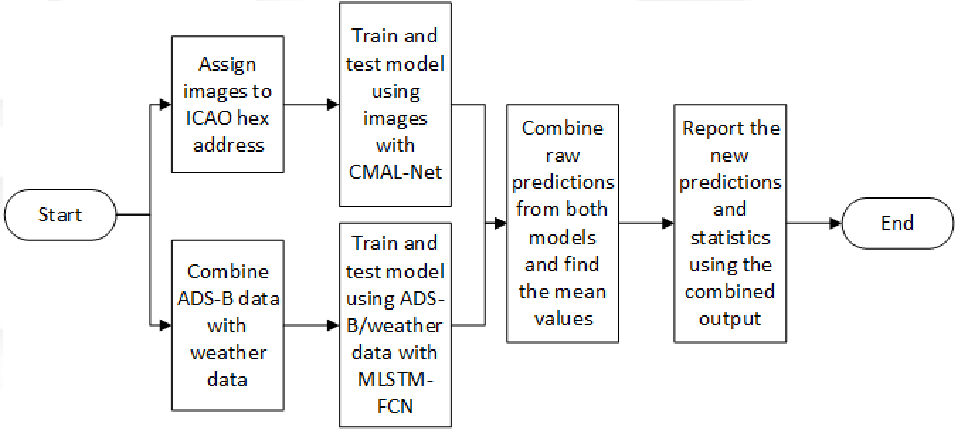
Study 3 - Sensor Fusion

- **Paper Title:** "Multi-sensor Aircraft Classification"
- **Venue**: 2023 World Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE'23)
- **Research Questions**
  - RQ-5: Does fusing weather and image data improve the predictive power of a model that uses ADS-B data?
  - RQ-6: Which fusion method, pre- or post-classification, creates models with better accuracy?

Data Preparation

- Obtained data:
  - Weather data - Meteostat [19]
  - ADS-B - ADS-B Exchange [20]
  - Images - FGVC-Benchmark [12]
- Found intersection of images and ADS-B $\Rightarrow$ 55 aircraft which is 325,822,800 ADS-B training observations and 3,736 training images

Methodology



Flowchart to combine ADS-B, weather and image data

Overview

Models

Model #	Input Data	Algorithm	Prediction
1	ADS-B	MLSTM-FCN	WTC
2	ADS-B	MLSTM-FCN	Description
3	ADS-B	MLSTM-FCN	Designator
4	ADS-B & Weather	MLSTM-FCN	WTC
5	ADS-B & Weather	MLSTM-FCN	Description
6	ADS-B & Weather	MLSTM-FCN	Designator
7	Images	CMAL-Net	WTC
8	Images	CMAL-Net	Description
9	Images	CMAL-Net	Designator
10	ADS-B & Images	Post-classification	WTC
11	ADS-B & Images	Post-classification	Description
12	ADS-B & Images	Post-classification	Designator
13	All	Post-classification	WTC
14	All	Post-classification	Description
15	All	Post-classification	Designator

Results

ADS-B and Weather Results

Class	Wx	Loss	Precision	Recall	Accuracy	F1
WTC	No	0.370	0.873	0.869	0.870	0.871
	Yes	0.389	0.859	0.853	0.857	0.856
Description	No	0.223	0.953	0.941	0.947	0.947
	Yes	0.233	0.958	0.929	0.949	0.943
Designator	No	1.849	0.619	0.201	0.410	0.303
	Yes	1.748	0.638	0.253	0.448	0.362

FGVC-Aircraft Image Results

Class	Loss	Precision	Recall	Accuracy	F1 Score
WTC	0.090	0.983	0.984	0.983	0.984
Description	0.083	0.989	0.969	0.987	0.978
Designator	0.283	0.954	0.953	0.953	0.953

Results

- In all cases, the image data improved the results compared to the ADS-B and weather data alone
- ADS-B and image data further improved the results for WTC and description when compared to just images alone

ADS-B with FGVC Aircraft Results

Class	Wx	Precision	Recall	Accuracy	F1 Score
WTC	No	0.9880	0.9750	0.9898	0.9814
	Yes	0.9847	0.9770	0.9890	0.9808
Description	No	0.9693	0.9113	0.9956	0.9334
	Yes	0.9736	0.9323	0.9960	0.9493
Designator	No	0.8972	0.9435	0.9245	0.9152
	Yes	0.8893	0.9316	0.9201	0.9049

Conclusion

Research Questions

- RQ-5: Does fusing weather and image data improve the predictive power of a model that uses ADS-B data to predict description, designator and WTC?
  - Yes. In all cases.
- RQ-6: Using pre- and/or post-classification fusion methods, how can a model be developed to predict description, designator and WTC using ADS-B, aircraft images and weather?
  - Weather needs pre-classification since it cannot predict aircraft characteristics on its own. Images and ADS-B require a different type of ANN to make predictions and work with post-classification.

Research Contributions

ID	Details	Study	RQ Ref
C-1	Development of various models that provide aircraft classification with kinematic and unattributed data that can be used as a surrogate for other data types	1, 2, 3	RQ-1
C-2	Finding a minimum dataset size for all types of deep learning classification problems is an open problem. This research provides a baseline for aircraft prediction models.	1	RQ-1
C-3	This research discovered the baseline features to identify an aircraft engine type during take-off with kinematic data: Speed, barometric pressure and vertical speed	1	RQ-2

Research Contributions

ID	Details	Study	RQ Ref
C-4	This research reimplemented the DSDEC model, and found that the attention mechanism and the dual-stage approach were unnecessary. This research achieved a slight improvement in accuracy by excluding those methods	1	
C-5	Adding a flight phase feature will allow for the use of the entire flight path and improve classification accuracy	2	RQ-3

Research Contributions

ID	Details	Study	RQ Ref
C-6	Using only ADS-B data to train and classify, we were able to more precisely classify aircraft using aircraft description and WTC, as described in ICAO Doc 8643	2	RQ-4
C-7	Weather improved classification accuracy of WTC. The addition of image data improved classification accuracy for all categories. ADS-B improved the classification accuracy of the images for WTC and description	3	RQ-5
C-8	Weather must be fused with ADS-B during pre-processing and images must be fused during post-processing	3	RQ-6

Questions?

References I

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ICAO Description — Return to slide 11 I

First letter:

- L - Landplane
- S - Seaplane - only lands on water
- A - Amphibian - lands on both water and land
- G - Gyrocopter - rotors powered by airflow
- H - Helicopter - rotors powered by engine
- T - Tiltrotor - both horizontal and vertical landing, i.e. V-22 Osprey

Last Letter:

- J - jet
- T - turboprop/turboshaft
- P - piston
- E - electric
- R - rocket

ICAO WTC — Return to slide 11 I

The WTC is based on the aircraft's maximum certified take-off mass and is categorized by the following [21]:

- H (Heavy) aircraft types of 136 000 kg (300 000 lb) or more
- M (Medium) aircraft types less than 136 000 kg (300 000 lb) and more than 7 000 kg (15 500 lb).
  - For the purposes of this research Medium is separated into two categories:
    - Small - 15,500 to 75,000 lbs
    - Large - 75,000 to 300,000 lbs
- L (Light) aircraft types of 7 000 kg (15 500 lb) or less.
- High Performance - greater than 5G acceleration and 400 kts

FNN — Return to slide 12 I

When building a neural network model, each node is provided a starting weight. The training of an ANN involves optimizing the weights of each node to more accurately reflect the data that is being processed. The first step requires computing the weighted sum of the inputs, adding on the bias and then feeding that value into an activation function. If we let x be the vector of input values, w be the vector of weights, and b be the bias, the weighted sum of the inputs would be expressed in equation 1.

$$z = x \cdot w + b \tag{1}$$

Then, we feed the result from equation 1 into an activation function like the sigmoid activation function as seen in equation 2 to produce the output after propagating all of the data.

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

FNN — Return to slide 12 II

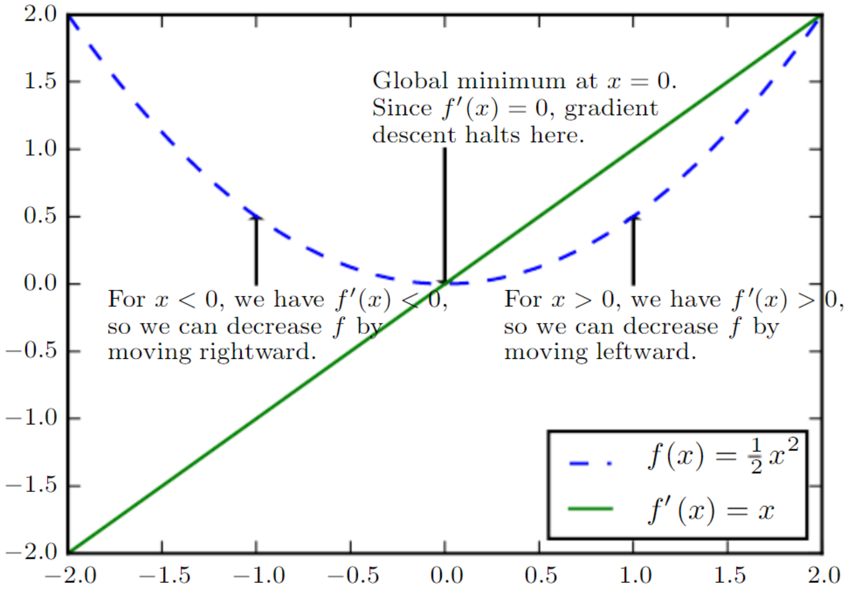
The next step in training the network is called backpropagation or *backward propagation of errors*. Backpropagation computes the gradient, or rate of change, of the loss function with respect to the weights to determine the direction the weight needs to move (positive or negative) in order to create a model with less error. There are various loss functions; the most common of these functions are mean square error for regression problems and cross entropy loss for classification problems. The loss function is calculated for the entire training dataset and the average loss is computed. This average loss is sometimes referred to as the cost function, C. To determine the best weights for the next or final iteration of an ANN model, the gradient of the cost function with respect to the weights and biases must be found. This is done with partial derivatives and the chain rule as shown in equation 3.

$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial w_i} \tag{3}$$

FNN — Return to slide 12 III

In the final step of training a neural network the algorithm updates the weights in the neural network to minimize error. It performs this algorithm repetitively using gradient descent as the model searches for the local or global minima. A graphic depiction of gradient descent can be seen in figure 16.

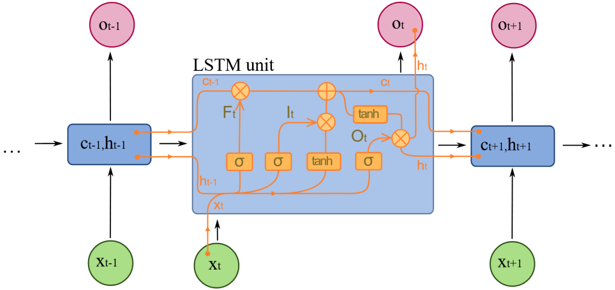
FNN — Return to slide 12 IV



Gradient descent. An illustration of how the gradient descent algorithm uses the derivatives

LSTM — Return to slide 12 I

- LSTMs solve the gradient problem by increasing the ANNs memory with gates
  - Forget, input and output gate



Long Short-Term Memory Network Diagram [23]

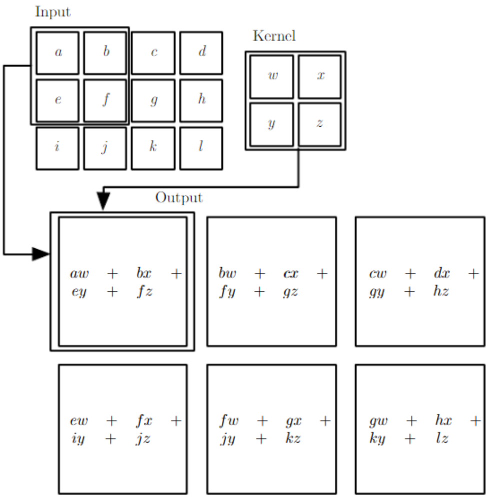
CNN — Return to slide 12 I

CNNs are made up of multiple convolutional layers, dense and pooling layers. The formal definition of a convolution is shown in formula 4.

$$(x * w)(t) := \int_{-\infty}^{\infty} x(a)w(t-a)da \tag{4}$$

- The input, x, is a multidimensional array or tensor of the grid-like input data.
- The filter or kernel, w, is another tensor that extracts features from the data.
- The output, or feature map, is the convolution of x and w.

CNN — Return to slide 12 II



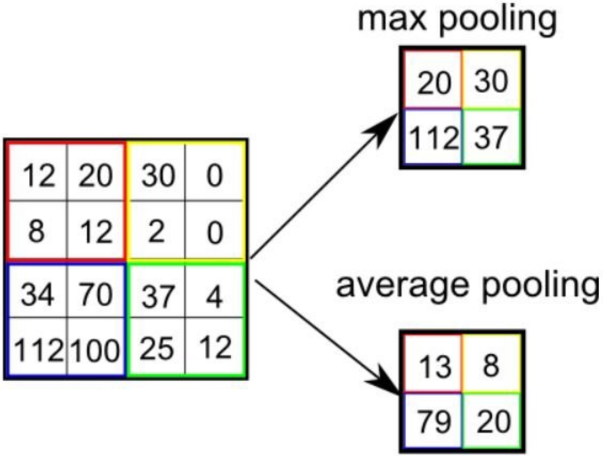
Example of a 2-D Convolution [22]

CNN — Return to slide 12 I

The pooling function provides a summary of the output by merging adjoining values to reduce dimensionality.

- Max pooling
- Average pooling

CNN — Return to slide 12 II



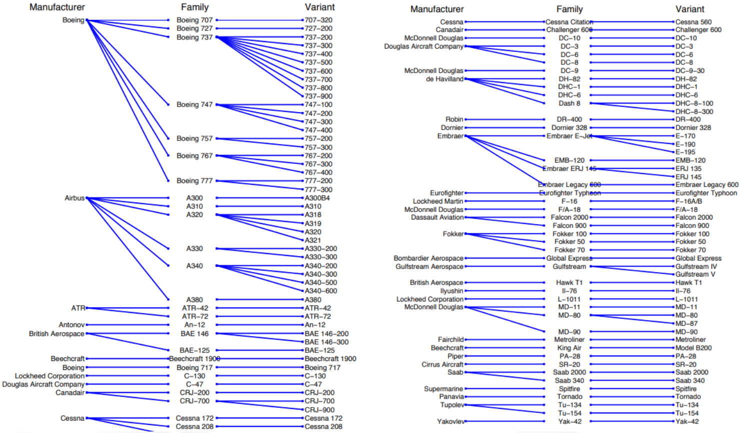
Example of Pooling [24]

CNN — Return to slide 12 I

To ready it for classification purposes, it must be flattened into a vector. This is the fully connected or dense layer.

Fully Convolutional Networks (FCNs) are CNNs without fully connected layers.

Image Classification — Return to slide 18 I



FGVC-Aircraft benchmark hierarchy [12]

Fuzzy Logic — Return to slide 19 I

$$
\begin{aligned}
H_{gnd}(\eta) &= \mathcal{Z}(\eta, 0, 200) \\
H_{lo}(\eta) &= \mathcal{G}(\eta, 10000, 10000) \\
H_{hi}(\eta) &= \mathcal{G}(\eta, 35000, 20000) \\
RoC_0(\tau) &= \mathcal{G}(\tau, 0, 100) \\
RoC_+(\tau) &= \mathcal{S}(\tau, 10, 1000) \\
RoC_-(\tau) &= \mathcal{Z}(\tau, -1000, -10) \\
V_{lo}(v) &= \mathcal{G}(v, 0, 50) \\
V_{mid}(v) &= \mathcal{G}(v, 300, 100) \\
V_{hi}(v) &= \mathcal{G}(v, 600, 100) \\
P_{gnd}(p) &= \mathcal{G}(p, 1, 0.2) \\
P_{clb}(p) &= \mathcal{G}(p, 2, 0.2) \\
P_{cru}(p) &= \mathcal{G}(p, 3, 0.2) \\
P_{des}(p) &= \mathcal{G}(p, 4, 0.2) \\
P_{lvl}(p) &= \mathcal{G}(p, 5, 0.2)
\end{aligned}
$$

Fuzzy Membership Functions for Flight Phase [17]

Sensor Fusion — Return to slide 20 I

Approach	Method	Description	Papers
Pre-classification	Data Level Fusion	Fuses raw related data	[25, 26]
	Feature Level Fusion	Extracts and combines features of related data using a data association technique such as clustering or grouping	[25, 26]
Post-classification	Abstract Level Fusion	Simplest type of fusion that uses majority voting to select classes	[25, 27]
	Rank Level Fusion	Assigns ranks to classes instead of selecting unique class choices. Common methods are the Borda count, the intersection, the highest rank and the union method	[25, 28]
	Measure Level Fusion	Sub-methods of this technique are classification and combination approaches. Each uses multiple classification methods to either score or combine the results produced by the classifier	[25, 29]
	Dynamic Classifier Selection	Another multi-classifier technique that uses the results of the classifier most likely to provide an accurate result. Essentially, a winner-takes-all or associative switch approach.	[25, 30, 31]

Sensor Fusion Techniques

3-Dimensional Location — Return to slide 23 I

$$x = \cos\phi * \cos\lambda \tag{5}$$

$$y = \cos\phi * \sin\lambda \tag{6}$$

$$z = \sin\phi \tag{7}$$

Weather Features

Weather Features Used from Meteostat

Feature	**Description**	**Type**
temp	The air temperature in °C	Float64
dwpt	The dew point in °C	Float64
rhum	The relative humidity in percent (%)	Float64
prcp	The one hour precipitation total in mm	Float64
snow	The snow depth in mm	Float64
wdir	The average wind direction in degrees (°)	Float64
wspd	The average wind speed in km/h	Float64
pres	The average sea-level air pressure in hPa	Float64