Multi-Sensor Aircraft Classification

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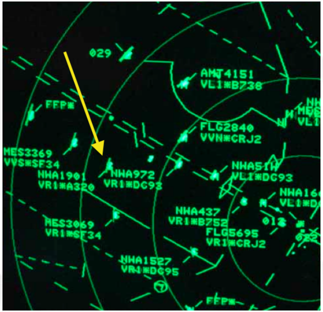
Motivation

- FY22/23 Department of the Air Force Posture Statement [1, 2]
  - 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 Advanced Battle Management System (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

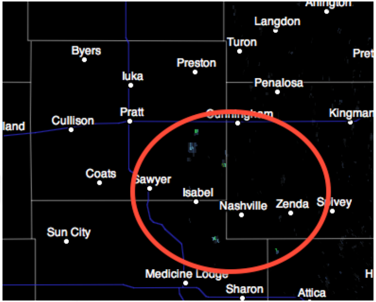
AFRL/RYA Mission Statement: Layered Sensing Exploitation Division Conducts basic research, exploratory and advanced development to provide efficient sensing exploitation for Air Force air, space, and C2 systems. Develops technology for target and threat detection, location, track, and identification 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

- ADS-B's main features are open sharing and availability $\Rightarrow$ vulnerable to cyber attack (jamming, eavesdropping, spoofing, injections)
- 2D/3D primary radar is passive, but collects kinematic data only. ADS-B can be used as a surrogate data source with truth data.
- Kinematic data alone, is not enough. Idea: Try sensor fusion.



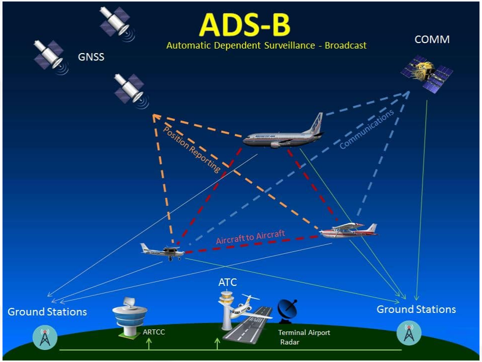
ATC radar with transponder on [3]



ATC radar with transponder off [3]

Automatic Dependent Surveillance-Broadcast (ADS-B)

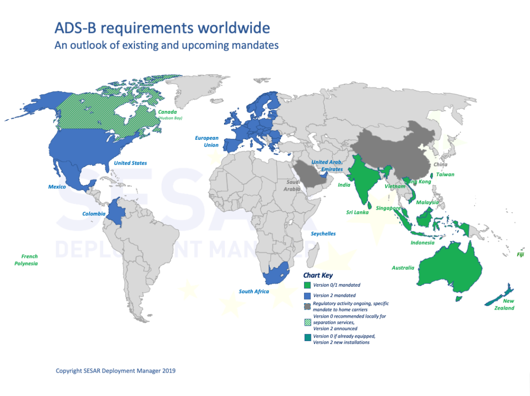
- 70 features: ICAO hex identifier, altitude, airspeed, vertical speed, directional heading, position time, latitude, longitude, and ground status
- Broadcast via ADS-B Out transponder @ 1090 and 978 MHz



ADS-B High Level Operational Graphic [4]

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 [5]

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)

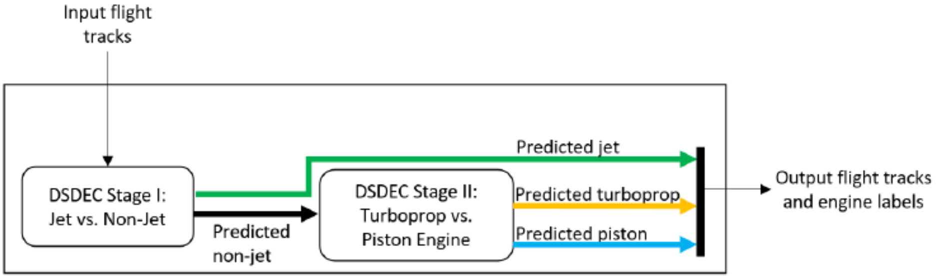
DESIGNATOR INDICATIF DESIGNADOR УСЛ. ОБОЗНАЧЕНИЕ	MANUFACTURER, MODEL CONSTRUCTEUR, MODÈLE FABRICANTE, MODELO ИЗГОТОВИТЕЛЬ, МОДЕЛЬ	DESCRIPTION DESCRIPTION DESCRIPCIÓN ВОЗДУШНОГО	WTC WTC WTC WTC
A1	DOUGLAS, Skyraider	L1P	M
	DOUGLAS, AD Skyraider	L1P	M
	DOUGLAS, EA-1 Skyraider	L1P	M
A2RT	KAZAN, Ansat 2RT	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 [6]

Dual-Stage Deep Engine Classifier

Problem: Difficult to differentiate between piston and turboprop

- Two stage approach, undersampling technique, only take-off phase, used MLSTM-FCN
- 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 [7]

My Research

- **Paper Title:** "ADS-B Classification Using Multivariate Long Short-Term Memory Fully Convolutional Networks and Data Reduction Techniques"
- **Venue**: Journal of Supercomputing
  - Predicted engine type
  - Removed need for 2-phase approach
  - Found optimum data type and amount

- **Paper Title:** "Aircraft Classification Using Flight Phase Identification"
- **Venue**: 2023 National Aerospace and Electronics Conference (NAECON)
  - Predicted designator, description and WTC
  - Generated flight phase prediction
  - Weighed samples instead of undersample
  - Determined most useful flight phase

Image Classification

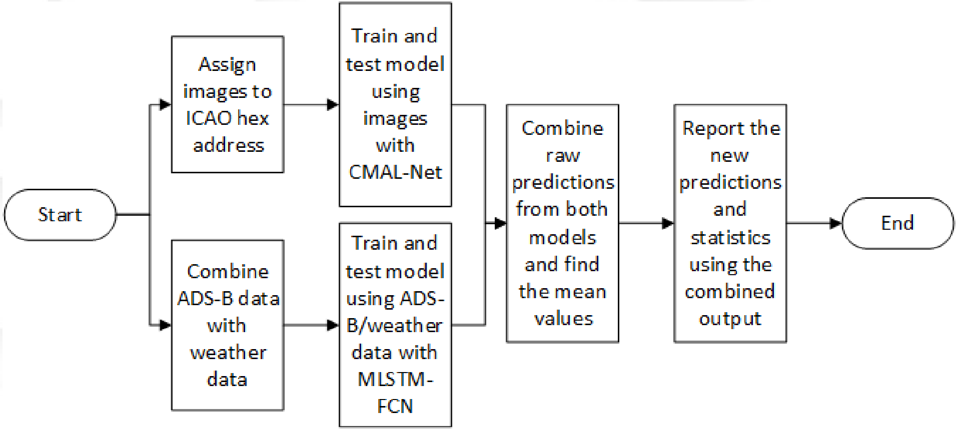
- Fine-Grained Visual Classification of Aircraft (FGVC-Aircraft) benchmark cited nearly 1,000 times
  - Contains 10,000 aircraft images identified by model, variant, family and manufacturer
- Top performing aircraft image classification studies use variations of CNN
  - CMAL-Net - CNN backbone with n separately trained experts that are eventually concatenated

Author	Year	Method	Accuracy Achieved
Maji et al. [8]	2013	Non-linear SVM	48.69%
Rong et al. [9]	2021	SSSNet	93.3%
Y Wang et al. [10]	2022	BA-CNN	89.2%
Lei Wang et al. [11]	2022	MFF net with PCB	91.4%
Liu et al. [12]	2023	CMAL-Net	94.7%

Data Preparation

- Obtained data:
  - Weather data - Meteostat [13]
  - ADS-B - ADS-B Exchange [14]
  - Images - FGVC-Benchmark [8]
- 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

Methodology

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

- Sensor fusion works with the right sources
- Weather does not provide enough information to assist in improving aircraft prediction
- This architecture helps reduce reliance on a very vulnerable ADS-B, but at least partial or small images are needed

Questions?

References I

- *Department of the Air Force Posture Statement Fiscal Year 2022*. [Online]. Available: https://www.armed-services.senate.gov/imo/media/doc/FY22%20DAF%20Posture%20Statement%20-%20Final%20(v23.1)1.pdf

- *Department of the Air Force Posture Statement Fiscal Year 2023*. [Online]. Available: https://www.armed-services.senate.gov/imo/media/doc/FY23%20DAF%20Posture%20Statement%20Final%20-%2027%20Apr%20(2).pdf

- M. Smith. (2014) Aircraft radar explanation. [Online]. Available: http://www.mikesmithenterprisesblog.com/2014/03/aircraft-radar-explanation.html

References II

- Airlive.net, "Alert over 400 flights canceled in the u.s. due to ads-b navigation system issue," Jun 2019. [Online]. Available: https://www.airlive.net/alert-over-400-flights-canceled-in-the-u-s-due-to-ads-b-navigation-system-issue/
- J. Stibor, T. Koerber, E. Vallauri, and K. Orteca, "Home - ads-b," Jan 2022. [Online]. Available: https://ads-b-europe.eu/
- "Icao document 8643," International Civil Aviation Organization, Quebec, Canada, Standard, 2016.
- K. Basrawi, R. Dill, G. Peterson, B. Borghetti, and J. Lopez, "Aircraft identification from ads-b kinematic data," *Journal of DoD Research and Engineering*, vol. 5, no. 2, pp. 31–43, 2022.

References III

- S. Maji, E. Rahtu, J. Kannala, M. B. Blaschko, and A. Vedaldi, "Fine-grained visual classification of aircraft," *CoRR*, vol. abs/1306.5151, 2013. [Online]. Available: http://arxiv.org/abs/1306.5151
- S. Rong, Z. Wang, and J. Wang, "Separated smooth sampling for fine-grained image classification," *Neurocomputing*, vol. 461, pp. 350–359, 2021.
- Y. Wang, Y. Chen, and R. Liu, "Aircraft image recognition network based on hybrid attention mechanism," *Computational Intelligence and Neuroscience*, vol. 2022, 2022.
- L. Wang, K. He, X. Feng, and X. Ma, "Multilayer feature fusion with parallel convolutional block for fine-grained image classification," *Applied Intelligence*, vol. 52, no. 3, pp. 2872–2883, 2022.

References IV

- F. Sun, H. C. Ngo, and Y. W. Sek, "Adopting attention and cross-layer features for fine-grained representation," *IEEE Access*, vol. 10, pp. 82 376–82 383, 2022.
- C. S. Lamprecht, "Meteostat Python."
- ADS-B Exchange, "Home - serving the flight tracking enthusiast - ads-b exchange," Mar 2023. [Online]. Available: https://www.adsbexchange.com/
- "Icao wake turbulence category." [Online]. Available: https://skybrary.aero/articles/icao-wake-turbulence-category
- J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7132–7141.

References V

- I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA: MIT Press, 2016. [Online]. Available: http://www.deeplearningbook.org
- fdeloche, "Long short-term memory.svg," 2017, [Online; accessed 20-May-2022]. [Online]. Available: https://commons.wikimedia.org/wiki/File:Long_Short-Term_Memory.svg
- S. Saha, "A comprehensive guide to convolutional neural networks â the eli5 way," Dec 2018. [Online]. Available: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b116

References VI

- F. Karim, S. Majumdar, H. Darabi, and S. Harford, "Multivariate lstm-fcns for time series classification," *Neural Networks*, vol. 116, pp. 237–245, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0893608019301200
- D. Liu, L. Zhao, Y. Wang, and J. Kato, "Learn from each other to classify better: Cross-layer mutual attention learning for fine-grained visual classification," *Pattern Recognition*, vol. 140, p. 109550, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0031320323002509
- J. Sun, J. Ellerbroek, and J. Hoekstra, "Flight extraction and phase identification for large automatic dependent surveillance–broadcast datasets," *Journal of Aerospace Information Systems*, vol. 14, no. 10, pp. 566–572, 2017.

References VII

- A. Vakil, J. Liu, P. Zulch, E. Blasch, R. Ewing, and J. Li, "A survey of multimodal sensor fusion for passive rf and eo information integration," *IEEE Aerospace and Electronic Systems Magazine*, vol. 36, no. 7, pp. 44–61, 2021.
- W. Elmenreich, "An introduction to sensor fusion," *Vienna University of Technology, Austria*, vol. 502, pp. 1–28, 2002.
- M. Przybyła-Kasperek and A. Wakulicz-Deja, "Comparison of fusion methods from the abstract level and the rank level in a dispersed decision-making system," *International Journal of General Systems*, vol. 46, no. 4, pp. 386–413, 2017.
- E. Marasco, A. Abaza, and B. Cukic, "Why rank-level fusion? and what is the impact of image quality?"

References VIII

- B. Habtemariam, R. Tharmarasa, M. McDonald, and T. Kirubarajan, "Measurement level ais/radar fusion," *Signal Processing*, vol. 106, pp. 348–357, 2015.
- L. Xu, A. Krzyzak, and C. Y. Suen, "Associative switch for combining multiple classifiers," in *IJCNN-91-Seattle International Joint Conference on Neural Networks*, vol. 1. IEEE, 1991, pp. 43–48.
- G. Gennarelli, M. G. Amin, F. Soldovieri, and R. Solimene, "Passive multiarray image fusion for rf tomography by opportunistic sources," *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 3, pp. 641–645, 2014.

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

ICAO Description — Return to slide 7 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

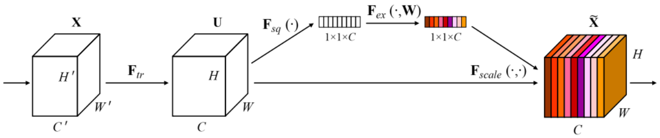
ICAO WTC — Return to slide 7 I

The WTC is based on the aircraft's maximum certified take-off mass and is categorized by the following [15]:

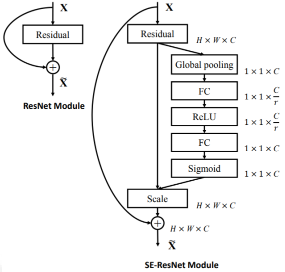
- H (Heavy) aircraft types of 136 000 kg (300 000 lb) or more
- M (Medium) aircraft types less than 136 000 kg (300 000 lb) and more than 7 000 kg (15 500 lb).
  - For the purposes of this research Medium is separated into two categories:
    - Small - 15,500 to 75,000 lbs
    - Large - 75,000 to 300,000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

Squeeze and Excite Blocks— Return to slide 2 I

- 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 [16]



The schema of the squeeze and excite model with a Residual Network [16]

FNN — Return to slide 2 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 2 II

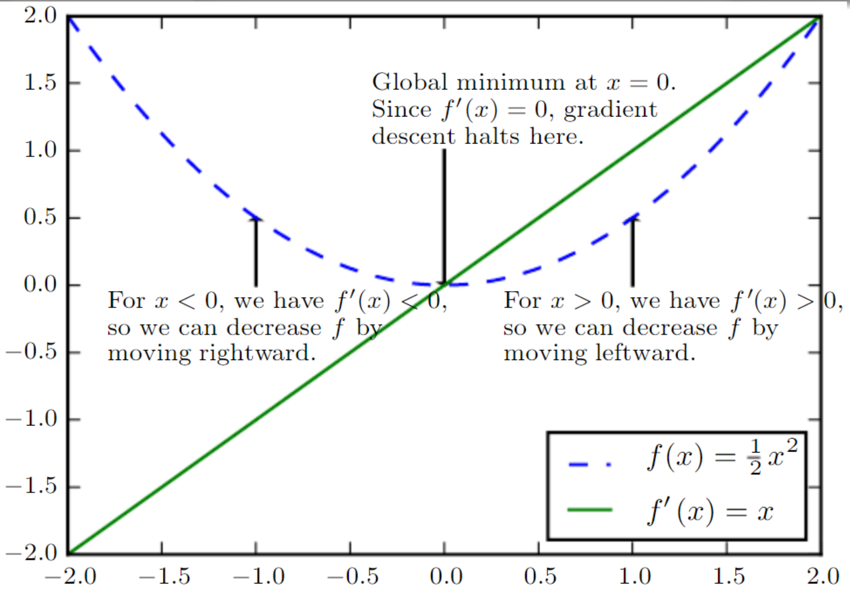
The next step in training the network is called backpropagation or *backward propagation of errors*. Backpropagation computes the gradient, or rate of change, of the loss function with respect to the weights to determine the direction the weight needs to move (positive or negative) in order to create 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 2 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 10.

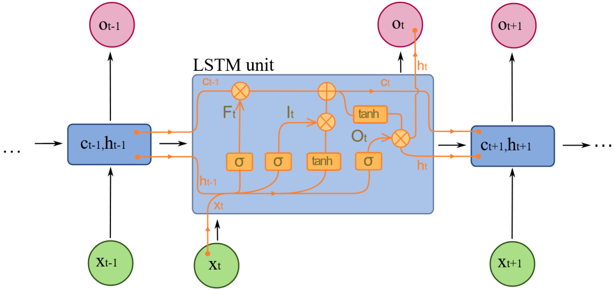
FNN — Return to slide 2 IV



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

LSTM — Return to slide 2 I

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



Long Short-Term Memory Network Diagram [18]

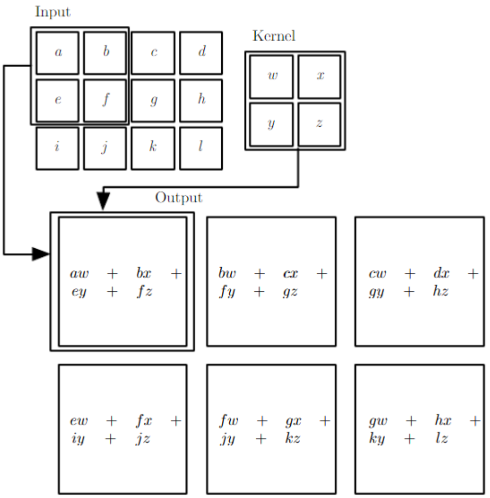
CNN — Return to slide 2 I

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 2 II



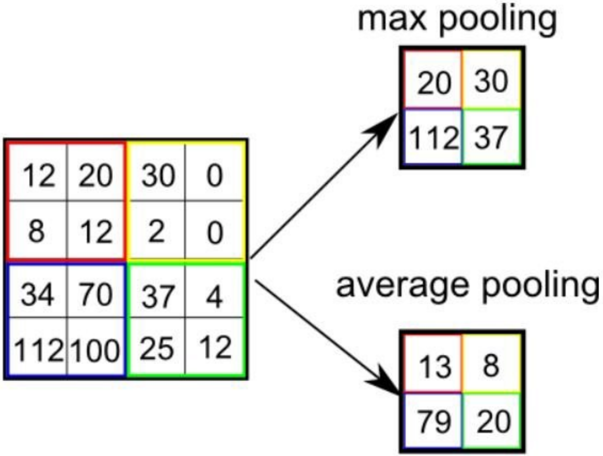
Example of a 2-D Convolution [17]

CNN — Return to slide 2 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 2 II



Example of Pooling [19]

CNN — Return to slide 2 I

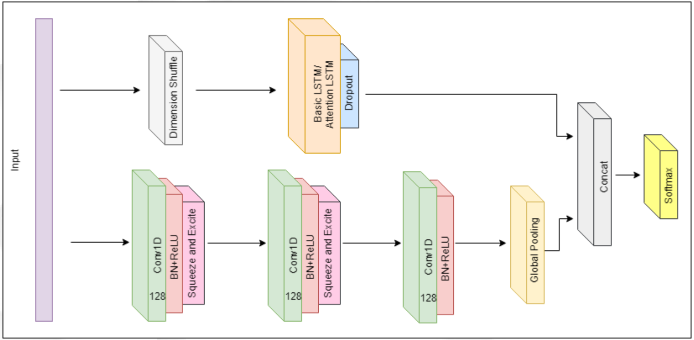
To ready it for classification purposes, it must be flattened into a vector. This is the fully connected or dense layer.

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

Multivariate Long Short-Term Memory Fully Convolutional Network (MLSTM-FCN)— Return to slide 2 I

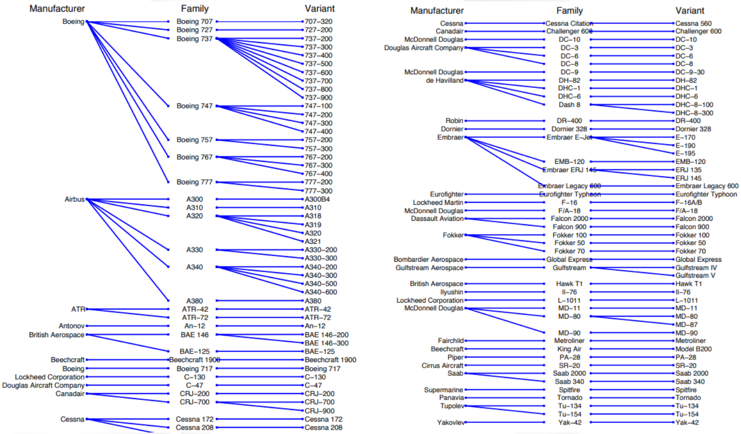
- Developed by Karim in 2019
- Uses Squeeze-and-excite blocks, LSTMs and FCNs for classification of time series data

Multivariate Long Short-Term Memory Fully Convolutional Network (MLSTM-FCN)— Return to slide 2 II



MLSTM-FCN architecture [20]

Image Classification — Return to slide 10 I

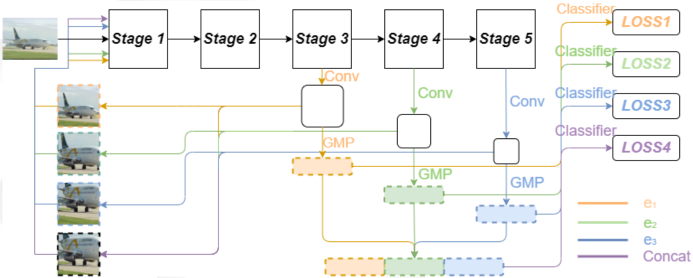


FGVC-Aircraft benchmark hierarchy [8]

Cross-Layer Mutual Attention Learning Network (CMAL-Net)— Return to slide 10 I

- 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

Cross-Layer Mutual Attention Learning Network (CMAL-Net)— Return to slide 10 II



Example CMAL-Net architecture with 3 experts[21]

Flight Path Classification and Fuzzy Logic I

- 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

Flight Path Classification and Fuzzy Logic II

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

Fuzzy Relationships for Flight Phase [22]

Fuzzy Logic 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 [22]

Sensor Fusion — Return to slide ?? I

Approach	Method	Description	Papers
Pre-classification	Data Level Fusion	Fuses raw related data	[23, 24]
	Feature Level Fusion	Extracts and combines features of related data using a data association technique such as clustering or grouping	[23, 24]
Post-classification	Abstract Level Fusion	Simplest type of fusion that uses majority voting to select classes	[23, 25]
	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	[23, 26]
	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	[23, 27]
	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.	[23, 28, 29]

Sensor Fusion Techniques

3-Dimensional Location — Return to slide ?? 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