

Aircraft Classification Using Flight Phase Identification

Presented by:
Sarah Bolton



Co-authors: Richard Dill, Michael R. Grimaila,
and Douglas D. Hodson

Department of Electrical and Computer Engineering
Air Force Institute of Technology

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- 1 Introduction
 - Motivation
 - Problem
- 2 Background
 - General ADS-B Info
 - Aircraft Classification Research
- 3 Methodology
- 4 Results
- 5 Conclusion

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

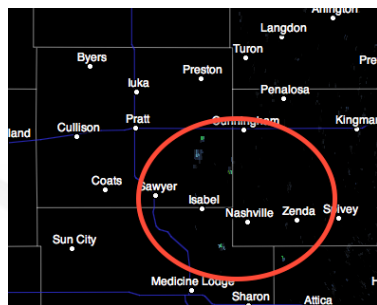
AFRL/RYA Mission Statement: Layered Sensing Exploitation Division Conducts basic research, exploratory and advanced development to provide efficient sensing exploitation for Air Force air, space, and C2 systems. Develops technology for target and threat detection, location, track, and identification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



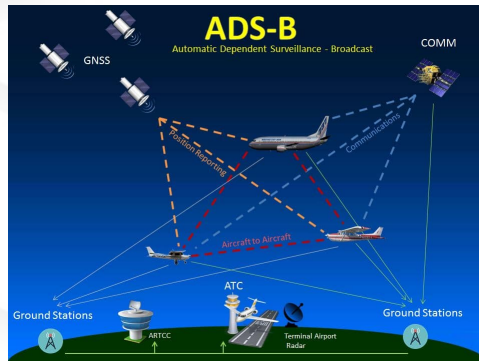
ATC radar with transponder on [3]



ATC radar with transponder off [3]

Automatic Dependent Surveillance-Broadcast (ADS-B)

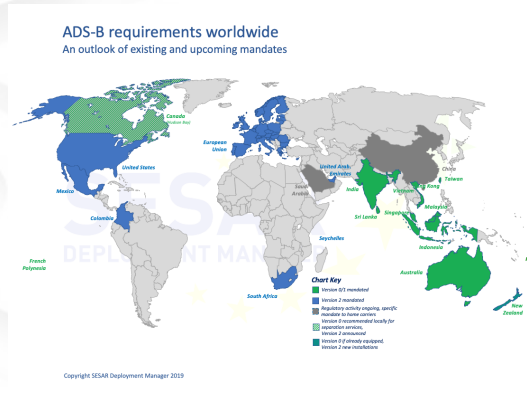
- 70 features: ICAO hex identifier, altitude, airspeed, vertical speed, directional heading, position time, latitude, longitude, and ground status
- Broadcast via ADS-B Out transponder @ 1090 and 978 MHz



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)

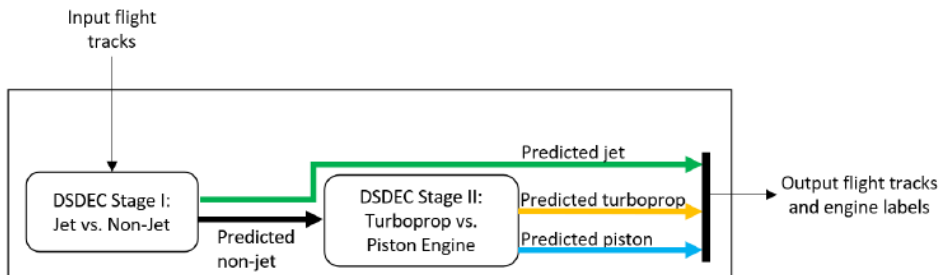
DESIGNATOR INDICATIF DESIGNADOR УСЛ. ОБОЗНАЧЕНИЕ	MANUFACTURER, MODEL CONSTRUCTEUR, MODÈLE FABRICANTE, MODELO ИЗГОТОВИТЕЛЬ, МОДЕЛЬ	DESCRIPTION DESCRIPTION DESCRIPCIÓN ВОЗДУШНОГО	WTC WTC WTC	DESIGNATOR INDICATIF DESIGNADOR УСЛ. ОБОЗНАЧЕНИЕ	MANUFACTURER, MODEL CONSTRUCTEUR, MODÈLE FABRICANTE, MODELO ИЗГОТОВИТЕЛЬ,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

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

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

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

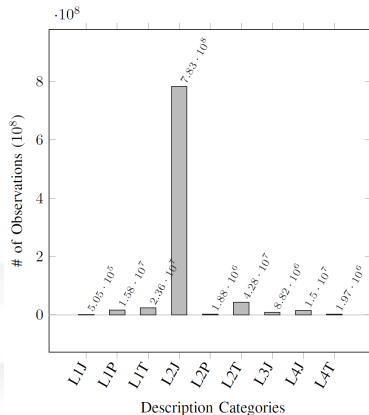
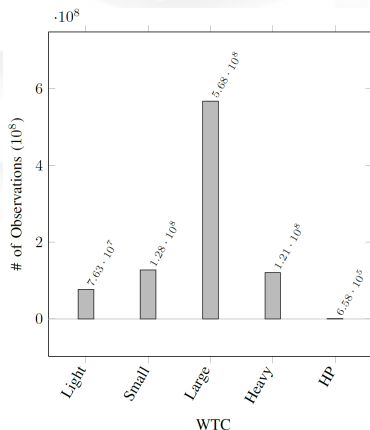
if $H_{lo} \wedge V_{mid} \wedge RoC_-$ then Descent

if $H_{lo} \wedge V_{mid} \wedge RoC_0$ then Level flight

Fuzzy Relationships for Flight Phase [8]

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:
 - 1 Data converted from JSON to Pandas
 - 2 Irrelevant/incorrect data is removed
 - 3 Aircraft with fewer than 300 observations removed
 - 4 Feature generation: Used lat/long to generate a 3-dimensional location, flight phase predicted using fuzzy logic, date features (generated, but not used)
 - 5 130 most common aircraft are used to train model.
 - 6 Data balanced by weighing samples
 - 7 Data formed into tensors (300 observations per tensor)
- MLSTM-FCN used to train models (without DSDEC)
- k -fold method used to evaluate models ($k = 10$)

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

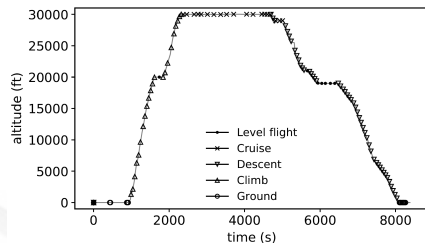
Class	Loss	Precision	Recall	Accuracy
WTC	.515 (.005)	.845 (.003)	.773 (.003)	.817 (.003)
Description	.743 (.008)	.781 (.005)	.620 (.006)	.722 (.004)
Designator	2.582 (.014)	.473 (.023)	.060 (.004)	.187 (.005)

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 [8]

Conclusion

- WTC saw a significant benefit to using flight phase as a feature. Description saw a minimal benefit. Designator had no benefits.
- Climb was the most useful phase for predicting WTC and description aircraft characteristics. Level flight performed the best for designator.

Questions?

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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

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

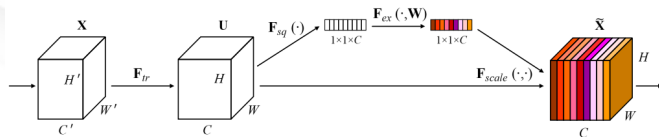
ICAO WTC — Return to slide 7 I

The WTC is based on the aircraft's maximum certified take-off mass and is categorized by the following [9]:

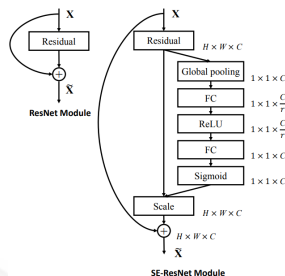
- H (Heavy) aircraft types of 136 000 kg (300 000 lb) or more
- M (Medium) aircraft types less than 136 000 kg (300 000 lb) and more than 7 000 kg (15 500 lb).
 - For the purposes of this research Medium is separated into two categories:
 - Small - 15,500 to 75,000 lbs
 - Large - 75,000 to 300,000 lbs
- 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 [10]



The schema of the squeeze and excite model with a Residual Network [10]

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.

$$z = x \cdot w + b \quad (1)$$

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.

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

FNN — Return to slide 2 II

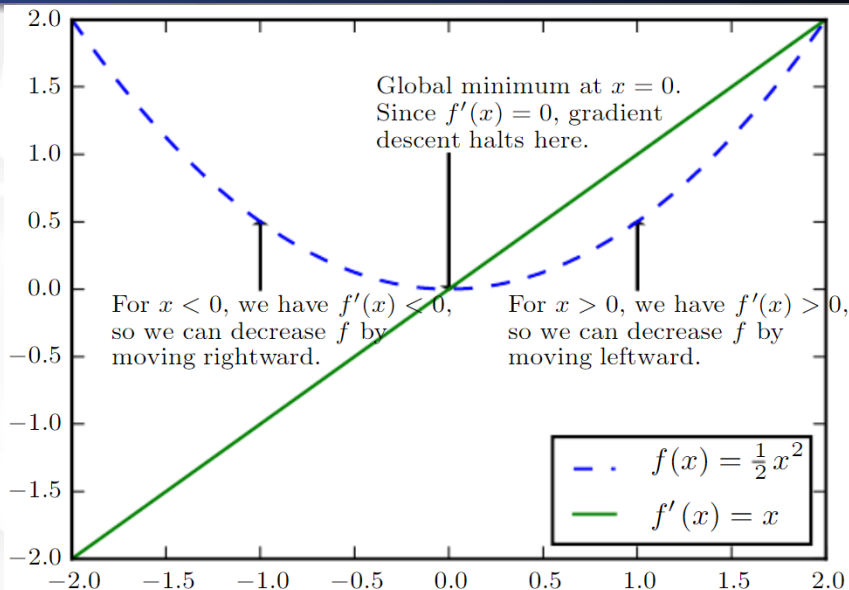
The next step in training the network is called backpropagation or *backward propagation of errors*. Backpropagation computes the gradient, or rate of change, of the loss function with respect to the weights to determine the direction the weight needs to move (positive or negative) in order to create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

$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial w_i} \quad (3)$$

FNN — Return to slide 2 III

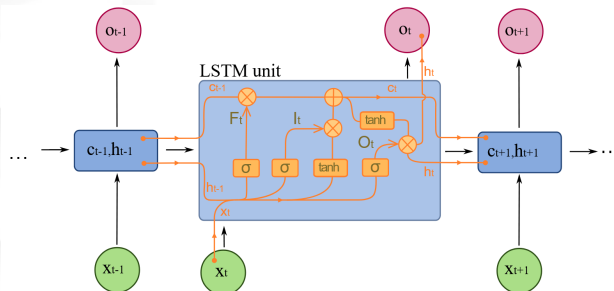
In the final step of training a neural network the algorithm updates the weights in the neural network to minimize error. It performs this algorithm repetitively using gradient descent as the model searches for the local or global minima. A graphic depiction of gradient descent can be seen in figure 11.

FNN — Return to slide 2 IV



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 [12]

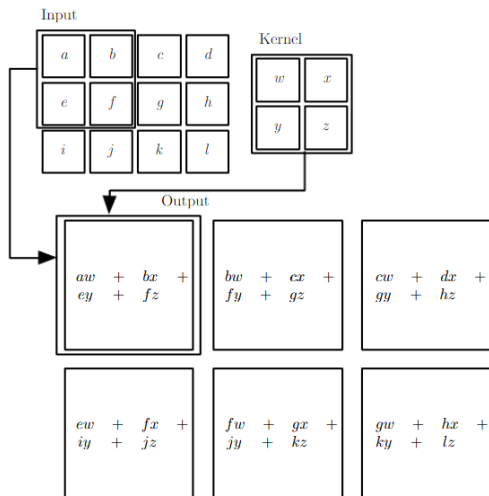
CNN — Return to slide 2 I

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

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

- 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



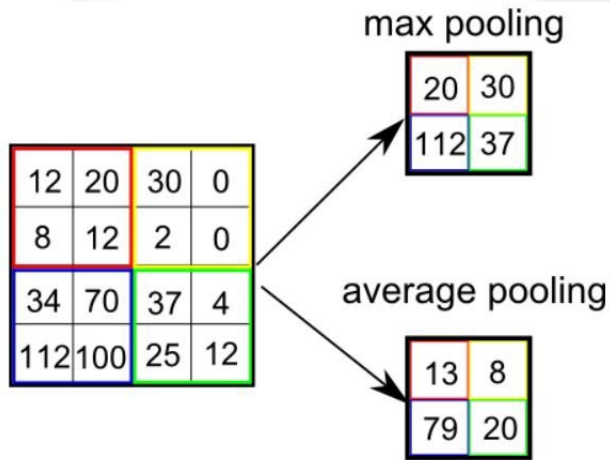
Example of a 2-D Convolution [11]

CNN — Return to slide 21

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 [13]

CNN — Return to slide 21

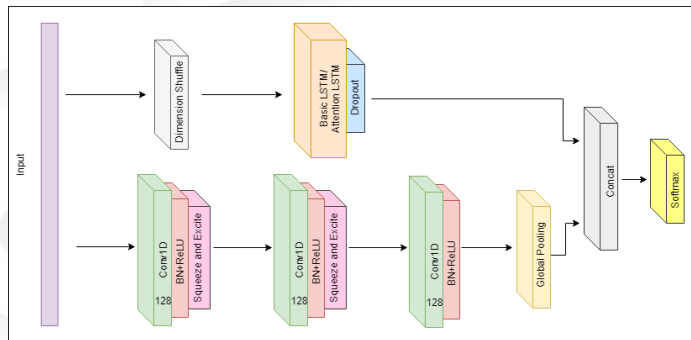
To ready it for classification purposes, it must be flattened into a vector. This is the fully connected or dense layer.

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

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

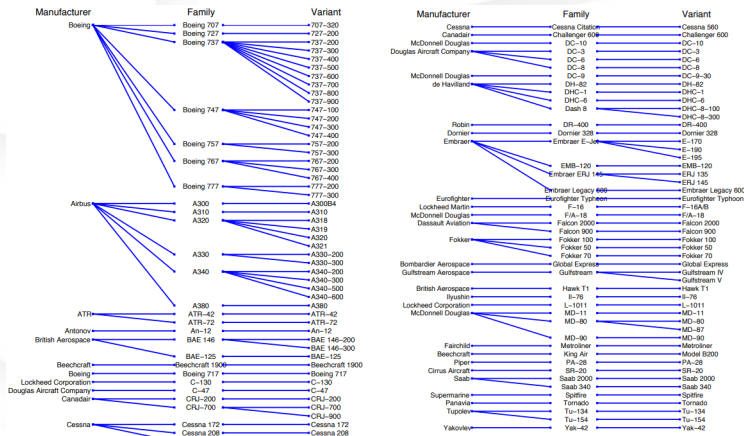
- Developed by Karim in 2019
- Uses Squeeze-and-excite blocks, LSTMs and FCNs for classification of time series data

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



MLSTM-FCN architecture [14]

Image Classification — Return to slide ?? !

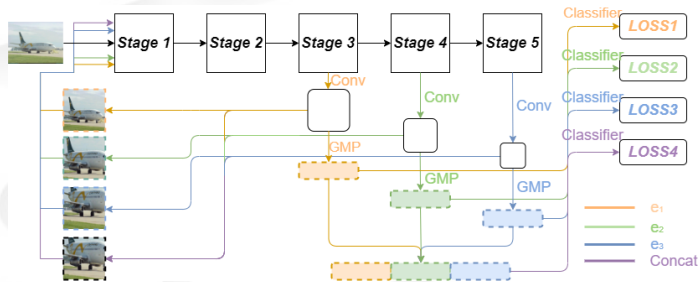


FGVC-Aircraft benchmark hierarchy [15]

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



Example CMAL-Net architecture with 3 experts[16]

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

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*

Fuzzy Relationships for Flight Phase [8]

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 [8]

Sensor Fusion — Return to slide ?? I

Approach	Method	Description	Papers
Pre-classification	Data Level Fusion	Fuses raw related data	[17, 18]
	Feature Level Fusion	Extracts and combines features of related data using a data association technique such as clustering or grouping	[17, 18]
Post-classification	Abstract Level Fusion	Simplest type of fusion that uses majority voting to select classes	[17, 19]
	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	[17, 20]
	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	[17, 21]
	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.	[17, 22, 23]

Sensor Fusion Techniques

3-Dimensional Location — Return to slide 12 I

$$x = \cos \phi * \cos \lambda \quad (5)$$

$$y = \cos \phi * \sin \lambda \quad (6)$$

$$z = \sin \phi \quad (7)$$

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