Aircraft Classification Using Flight Phase Identification

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***Abstract*—Flight data collected from an Automatic Dependent Surveillance–Broadcast (ADS-B) can be used to make inferences about aircraft characteristics. This work uses all flight phases to identify an aircraft's Wake Turbulence Category (WTC), aircraft description and type designator as described in the International Civil Aviation Organization (ICAO) Document 8643.**

***Index Terms*—Multivariate Long Short-Term Memory – Fully Convolutional Network, Automatic Dependent Surveillance-Broadcast, open-source data, classification, machine learning**

I. Introduction

Automatic Dependent Surveillance–Broadcast (ADS-B) provides aircraft tracking and identification data that can be received by satellites and ground stations. It is open source and can be captured by any receiver within line-of-sight of an aircraft that is transmitting ADS-B data. While it is not used globally, much of North America, Europe, Asia and all of Australia have some form of ADS-B usage mandate. In January 2020, the United States mandated the use of ADS-B within controlled airspace with Federal Regulation 14 CFR 91.225 and 14 CFR 91.227.

Since it is widely available and setting up an ADS-B receiver is relatively simple, thousands of receiver owners share their data to create a full air picture in any place that ADS-B is used. Two common repositories of aircraft data are the ADS-B Exchange and FlightAware [1], [2]. Each of these sites accept data from the ADS-B receiver owners, compile the data, and provide the compiled data to other feeders or to paying customers. Per the ADS-B Exchange, as of March 2023, there are over 9,500 active feeds that track over 15,000 aircraft [1]. ADS-B has become a powerful resource for aircraft researchers and operators.

One important feature of ADS-B is the transmission of identifying information within the data. One of the more useful pieces of information is the aircraft's International Civil Aviation Organization (ICAO) 24-bit aircraft address or Mode S hex code. The ICAO 24-bit identifier is like a phone number or Internet Protocol (IP) address for an aircraft. As the name implies, it is a 24-bit address that is textually represented by 6 hexadecimal digits. ICAO Annex 10, Volume 3 outlines the regulations regarding Mode S code allocation [3]. Having an aircraft's Mode S code allows the lookup and tracking of the specific aircraft with that address. This provides the ability to determine aircraft characteristics such as designator, model, manufacturer, weight and any other performance parameters that have been previously assigned to that hex code.

Two downsides to ADS-B are that the broadcast is vulnerable to cyber attacks and the broadcast is not passive. It is not passive since the aircraft has to turn on its ADS-B Out device for the broadcast to occur. If an aircraft chooses not to turn on their ADS-B, no identifying information about the aircraft is transmitted and it must be tracked by a more passive form of aircraft tracking such as radar. When ADS-B is broadcast, invalid data can be easily transmitted either intentionally (i.e. cyber attacks) or unintentionally (i.e. typos or miscalibrated sensors). While passive aircraft tracking does not require input from the pilot and can be done without the pilot's knowledge, passive tracking can not provide the specific details that are found in an ADS-B transmission like the ICAO hex code. Since ADS-B provides truth data, usage of ADS-B opens an area of research where the kinematic data found in ADS-B can be used as a surrogate for more passive forms of aircraft tracking. Aircraft classification models can be built to be used by passive forms of aircraft tracking, which can then validate the authenticity of ADS-B.

This paper presents methods to use the kinematic data found in ADS-B broadcasts to predict aircraft characteristics using deep learning. It is structured as follows: Section II discusses previous work with ADS-B classification. Section III outlines the process and discusses the models that were used to convert raw ADS-B files into predictive models. Section IV reviews

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the findings from 3 different experiments that were created to determine the effectiveness of the process described in this paper. Finally, section V concludes the paper.

II. Background & Previous Work

ADS-B has been used in research for a variety of purposes. Notably, ADS-B data has been used to predict flight patterns [4]–[8], improve ADS-B transmission security [9]–[11], enhance aircraft operations [12]–[15] and to classify aircraft characteristics [16]–[19]. Due to the complex nature of the data found in ADS-B broadcasts, previous research in aircraft classification has fallen victim to two challenges. First, ADS-B data is extremely imbalanced towards jet aircraft. In the research completed in [16], Ginoulhac et al. created 6 categories of aircraft based on the type of aircraft (airplane/helicopter), wake turbulence category (WTC) and engine type. They found that 94% of their dataset contained medium WTC airplanes with jet engines. They were able to achieve a mean precision, recall and f1-score of 87%, but did not account for the imbalanced nature of the data. While their research was a great start in the field of aircraft classification, not accounting for such a severe imbalance made the results less reliable. While their accuracy for the dominant class was 98%, the average accuracy for the other 5 classes was 56% (ranged from 86% to 37%).

The second challenge in ADS-B classification research is the extreme differences in aircraft operations during each flight phase. For example, an aircraft will fly at a different velocity, altitude and rate of climb during the take-off phase than it will during its cruise phase. This can complicate classification model development if researchers do not account for these differences. To circumvent this problem, previous research has attempted to classify aircraft characteristics based on just the take-off phase and has omitted data from other phases [17]–[19]. However, it is important to note that if an aircraft needed to be identified without access to its ADS-B data (i.e. the aircraft cannot or will not transmit it), the take-off and ground phases would be the least useful phases to classify since the aircraft could easily been seen and identified by the Air Traffic Control (ATC) tower without the need for ADS-B. For that reason, it is important to include all flight phases in research.

To include all flight phases, knowing which phase an aircraft is in during a given time period is important to annotate within the data. Various researchers have effectively developed methods to predict flight phase using fuzzy logic [5], [7], [20]. The input values commonly used for the fuzzy sets are *altitude, velocity* and *vertical rate/rate-of-climb*. The outputs are the flight phases. Research completed by [7] categorized the flight phases into *ground/taxi, climb, cruise, descent, level flight* and *unknown*. The phases were defined by the rules outlined in table I. Research completed by [20] used similar flight phases, but removed *level flight* (i.e. leveling out temporarily during climb or descent) and broke *descent* into two parts. This paper will use the design created by [7] in table I.

Accounting for the imbalanced data with an undersampling technique but using only the take-off phase, researchers were able to effectively predict aircraft engine type using a Multivariate Long Short-term Memory–Fully Convolutional Network (MLSTM-FCN) [17]–[19]. This type of neural network was developed in 2019 to classify time series data [21]. The MLSTM-FCN implements a *squeeze-and-excitation* block to improve accuracy beyond the capability of just the LSTM and FCN. Work from [17] used a dual stage deep engine classifier (DSDEC) where a binary classification model was created that first predicted *jet* or *not jet*. If the observation was determined to be *not jet*, it was fed into another model that was built to predict the difference between *turboprop* and *piston* engines. The model achieved an 89.2% accuracy which surpassed previous statistical machine learning (SML) classification techniques [4], [17]. Research completed by [19] focused on reducing the input data and the feature set. The feature set that provided the highest accuracy was *speed*, *barometric pressure* and *vertical speed*. Using half the number of tensors (4,110 compared to 7,749), a third of the features and a multi-class classifier instead of the DSDEC technique, [19] obtained similar results to [17] with an accuracy of 89.4%.

TABLE I
Flight Phase Fuzzy Logic Rules [7]

Flight Phase	***Altitude***	***Velocity***	***Vertical Speed***
Ground	Ground	Low	Zero
Climb	Low	Medium	Positive
Cruise	High	High	Zero
Descent	Low	Medium	Negative
Level Flight	Low	Medium	Zero
Unknown[a]	—-	—-	—-

[a] *Unknown* is defined by any aircraft states that are not defined by the rows above it

III. Methodology

The goal behind this research is to predict an aircraft's WTC, description, and type designator as listed in the ICAO doc 8643 using a deep learning model during all flight phases. Table II defines each of these aircraft characteristics. This paper focuses on the use of the MLSTM-FCN for classification due to its performance. During the course of the research, other deep learning architectures, such as a few variations of a bidirectional LSTM, Temporal Convolutional Network (TCN), and a binary classifier modeled after the DSDEC method [17] were attempted, but if after 15 epochs they did not show improvement over the MLSTM-FCN, training was discontinued. Ultimately, this paper solely discusses the use and training of an aircraft classifier with the MLSTM-FCN architecture as shown in figure 1.

A. Data Preparation

Provided by the ADS-B exchange [1], the data in this research spans the months of October and November 2021. October 2021 is used as the training set and November 1-2, 2021 is used for the test set. Raw data files are in a JSON format with 5 seconds between each observation. First, these files are converted to compressed CSV files for usage in our

TABLE II
ICAO Doc 8643 [22], [23]

Name	***Definition***	***Options***
Wake Turbulance Category (WTC)	Maximum certified take-off mass	ICAO 8643 defines WTC by heavy, medium or light. For the purposes of this research, medium is separated into two categories (small and large). • Light (< 15500 lbs) • Small (15500 to 75000 lbs) • Large (75000 to 300000 lbs) • Heavy (> 300000 lbs) • High performance (> 5g acceleration and 400 kts)
Description	3-characters used to describe aircraft type, number of engines and engine type	First character (aircraft type): • L - Landplane • S - Seaplane • A - Amphibian • H - Helicopter • G - Gyrocopter • T - Tilt-wing Aircraft Second character (# of engines): 1, 2, 3, 4, 6, 8 Third character (engine type): • P - Piston • T - Turboprop/turboshaft • J - Jet • E - Electric Example: L2T - a landplane with two turboprop engines
Type Designator	Up to a 4-character code that identifies an aircraft's model	There are 653 different designators in our dataset. The five most common ones are B738, A320, A321, B737 and A319.

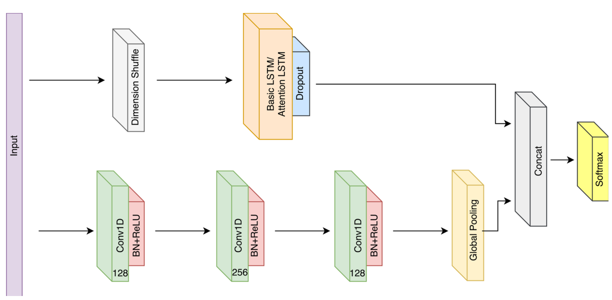

Fig. 1. MLSTM-FCN [21]

model. Next, all non-kinematic and non-time-based features are removed from the data, but the ICAO hex code and aircraft designator are kept. Finally, air tracks are analyzed to remove tracks that are either impossible or inconsistent.

The next phase of data preparation focuses on feature generation. Various features that are not available in the original data set are either inferred and generated using the data that is available. Latitude and longitude is a feature within the ADS-B dataset that has been determined to not be useful for classification purposes without manipulation [17], [19]. To improve its utility, latitude and longitude is altered to create a location that takes into account the Earth's 3-dimensional nature. Assuming latitude is ϕ and longitude is λ (1), (2) and

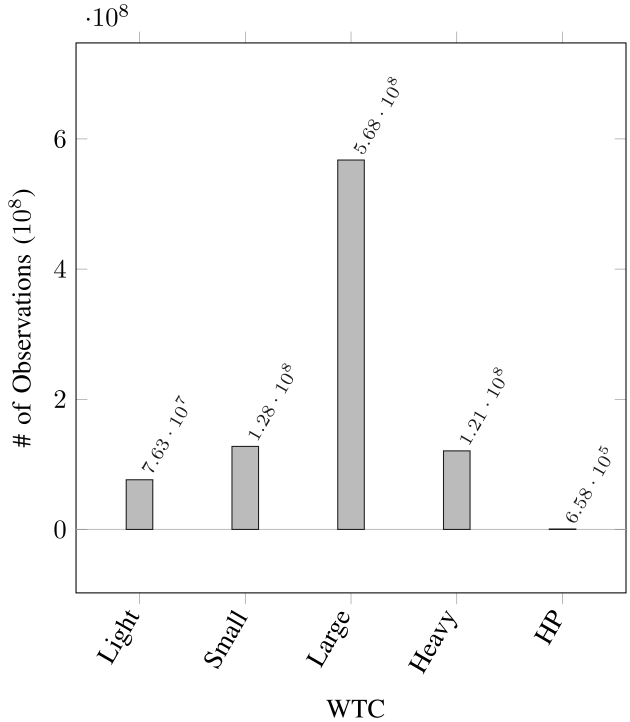

Fig. 2. Number of observations per WTC class

(3) become the new location coordinates.

$$x = \cos\phi * \cos\lambda \tag{1}$$

$$y = \cos\phi * \sin\lambda \tag{2}$$

$$z = \sin\phi \tag{3}$$

Since flight phase is not a feature that is inherent to ADS-B, the fuzzy logic flight phase method developed by [7] is used to determine the phase of each observation in the dataset. The rules for each phase are shown in table I. These features are added to the already processed data in preparation for the final steps.

In the last two steps, WTC and description are obtained from the Opensky Network Aircraft database [24]. These results are double checked with the ICAO Doc 8643 and added to the database. Finally, files are broken up into 300 time-step tensors and saved for model development.

For training, there are a total of 2,976,027 tensors available made up of 892,808,100 observations. However, since some aircraft do not have enough samples to train the model, only the 130 most common aircraft and the 9 high performance aircraft are used for training. This leaves 870,378,000 observations which form 2,901,260 tensors. Even with removing aircraft, there is still a huge imbalance between datasets. Figures 2 and 3 show the number of observations per class.

To handle the imbalanced dataset, previous research used the undersampling technique [17], [19]. However, as can be

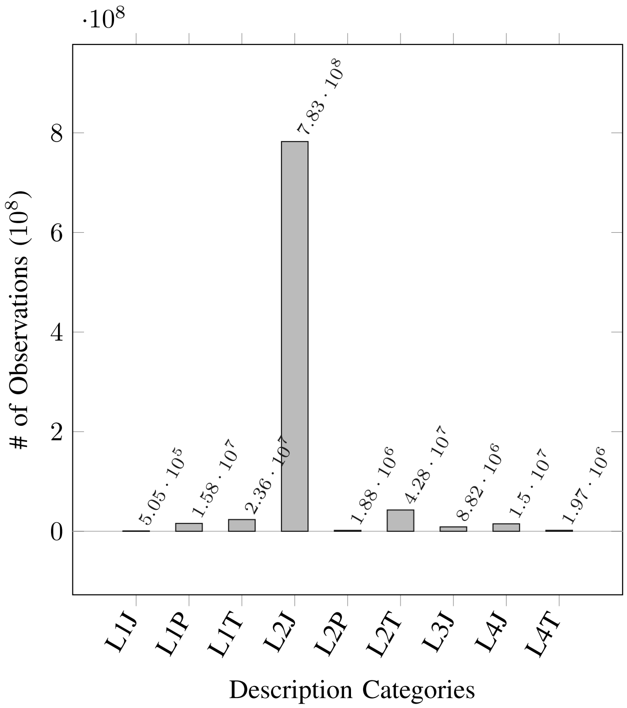

Fig. 3. Number of observations per description class

seen in figures 2 and 3, the undersampling technique would result in a large number of lost observations. For this research, class weights are used during the model's training to lessen the impact of the majority class instead of removing those observations entirely. The use of class weights is a function in Tensorflow to aid in the classification of imbalanced datasets [25].

B. Model Development

Previous work has shown the MLSTM-FCN to perform well with the ADS-B dataset [17], [19]. With the exception of the feature set selection, 50 epochs are used to train each model with data from the entire month of October 2021. November 1-2, 2021 is used to test the model. The models are built using dropout and learning rates that were found to work well in previous work [17]–[19]. The dropout rate remains at 0.5 and the learning rate is 0.001. Timesteps per tensor are kept at 300. While multiple feature sets are used to determine the one that provided the most accurate model, table III shows the features that were eventually settled on for analysis purposes. These features align closely to the most useful features found in [19].

C. Experiments

In order to predict WTC, description and designator, 3 experiments are created.

1) Compare two models to determine the effectiveness of identifying flight phase
2) Develop and analyze models for WTC, description and type desginator while accounting for class imbalances
3) Analyze and report the accuracy per flight phase

TABLE III
FEATURES [1]

Feature	***Definition***
alt_baro	Barometric altitude in feet as a number OR "ground" as a string
alt_geom	Geometric (GNSS / INS) altitude in feet referenced to the WGS84 ellipsoid
gs	Ground speed in knots
ias	Indicated air speed in knots
tas	True air speed in knots
track	True track over ground in degrees (0-359)
track_rate	Rate of change of track, degrees/second
baro_rate	Rate of change of barometric altitude, feet/minute
geom_rate	Rate of change of geometric (GNSS / INS) altitude, feet/minute
x, y, z	normalized location based on latitude and longitude
phase	flight phases listed in table I

1) Experiment 1 - Flight Phase Features: During the exploratory phase of this research, we build two models for each classifier without adding class weights. The two models use the features listed in table III. One of the models includes the flight phase and the other does not. The goal of this experiment is to determine the effectiveness of including flight phase as a one-hot-encoded feature within the dataset.

2) Experiment 2 - Model Development: In experiment 2, we develop models for each classifer with class weights. The class weights were calculated with (4). In this equation, w is weight, l is the size of the largest class, and c is the size of the class being calculated. This ensures that the largest class has a weight of one, and all smaller classes have a weight that is larger than one. The smaller the presence of the class, the greater the weight of that class.

$$w = \frac{l}{c} \tag{4}$$

3) Experiment 3 - Flight Phase Analysis: The accuracy per flight phase is calculated and reported using the test set to determine which flight phase provides the most accurate predictions of WTC, description and designator.

IV. Results and Discussion

A. Experiment 1 - Flight Phase Features

In experiment 1, we build two models for each prediction class. One that includes the flight phase in the feature set, and one that does not include flight phase. The phases are one-hot-encoded into one of the six options listed in table I. The results from this experiment are shown in table IV. As can be seen, WTC heavily depended on flight phase to provide improved results. With description and designator, the results were negligible.

B. Experiment 2 - Model Development

Experiment 2 accounts for the imbalanced dataset by weighing the classes to balance the impact each class has on the dataset. The results can be seen in table V. WTC improves with the weighted model, but description and designator have

TABLE IV
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)

much less favorable outcomes. Since weighing the classes fixes the imbalance problem, this is likely due to the fact that the imbalance between classes in WTC is less significant than balances between description and designator. However, weighing the classes is necessary to prevent the model from having inflated results for the majority class.

TABLE V
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)

C. Experiment 3 - Flight Phase Analysis

The final experiment focuses on the flight phases to determine how much the model's accuracy depends on that particular phase. The results of this analysis are shown in table VI. As expected from previous research [17], [19], the climb and descent phases produce the most accurate models in both WTC and description. The ground phase produces the least accurate model for WTC and description. The ground phase producing the least effective model is not surprising. The difference between aircraft as they are parked or taxiing is not significant. Most of the classification power of aircraft on the ground is likely related to other observations within the same tensor as the ground observations. Since the tensors are 300 timesteps long, each tensor lasts about 25 minutes. Over this 25 minute period, many of the tensors with ground observations also contain observations from the climb or descent phase.

V. CONCLUSION AND FUTURE WORK

Including all phases of flight creates difficulties in making predictions about aircraft characteristics due to the dynamic nature of air flight. However, the ability to predict aircraft characteristics anytime during flight is important since only obtaining data from takeoff or landing is not always feasible or desirable. This research shows that depending on which characteristic is being classified, sometimes generating features to predict flight phase is useful, but sometimes it is not. In this case, WTC benefits from flight phase prediction, but classification is not improved when predicting description and designator. When predicting characteristics from the entire

TABLE VI
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

flight path, it is important to determine if the characteristic being predicted is heavily influenced by flight phase or not.

Having a dataset feature imbalance can falsely inflate the classification power of a model. In the case of aircraft description, the majority class accounts for 87.7% of the dataset. When weighing the classes so that they provide equal input, the accuracy of the model is reduced by 20% from 92.9% to 72.2%. The majority class in WTC is only 63.6% of the total observations causing the weighted version of the model to be less affected by the modification. However, the weighing of the classes ensures that the model learns to predict the actual features needed to learn about the aircraft instead of learning to favor the majority class.

With 139 different class options, creating an effective model to classify an aircraft designator is a difficult problem. During the model building phase, various architectures are attempted such as a Temporal Convolutional Network (TCN), a bidirectional LSTM, and a binary classifier modeled after the DSDEC method [17]. None of architectures showed promise after a handful of epochs and were abandoned to focus on the MLSTM-FCN [21]. Not accounting for the imbalance, we were able to achieve an accuracy of 28%, but with a recall of only 9%. Future research will look at including other sensors and data types such as weather or images to improve the classification ability when predicting aircraft designator.

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