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Aircraft Damage Classification by using Machine Learning Methods

Tüzün Tolga İnan

In the general concept of aviation safety comes first, so country authorities and airlines have focused on increasing aviation safety. The introduction of cockpit voice recorder and flight data recorder, crew resource management (following the Tenerife disaster), the airborne collision avoidance system (ACAS), and ground proximity warning systems (GPWS) are the examples of specific improvements for aircraft's configuration because of various accidents (ICAO, 2013c). Due to the increasing trend of air transportation, the rate had risen to approximately 3 accidents in 1 million departures to approximately 50 accidents in 1 million departures in 1960 and fell approximately 5 accidents in 1 million departures in the 1980s (Boeing, 2016). The International Air Transport Association (IATA) stated commercial aircraft carriers, which already provide the transportation process of more than 3 billion people across the world each year in 2019 (IATA, 2019; Zhang & Mahadevan, 2019). To prevent aviation accidents, it is crucial to understand how minor mishaps turn into major catastrophes by specifying the processes about abnormal occurrences spread throughout the system. Therefore, the safety of air transportation is impacted by several issues such as passenger number, temperature, dew point, wind speed, wind direction, latitude, longitude, and time-periods as time, month, and year (Alle et al., 2009).

It is essential to develop a systematic approach to identify the intervention strategies and emphasize potential safety measures to lower the frequency of low-probability high-consequence aviation accidents. To summarize, causal relationships should systematically solve the uncertainties that resulted from multiple sources like lack of data and knowledge. These sources need to be characterized and disseminated in a quantitative way. The knowledge learned from past accidents may be helpful in controlling risks by prohibiting the potential rising of hazardous events in future flights (Zhang & Mahadevan, 2021). Every aviation stakeholder should carefully operate the safety management system (SMS), which is governed by ICAO known as the primary element of safety and safety risk management in terms of civil aviation. The primary requirement in the aviation sector that every airline must follow is put into practice the applications to ensure aviation safety. Being close to SMS, civil aviation authorities, airports, air traffic control and maintenance centers, ground handling and meteorological offices, and other infrastructures are important to understand the human life problems. Flight attendants implement the safety procedures to protect the passengers from potential abnormal situations. The requirements for flight safety in an airline are tightly connected to the airport's safety system. The services related to air transportation have risen the safety system of aviation industry to the top level since it is reliant on the countries' overall safety and security culture (Alves et al., 2019; Sadi-Nezhad, 2021).

Over time, many different issues have contributed to safety improvements. The aviation safety has improved with the technological advancements in engines, avionics, and aircraft. The development of cockpit voice recorders and flight data recorders has helped accident investigations. For airplanes equipped with such equipment, the creation and usage of ground proximity warning devices has all but eradicated an accident known as controlled flying into terrain. The usage and development of advanced flight simulators in both basic and ongoing pilot training has improved pilot training. The increased understanding of human factors and its application to training and regulations have had a significant positive impact on pilot training. Flight safety has increased thanks to advancements in navigational aids and air traffic control. Additionally, helpful have been improved weather forecasts and a better knowledge of meteorological phenomena including downdrafts and wind shear. A thorough analysis of previous accidents to ascertain what caused them and what needs to be done to prevent such events from occurring again is another significant factor in the better safety record (Oster et al., 2013).

Since the 1960s, there have been fewer aircraft accidents all over the world. This opinion can be explained with the advancements and innovations in the usage of aircraft, reliability, safety, and design. This downward trend persisted until the last period of 1990s because this trend stabilized from roughly 1997 to 2006 (Boeing, 2013). The U.S. National Transportation Safety Board's (NTSB) analysis about the operation process of incidents and accidents in scheduled transportation from 1992 to 2011, showed approximately the same trend (NTSB, 2012). Even though the years from 1997 to 2006 have shown a stable trend, it is focused on mitigation measures related to prevention of aviation incidents and accidents (ICAO, 2013a, 2013b). To summarize all information, according to Gramopadhye and Drury (2000) and Reason (1995), aviation incidents and accidents are caused by internal and external factors. When it is analyzed internal and external factors according to crash investigation reports, internal factors can be classified as; passenger number, the position of the aircraft as latitude, longitude, and the time-period as time, month, and year. External factors are related to weather circumstances that can be classified as temperature, dew point, wind speed, and wind direction.

In the introduction section, general information about aviation safety issues are explained in detail from past to present. In addition to the introduction section, literature review part gives information about related studies in safety concept of aviation. In the material and method section, the selected 10 factors are applied to machine learning (ML) algorithms by utilizing Artificial Neural Networks (ANNs), Multinomial Logistic Regression, Decision Trees (DTs) to classify aircraft damages as substantial, minor, none. In the sample of data section, the selected 10 factors are explained in detail by giving information about the data used in the study. In the results section, it is provided the results of multinomial logistic regression models by showing the odds ratios that are produced by multinomial logistic regression. The performance of the ANN and DT models are shown to classify data and the normalized relevance of independent features. The study is summarized in the discussion and conclusion sections.

Literature Review

When examining the previous studies about aviation accidents, 10

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studies found. The first study was written by Shappell et al. (2017) and it had three objectives. These objectives are used to broaden the scope of the Human Factors Analysis and Classification System (HFACS) including (a) commercial aviation; (b) to harness the power of a theoretically derived human error system with traditional, situational, and demographic data from the commercial aviation, such as visual conditions, injury severity, and regional differences; and (c) investigate the previous accidents to prohibit the accidents that might exist in the future. The second study is related to information on the aviation accidents acquired from the National Transportation Safety Board's (NTSB) database. Fultz and Ashley (2016) examined general aviation (Part 91) accidents (up to 19 seat capacity aircraft) happened between the period 1982 to 2013.

In third study, Kelly and Efthymiou (2019) determined the human elements associated with aircraft accidents that resulted in the phase of CFIT. The study, which covered the ten-year period from 2007 to 2017, employed the Human Elements Analysis and Classification System (HFACS) system to identify the contributing factors in 50 CFIT incidents from 24 countries. In the fourth study, Kaspers et al. (2019) found that the measuring of safety performance has been constrained by the long-held conception of safety and the indicators of unfavorable events connected to the lack of losses. The only use of outcomes indicators, however, is insufficient to further improve safety, it is determined that given the rarity of incidents and accidents in comparison to the volume of aviation operations.

In the fifth study, Burnett and Si (2017) tried to forecast circumstances regarding the likely increase in aviation accidents, including occurrences and accidents. This study's goal is to examine the variables that include type ratings connected to occupation, recent flight experiences, and specific weather conditions that affect the degree of injuries. In the sixth study, Nimmagadda et al. (2020) suggested research about ddeterminingwhether airline crashes occurred because of failing to apply data mining techniques, particularly for bird strikes. The research that is recommended in this article uses algorithms about supervised learning. It teaches how to use Naive Bayes, KNN, and decision tree algorithms to categorize data based on prior knowledge.

In the seventh study, Truong and Choi (2020) suggested a study to develop and evaluate the forecasting models for accidents and incidents involving unmanned aircraft systems (UAS) in the National Airspace System (NAS). By using the FAA's notion of UAS sighting, this model is utilized to calculate the risks of violation incidence. The pattern size covered by this data is 2088. The goal of this work is to enhance predictive models to calculate the risk of sUAS infringement occurrences in NAS. In the eighth study, Baugh (2020) described how to simplify a large amount of data for the prediction of modeling and estimate safety management. The aim of this study is to establish an investigative analysis of data-driven general aviation accidents in the United States that occurred between 1998 to 2018. The goal was to identify which model best estimates the aircraft accidents cover death and severe injuries and investigate what characteristics were most essential in this estimation model.

In the ninth study, the machine learning program should be developed to identify danger variables throughout the flight phase using causal chains, according to Lee et al. (2020). The goal of this study is to forecast critical parameters (and potential causal elements) that result in safety-related causes from internal stages that are deemed insignificant, unrelated, or distantly unified ones. In the tenth and the last study, Dangut et al. (2020) estimated anomalous failure of aircraft components. They also suggested a hybrid machine learning approach that combines communication in working approaches and group learning with a model. The model relates to the identification of a log-based pattern technique that incorporates group learning for pattern determination and classification together with the transformation and integration of well-known native language working techniques suitable for to prevent potential accidents in aviation.

Material and Method

Potential factors such as total number of injury passengers, temperature, dew point, wind speed, wind direction, latitude, longitude, time, month, and year play a significant role in aircraft accidents classifying aircraft damage. These factors are applied to machine learning (ML) algorithms. The incidents and accidents that are collected after 11 September 2001, are examined with machine learning (ML) algorithms to estimate non-linearity by using several feature elimination techniques and the cross-validation. Compared to linear models, these models can perform classification tasks with more accuracy in evaluating aircraft damage. Supervised learning algorithms are used due to having labeled classes: substantial, minor, none aircraft damages. Artificial Neural Networks (ANNs), Multinomial Logistic Regression, Decision Trees (DTs) are utilized in this study.

According to statistical learning theory, it is crucial to reduce the feature vector's dimensions to adjust the model complexity (Bozdogan, 2000; Kocadagli & Langari, 2017). For the dimension reduction of feature matrices, there are several methods. For instance, Backward Elimination, Forward Selection, Stepwise Selection, Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA) as transformation method are the dimension reduction methods in the literature. ML algorithms are implemented with RFE and PCA-based dimension reduction. A feature selection method called RFE fits a model, eliminates the weakest feature or features, then repeats the procedure with the remaining features until the desired number of features is reached or exhausted (Mathew, 2019). The weights required to create the new feature that best explains the variation in the dataset are provided by the PCA. The first principal component is the name given to the new weighted variable. Furthermore, cross-validation methods are utilized to automatically adjust the model's complexity.

Firstly, multinomial logistic regression models were trained by using RFE. LBGFS optimization solver is used to handle multinomial loss with l2 regularization to avoid overfitting. Then, ANN and DT models were trained by using features obtained from PCA. The features are normalized prior to analysis,

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and the cross-validation type is decided upon as k-fold and leave-one-out. By feeding the models the inputs from PCA, the min-max normalization process is used to train the models. The following is a formula for min-max normalization (Inan & Gokmen, 2021):

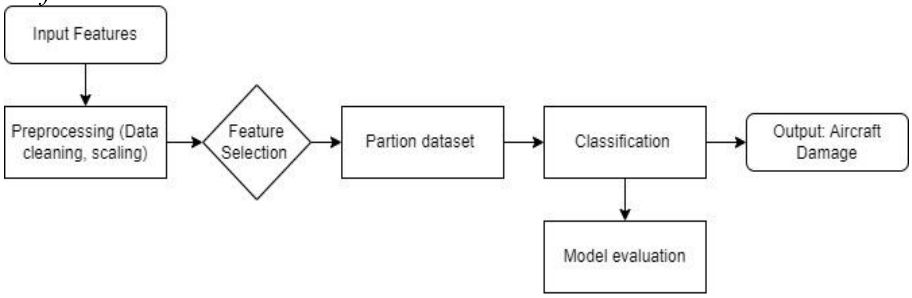
$$x_i^* = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \quad i = 1,2,\dots,677$$

The Classification and Regression Tree (CART) model is utilized to train DTs. It has a hierarchy of univariate binary decisions. The "Tree" has a "root" and is made up of branches, nodes, and leaf nodes. The internal node represents a binary test on a single variable, with branches showing the test's results; each leaf node, however, displays class labels. When using CART, the data are first split into two groups at the root branch, that is as homogeneous as is possible. This splitting process is then repeated for each branch. Current "purity" computations are used to determine remaining attributes that should be divided. CART makes use of the Gini index. Gini index is an impurity-related entropy minimization technique. The lowest Gini index determines how the nodes are divided. Recursively expanding the tree from the root node, CART then prunes the enormous tree down to its original size (Chong et al., 2005).

The robust models apply a feature selection process and a variety of kernels, including complex, medium, and simple kernels, while training DTs. ANN is inspired by the human brain. Several neurons are formed in the brain. The link between neurons is provided by synapses. The neurons of ANNs are modeled by perceptrons. There are inputs and outputs in this model. Weight in synapses is an input. Output should be as simple as the weighted sum of the inputs. In other words, a perceptron can apply activation or transfer functions like a linear, sigmoid, and hyperbolic tangent function. ANNs contain hidden layers. An input layer and an output layer are connected by these layers. To train networks, backpropagation is the fundamental technique (Alpaydin, 2014; Burnett & Si, 2017).

ANNs are trained using several gradient-based algorithms, including the stopping criterion of MSE or cross-entropy: Levenberg Marquardt (LM), Gradient Descent with Momentum (GDwM) and Scaled Conjugant Gradient (SCG) (Kocadagli, 2015). Figure 1 shows the classification framework for aircraft damage classification.

Figure 1
The Classification Flowchart



Area Under Curve (AUC), accuracy ratio, false positive (FP) and false negative (FN) rates are used to assess the model's performance as follows:

The Receiver Operating Characteristic (ROC) curve's total two-dimensional area is measured by AUC. An overall measure of performance across all potential classification criteria is provided by AUC. For a given dataset, accuracy ratio is the proportion of accurate predictions. The ratio of the number of negative occurrences that were negative but were mistakenly classified as positive is used to compute the false positive rate. The likelihood that a true positive will go unnoticed by the test is known as the false negative rate.

Sample of Data

In this study, the latitude, longitude, wind speed, wind direction, temperature, dew point, hour, month, year, and number of injured passenger variables are used to analyze the factors that affected scheduled incidents and accidents in civil aviation history. The first variable latitude is represented by the Greek letter phi, which denotes the angle between the equatorial plane and a straight line at a given position. Latitude is measured in degrees, from 0° to 90° on either side of the equator, defining Northern and Southern latitude. The line with 0° latitude is the equator. Another angular coordinate used to describe the location point on the earth's surface is the second variable known as longitude, which is represented by the symbol lambda. The Greenwich Meridian, which is the Prime Meridian, is used to define longitude as an angle pointing west or east. The maximum definitions for longitude are 180 degrees east and 180 degrees west of the Prime Meridian. Degrees, which are further subdivided into minutes and seconds, are used to measure both latitude and longitude. For instance, the borders of the tropical zone, which is situated south and north of the Equator are 23°26'13.7" S and 23°26'13.7" N (Latitude and Longitude, 2022).

The third variable wind speed can be explained by three factors that are affected the aircraft flying in air. These three factors can be calculated - the wind speed from the ground speed and airspeed as we cannot measure the wind speed directly from the airplane. The vector difference between ground speed and airspeed is known as wind speed.

$$Wind\ speed = Air\ speed - Ground\ speed$$

In the formula, the wind speed is taken zero and the airspeed is equal to the ground speed in a perfect day in terms of weather. The wind speed is positive if the measured airspeed is higher than the observed ground speed (NASA, 2022). The fourth variable is related to when calculating mean values for surface wind, only data collected after a clear discontinuity in the wind direction and/or speed should be considered, and the time interval should be adjusted accordingly. Surface wind should be calculated using an average period of ten minutes. This variable known as wind direction is expressed as three numbers, such as 030 or 240, in steps of 10 degrees. In addition to the numbers used, the wind speed is given in steps of 1 knot or 1 meter per second using two figures, such as 05 or 15 (Meters per Second [MPS] or Knot [KT]). When an aircraft's heading and wind direction are the same, the wind is determined to be in front of the aircraft. 0 is always placed in front of the wind direction values below 100 degrees. A wind is indicated by 360° (rather than 000°), a wind is coming from the true north. Both routine local reports and Meteorological Aerodrome Reports (METAR) should provide the unit of measurement for wind speed (IVAO Documentation Library, 2022).

The fifth variable is detailed by the International Civil Aviation Organization (ICAO) determined a baseline temperature for aviation to allow manufacturers to produce performance data that pilots could use all over the world. The ICAO Standard Atmosphere, or "ISA," is the name given to this specified temperature. Maintaining this temperature allows pilots and crews to navigate the skies more safely without unforeseen weather threats. While the weather can occasionally change, being able to accurately predict the situation can frequently help pilots stay ahead of the process. The standard temperature in aviation is calculated at a pressure of 29.92 inches of mercury (Hg), or 15 degrees Celsius, or 59 degrees Fahrenheit. For every 1.000 feet increase, the normal temperature drops by 2 °C (3,5 °F), and this measure is wholly accurate up to 36.000 feet. The temperature zone changes -55 °C to -65 °C between 36.000- and 80.000-feet altitude (Flying, 2022).

The sixth and the last variable dew point can be explained with several definitions. Firstly, dewpoint is the temperature at which saturated air made of humid air must be cooled at constant pressure. Secondly, it is defined as the minimum temperature at which a sample of air can be cooled to reach saturation with respect to water while maintaining a consistent amount of water vapor and barometric pressure. Thirdly, it is defined as the temperature at which water is completely dissolved in air. Fourthly, it is related to the temperature at which cooled air starts to condense. Different amounts of atmospheric pressure, air humidity, etc. affect the temperature and dew point differently. For instance, when the temperature is measured as 11, at the same time the dew point can be measured as 9. Lastly, dew point is a measurement of the humidity in the air. To obtain saturation, air must be chilled to this temperature (presuming air pressure and moisture content are fixed). More moisture is existed in the air when the dew point is higher (Aviation Glossary, 2022).

The total number of incidents and accidents in civil aviation history related to scheduled flights is 1988. To obtain the best result for application of the analysis, a total of 677 flights were taken to apply for the data visualization. These accidents are taken between 11.09.2001 to 31.12.2022 (specified as all scheduled accidents after 9/11) and all scheduled accidents in this period are added to the data visualization. These years are selected due to the 9/11 effect on civil aviation because the safety regulations especially in-flight operations substantially changed after the 9/11 events. So, the data from 11.09.2001 to 31.12.2022 reveals a proper examination for the data visualization. The total incidents and accidents are evaluated with the terms of none, minor, and substantial. The none and minor terms are related to incidents (also known having no dead passengers and known as unfatal). The term of none means there has no fatal passenger and no damage in the aircraft. The term minor is used related to events that aircraft damage, but there is no fatality related to passengers. The substantial ones are related to accidents about having dead passengers (also known as fatal) and damage in the aircraft. All the variables that are mentioned in the sample of data part are taken from four different websites. These are National Transportation Safety Board (NTSB, 2022), Kathryns Report (2022), Graham-Ely Aircraft Incidents (2022), and Aviation Safety Network (2022) websites. NTSB website is used to obtain the selected data, Kathryns Report, and Aviation Safety Network websites are related to the missing data that is not found in the NTSB website. Graham-Ely Aircraft Incidents website is used to reveal the list of the total incidents and accidents in the civil aviation history related to scheduled flights. The term of scheduled flight can be defined as the planned flights, which the date, time, flight code, flight number, and other related information has been finalized several months ago. Due to the availability of real data in accident reports, the scheduled flights (all flights that are not included the commercial general aviation flights use 19 and lower seat capacity aircraft known as on demand and charter transportation) are examined in this study.

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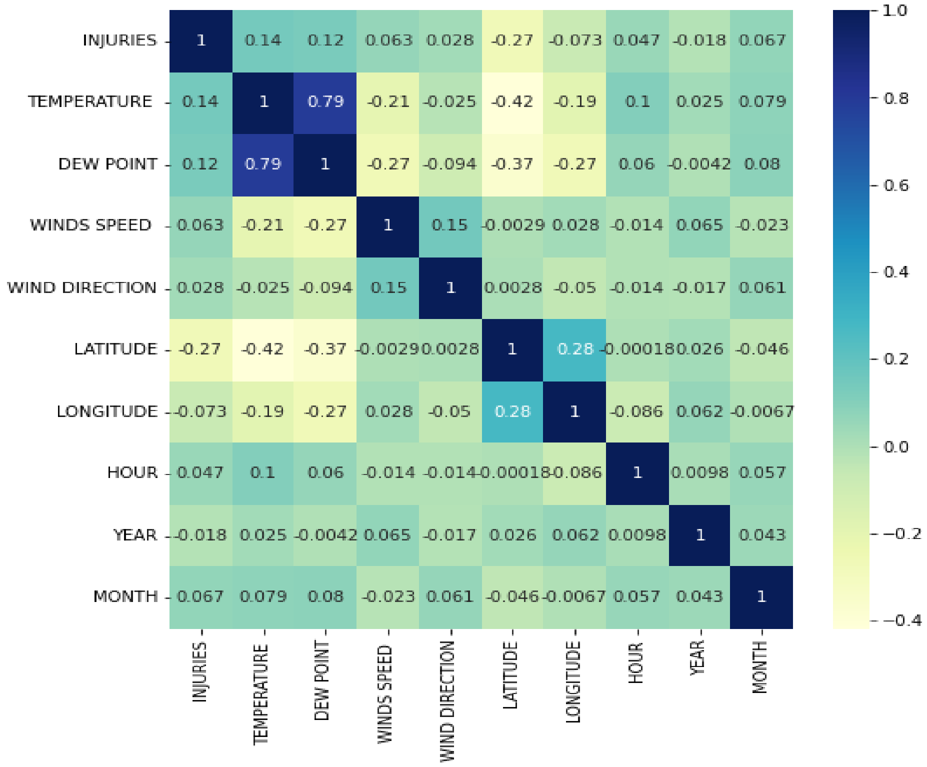
Table 1
The Distribution of the Features

		N	%
Aircraft Damage	None	209	28.2
	Minor	191	30.9
	Substantial	277	40.9
		Median	**Q1-Q3**
Injuries		66	15-136
Temperature		17	6-24
Dew Point		8	-1-16
Wind Speed		8	5-13
Wind Direction		190	100-270
Latitude		39.424990000	34.1670228-41.97861
Longitude		-87.8905560000	-104.673057--74.169147
Hour		14	10-18
Year		2008	2005-2014
Month		6	3-10

The distribution of these features is given in Table 1 and the correlation between them is shown in Figure2. Twenty-eight-point two percent (28.2%) of the accidents have none type of damage. Thirty-point nine percent (30.9%) of the accidents have minor type of damage and 40.9% of the accidents substantial type of damage. The median number of total passengers is 66 (15-136). The heatmap of the correlation coefficient shows that there is only a significant positive correlation between the temperature and dew point, longitude and latitude. Therefore, dimension reduction techniques are applied.

Figure 2

Correlation Between the Input Features



The geographical locations of the incidents and accidents are shown in Figure 2 by considering the longitude and latitude information. In Figure 3, the total incidents and accidents are evaluated with the terms of none, minor, and substantial as mentioned in sample of data section. The blue color shows the none incidents that have no fatal passenger and also no damage in the aircraft. The green color shows the minor incidents that is related to events that have resulted with aircraft damage in terms of no injury passengers (knows as non-fatal). The red color shows the substantial ones that are related to accidents having dead passengers (also known as fatal) and damage in the aircraft. The none and minor air incidents are generally observed in North America and West Europe regions. The substantial air accidents are generally observed in the north regions due to harsh weather conditions in addition to North America and Europe Continents.

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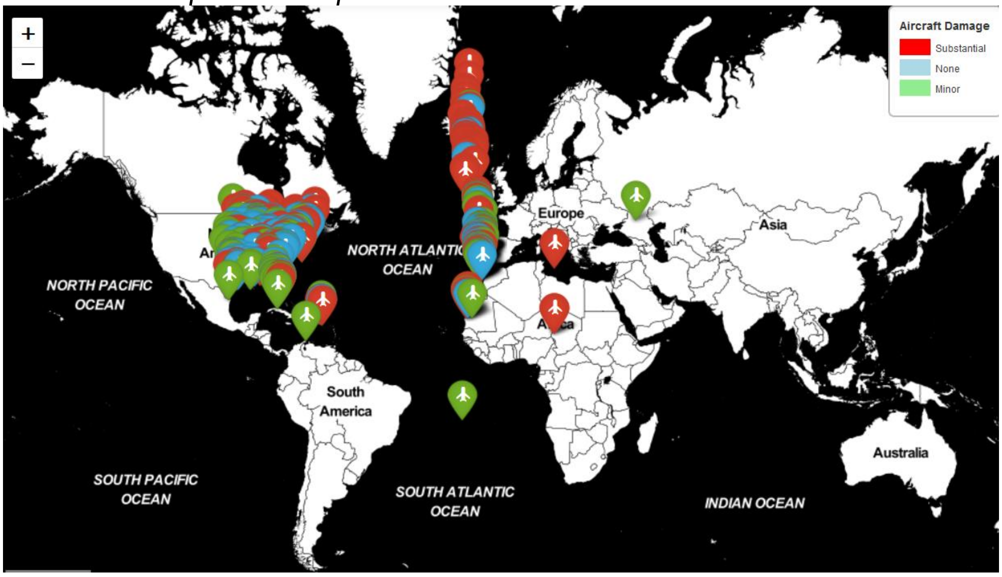
Figure 3

Visualization of the Aircraft Accidents



Results

The methodology's results are reported in this section to show the significance of the study. These outcomes also aim to demonstrate the study's contribution to literature. Table 2 provides the results of multinomial logistic regression models. Table 3 shows the odds ratios produced by multinomial logistic regression, and Table 4 shows the performance of the ANN and DT models for classifying data. The normalized relevance of independent features in Figure 4 indicates the outcomes of the methods used to determine the significance of independent variables.

Model Estimation

The analysis considers different machine learning techniques to estimate reliable models that provide high classification accuracy with low false positive and false negative rates for classifying aircraft damage. The algorithms are trained by k-fold during the training process. The methods RFE and PCA feature selection procedures are applied. The scikit-learn module is used during the ML algorithm training procedures under Python. The results below show the model performance for each ML algorithm.

Multinomial Logistic Regression Results by Applying RFE

Results from multinomial logistic regression models are included in this section of the research to demonstrate the impact of input features on the classification of aircraft damage in aviation accidents. Multinomial logistic regression models are estimated using RFE with 10-fold procedures. The effectiveness of estimated models is evaluated using AUC, accuracy ratio, false-positive, and false-positive rates. The outcomes of the multinomial logistic regression analysis are presented in Table 2.

Table 2

The Multinomial Logistic Regression Models' Performance

	Overall				Substantial Aircraft Damage				Input Features
Models	**#Input**	**NSV**	**AUC**	**Acc**	**AUC**	**Acc**	**FP**	**FN**	
Model 1 No elimination No CV	10	10	0.744	0.463	0.555	0.603	0.039	0.850	All
Model 2 No elimination 10-fold CV	10	0	0.735	0.515	0.553	0.552	0.460	0.433	All
Model 3 RFE No CV	10		0.733	0.492	0.563	0.610	0.039	0.833	Injuries, latitude, year
Model 4 RFE 10-fold CV	10		0.738	0.551	0.581	0.580	0.421	0.416	Injuries, temperature, dew point, winds speed, latitude, longitude, year

Note. **NSV** = Number of selected features; **Acc=**Accuracy Ratio, **FP=**False Positive; **FN=**False Negative, **CV**=Cross validation

Table 2 shows that Model 4 consists of injuries, temperature, dew point, winds speed, latitude, longitude, and year according to RFE. AUC and accuracy of Model 4 are the highest among the other models in addition to the lowest FN (0.416).

Table 3

The Odd Ratios of the Selected Features

Aircraft Damage		p	R	95% Confidence Interval for OR	
				Lower Bound	Upper Bound
Minor	Intercept	**<0.001**			
	Zscore: Injuries	0.167	0.867	0.707	1.062
	Zscore: Temperature	0.522	1.111	0.805	1.532
	Zscore: Dew Point	**0.044**	0.722	0.525	0.992
	Zscore: Winds Speed	0.851	1.020	0.832	1.251
	Zscore: Latitude	0.395	0.911	0.735	1.129
	Zscore: Longitude	**0.013**	0.741	0.585	0.938
	Zscore: Year	0.475	1.073	0.884	1.304
None	Intercept	**0.001**			
	Zscore: Injuries	0.600	0.952	0.791	1.145
	Zscore: Temperature	**0.060**	1.363	0.987	1.881
	Zscore: Dew Point	0.262	0.835	0.610	1.144
	Zscore: Winds Speed	**0.051**	1.219	0.999	1.489
	Zscore: Latitude	**0.057**	0.804	0.642	1.006
	Zscore: Longitude	0.616	0.942	0.745	1.190
	Zscore: Year	**0.012**	0.779	0.640	0.947

Substantial aircraft damage is taken as reference category in multinomial logistic regression. Table 3 displays the odds ratios and p values of the logistic regression model. 1 unit increase in dew point will decrease being minor to substantial (1/0.722) 1.385 times. 1 unit increase in longitude will decrease being minor to substantial (1/0.741) 1.349 times. 1 unit increase in temperature will increase being none to substantial 1.363 times. 1 unit increase in winds speed will increase being none to substantial 1.219 times. 1 unit increase in latitude will decrease being none to substantial (1/0.804) 1.244 times. 1 unit increase in year will decrease being none to substantial (1/0.779) 1.284 times.

DTs and ANNs Estimation Results by Applying PCA

The variable selection process runs automatically when ANNs and DTs are being trained in the ML technique. It performed initial tunings before to the training stage. The models are selected based on classification accuracy, false positive and false negative ratios, overtraining, testing, and overall datasets. This is for completing the training and variable selection process with the best performance.

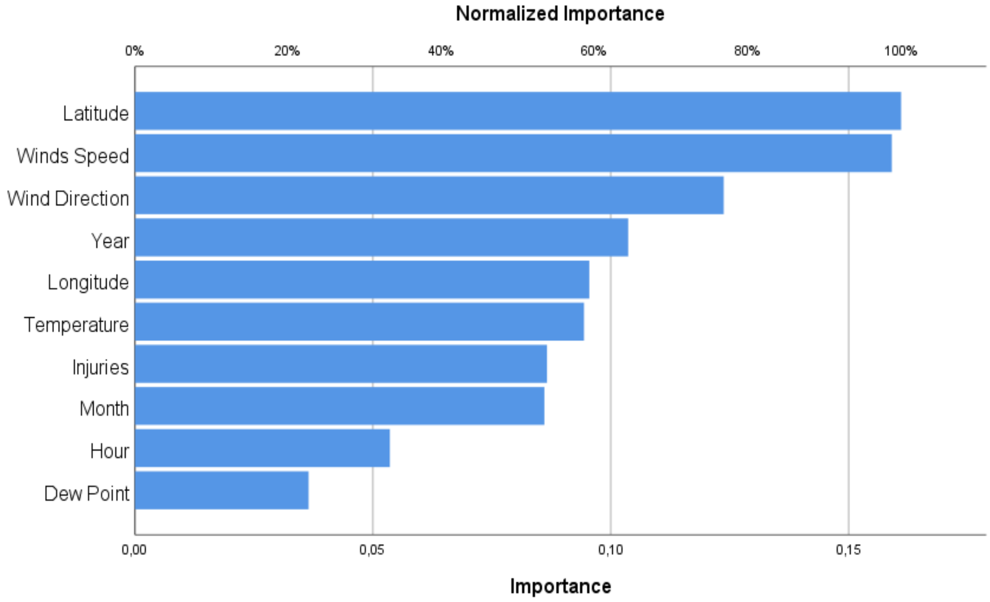
The PCA is utilized to reduce the number of dimensions during the variable selection, and the findings reveal that 10 features are adjusted over 4 dimensions with a 57.75% variance explanation rate. The first component comprises of the terms temperature, dew point, and latitute. It is called the zone component (C1). The second component comprises of wind speed and wind direction called the weather component (C2). The third component comprises of longitude and year called the time component (C3). The fourth and the last component comprises of hour, month and total number of injury passenger called the history component (C4). PCA results with the normalized component scores. In ANNs and DTs, they are considered as input features. The best-estimated models provide accuracy ratios, false positive and false negative rates, and performance metrics in Table 4 in accordance with the results of ANNs and DTs. By taking into account all of the performance criteria, Table 4 demonstrates that the models perform better than logistic regression models. According to performance evaluations, the best models with PCA-selected features perform better than full models with all independent features when these methods are evaluated.

Table 4
The ANN and SVM Models' Classification Performance

Models	Procedure	Overall			Substantial Aircraft Damage			
		#Input	AUC	Acc.	AUC	Acc	FP	FN
ANNs (GDwM)	PCA Leave-one-out	4	0.589	0.387	0.547	0.436	0.850	0.046
	Full Model Leave-one-out	10	0.601	0.667	0.533	0.654	0.352	0.333
DTs (complex tree)	PCA 5-fold	4	0.630	0.526	0.652	0.641	0.391	0.299
	Full Model 5-fold	10	0.634	0.513	0.673	0.692	0.224	0.430
Multinomial Logistic Regression	RFE 10-fold CV	7	0.738	0.551	0.581	0.580	0.421	0.416

To reveal the importance of features for the aircraft damage classification, ANN architecture is used to estimate weights. Input features' normalized importance over the best full model shows in Figure 4. According to this figure, the top 5 variables above 50% normalized importance are latitude, winds speed, wind direction, year and longitude. Multinomial Logistic Regression analysis supports the results by revealing significant results for latitude, longitude, winds speed, and year.

Figure 4
Normalized Importance of Features



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Discussion and Conclusion

Safety is the most significant factor that affected incidents (non-fatal) and accidents (fatal) in civil aviation history related to scheduled flights. These incidents and accidents are generally affected by four components that are mentioned in the study. These are zone, weather, time, and history. These components are used to analyze the factors that affected all scheduled accidents in civil aviation history and they play a significant role in aircraft accidents in the classification of aircraft damage. The study are detailed in five sections. In the introduction, general information about aviation safety issue is explained in detail from past to present. In the literature review, the related studies about safety concept in aviation is explained. In the material and methods, the input features, preprocessing, feature selection, partion dataset, classification with model evaluation are used to reveal the affecting factors of aircraft damage classification under ML approach. In the sample of data, the selected features under four components are examined with their definitions. In the results, the methodology, which are presented to reveal the importance of the study show the contribution to the literature.

In this study, the performance of multinomial logistic regression models are given, the output of multinomial logistic regression related to odds ratios are stated, and the classification performance of ANN and DT models are shown to figure out the importance of input features about the normalized importance of independent features according to the results of the methodology. Therefore, these input features are applied to ML algorithms since 11 September 2001 algorithms by using several feature elimination methods and the cross-validation. In the visualization of incidents and accidents, the none ones that are related to non-fatal, without aircraft damage incidents and minor ones that are related to on fatal, but with aircraft damage incidents are generally observed in North America and West Europe regions. The substantial ones related to fatal and with aircraft damage accidents are generally observed in the north regions due to harsh weather conditions additionally, North America and Europe Continents. ML algorithm results show that latitude, wind speed, wind direction, year, and longitude are the top 5 features for classifying aircraft damage. These incidents are accidents can be analyzed from different perspectives in future studies. Additionally, the radar images can be evaluated to show the details on aircraft damage by using deep learning methods.

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