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Classification of Survivor/Non-Survivor Passengers in Fatal Aviation Accidents: A Machine Learning Approach

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The Article Title: Classification of Survivor/Non-Survivor Passengers in Fatal Aviation Accidents: A Machine Learning Approach Corresponding Author Name and Surname: Tüzün Tolga İNAN Title: Asst. Prof. Dr. / Head of Pilotage Department PhD Area: Civil Aviation Management Institution: Bahcesehir University, School of Applied Disciplines, Pilotage Department Address (Work): Yildiz, Ciragan Street, 34349, Besiktas, Istanbul E-Mail: tuzuntolga.inan@sad.bau.edu.tr Telephone Number: +90 554 426 06 04 ORCİD İD: https://orcid.org/0000-0002-5937-9217 Declaration of Competing Interest The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this paper. Author Contributions Corresponding Author Tüzün Tolga İNAN: Data curation, Conceptualization, Investigation, Writing, Original draft preparation, Reviewing and Editing, Supervision, Resources Corresponding Author Biography As the corresponding author of this research paper, I worked between the years 2009 and 2015 in the civil aviation sector including Turkish Airlines and Pegasus Airlines. Also, I worked in the Turkish Ground Service as an operations coordinator at Ataturk Airport. I graduated with civil aviation management Ph. D. degree in 2017 from Eskisehir Anadolu University. I am head of the department at the School of Applied Sciences Pilotage Department at Bahcesehir University. My purpose is to develop myself and academic literature by publishing research papers related to the management perspective of civil aviation. I use in my research statistical models like machine learning, time series, multidimensional scaling, fuzzy data envelopment analysis, etc. I also continue to develop research in civil aviation concepts (airline and airport management) at the global level.

Aviation safety specialists and researchers have determined that aircraft accidents (fatal) and incidents (non-fatal) are caused by a sequence of events, each one with several causal factors. The International Civil Aviation Organization's (ICAO) descriptions of the status of the aircraft accident and incident investigations are classified below (ICAO, 1994):

- Causes are activities, failures, cases, situations, or combinations that lead to an accident and incident

- Accidents are cases related to the aircraft operation when people board an aircraft for flight until the time all people have disembarked, which ends in one or more cases below:

- Fatal or serious injury of a person

- Aircraft's continuing damage or structural failure negatively influences the mechanical structure, performance, and flight characteristics

These issues would generally need significant maintenance and overhaul of the influence component if:

- If the aircraft is missed or entirely unattainable

Furthermore, incidents are defined as cases, and they differ from accidents. Incidents are related to the aircraft operation influence or could affect operational safety (ICAO, 1994).

Practitioners of aviation safety often construct reactive examinations of previous accidents. The introduction of reformative strategies prevents the repetition of these incidents. For this reason, according to the development in worldwide air traffic, civil aviation research has operated by requirements to guarantee safety (Singh et al., 2019). Although aviation safety was introduced in 1938 by the Civil Aeronautics Authority, it developed into a substantial trend later in the 1990s (Harizi et al., 2013). Oster et al. (2013) emphasized that the worldwide air transportation accident and the incident ratio was one accident and incident per every 1.6 million flights. This ratio suggests that the positive evaluation of safety is related to the consequence of the ultra-safe civil aviation industry. This is specifically appropriate for leaders and managers in the civil aviation industry. They are liable for providing and enhancing safety performance. They also direct the demand for strategic business purposes (Lofquist, 2010). Civil aviation safety relies on the operational processes of all elements in the system that cannot be risk-free. Human factors can generally be the cause of aviation accidents. Researchers have conventionally intensified regulations related to the errors of flight crew personnel and air traffic controllers. A growing number of maintenance and examination errors have increased the requirement for research and studies related to human factors (Gramopadhye & Drury, 2000).

Aviation safety is a crucial term, and the investigation of accidents plays a significant role in the risk management concept to reduceaviation accidents. Aviation safety is an issue of survival, prestige, international reputation, and passenger trustworthiness in airlines. In the previous years, air transportation in the aviation industry has developed immensely, and the safety condition has also evolved (Cui & Li, 2015). Therefore, the sustainability of the effort increased the safety condition of the aviation industry, and the aviation fatalities (the accidents which ended with death) have decreased since the publication of the ICAO Safety Management System (SMS) Manual (ICAO, 2020). Presently, billions of citizens use air transportation in national and international travel. Despite the increasing air transportation demand, the number of accidents has gradually decreased for approximately 40 years, in part because of technological innovations; these have helped efficiently prevent aviation accidents (Iwadare & Oyama, 2015).

To analyze the issue of human factors, aviation safety has changed from reactive to proactive safety management systems (SMS). Therefore, Brown et al. (2000) specified that every accident stemmed from an unsuccessful organization. Because of this situation, airlines should consider and repair organizational and management issues within their SMS to facilitate a standardized approach ot avaiation safety (McDonald, 2000). However, the base reasons for accidents generally constitute many complex and connected concepts inside the organizational level. These concepts include organizational management structure and management issues (Santos-Reyes & Beard, 2002).

Furthermore, aviation safety is related to protecting airlines' and air companies' reputations, passenger reliance, and brand image at the international level. In recent years, air transportation in the civil aviation industry has expanded dramatically, and the safety concept has also improved immensely. Despite this increased level, the accident rate of air transportation has seen a decrease at the global level (Cui & Li, 2015). Besides aviation safety, machine learning techniques can help industries with time-consuming processes. These processes can also be used in the knowledge-based development system architecture for sustainable manufacturing (Jamwal et al., 2021). The application of machine learning algorithms has also increased in the last 15 years (Cavalcante et al., 2019).

In light of these explanations, this paper examines the most fatal 100 aviation accidents with different variables to provide a detailed justification for all-time aviation accidents. The research question sought to specify the affecting factors; aircraft type, distance, the phase of flight, the primary cause, the number of total passengers, and period of the most 100 fatal accidents by classifying survivor/non-survivor passengers with the machine learning approach. In the preprocessing step of the framework, the data cleaning removes irrelevant data by merging sub-categories. The aircraft type classifies three dimensions; Boeing, Airbus, and other brands. The most used commercial aircraft in the World are Boeing and Airbus. The number of accidents with other brands is 41 (%41), and they comprise 11 different brands. Therefore, these aircraft types determine other brands to obtain a suitable sample. Distance classifies into three classifications; short-haul (0-3 hour flights), medium-haul (3-6 hour flights), and long-haul (6 and more hour flights). The flight phase classifies three dimensions; flight, landing, and take-off. The primary cause of the accident classifies into three dimensions; human factor, technical, and terrorism/sabotage. The number of total passengers classifies two dimensions;

affected passengers, and non-affected passengers from the fatal accident. The period classifies into four classifications; 06-12, 12-18, 18-24, and24-36. All classifications are obtained by the Bureau of Aircraft Accident Archives (2021), and Plane Crash Info websites (2021).

Literature Review

Effective aviation safety is an outcome frequently challenged by many factors. In some regions in the world, for example, terrain and complicated operational activities, as well as a significant percentage of routes are not equally safe. Therefore, the safety issue should take importance in the air transportation decision-making process (Baidya et al., 2014). Furthermore, air transportation traffic is rapidly growing worldwide, and civil aviation safety becomes a problem in many countries. The accidents in civil aviation may conclude in human injury or death. Human injury or death affects the prestige and economic status of the air transportation industry in a country (Shyur, 2008).

The Assessment of Safety Concepts in Aviation

This concept has focused on the assessment process of safety concepts from many perspectives such as; safety target level (Li et al., 2009), identification system needs (Persing & Ng, 2009 August), safety supervisor performance in aviation (Chen, 2010 August), evaluating the safety concept in the changing industry of aviation (Lofquist, 2010), the evaluation of risk in aviation (Brooker, 2011), and the climate of safety culture (O’Connor, 2011).

The Factors That Affected the Safety of Aviation

Factors that have been known to affect aviation safety include, but are not limited to: the passengers’ perception of seating exit door (Chang & Liao, 2008), training of passengers in aviation safety (Chang & Liao, 2009), threats, human factors with errors related to the flight phases (Chen et al., 2009), the grand amendments in the organizational structure of the human factors (Herrera et al., 2009), the behaviors of personnel with the relationship between SMS (Remawi, et al. 2011), the severe weather conditions (especially in the winter season) related to the time period and the flight distances (Mäkelä et al., 2013), and the personal usage of electronic devices (Molesworth & Burgess, 2013).

The present literature principally analyzes static assessment of safety in aviation, and determination of the affected elements; however, the efficiency of aviation safety, and the airlines’ performance have not been measured. The efficiency of aviation safety is a marker of the causes of the safety inputs reliant on the vital safety performance of airlines (Cui & Li, 2015). Safety is the most important concept related to the operational processes of all activities in aviation. In recent years, the widespread development of SMS has affected the operation of safety performance of new missions, and defiances for protecting against potential accidents. SMS describes the measurable performance of the consequences. The development of the SMS system has also been related to the expectancies in design that meet the recent regulator necessities (ICAO, 2013). The safety performance indicators (SPIs) are applied to examine the safety risks, which are known. These indicators determine the safety risks to specify the corrective actions. The Federal Aviation Administration (FAA) operates the regulations in the United States. FAA also publishes reports about the performance indicators and responsibilities every year (FAA, 2014). Moreover, the safety air navigation of the European Organisation (Eurocontrol) has published yearly performance reports related to the evaluation of air traffic management (ATM) in Europe (EPRC, 2014). In addition to these reports, there are three basic concepts related to safety in aviation as described by ICAO and added in the post-SMS era. After 2010, the beginning of the post-SMS era was marked by the Safety Management Manual. Defining these concepts could list and distinguish complex efforts to manage safety These concepts are human factors, organizational factors, and technical factors (Huang, 2020).

The most closely related machine learning studies are examined inside the aviation concept. To constitute the database, this paper examines five studies in addition to real-life problems of air transportation. First, Burnett and Si (2017 May) were concerned about the application process connected the number of machine learning techniques to provide classification models. This study's purpose is to take into account the following factors: type ratings related to profession, flight experiences, and particular weather conditions which act in the injury severities in aviation accidents. Second, Ayres et al. (2013) examined five sets of models; the first three are: landing overruns, veer-offs, and undershoots. The other two classifications in takeoff are veer-offs and overruns. Each set comprised the frequency models of accident and incident by adding location and consequence models. Third, Goode (2003) examined how pilot schedules can lead to fatigue, thereby increasing the chance of an aviation accident. This study aims to find the empirical connection between pilot schedules and accidents in aviation. Fourth, Lee et al. (2020) examined the machine learning application to reveal risk factors during the flight phase with the causal chains. This study aims to predict the application of machine learning capability against the isolation of crucial parameters (and potency causal factors) leading to safety-related causes from the inside stages classified as unimportant, unconnected, or tangentially unified ones. The fifth and last study was published by Dangut et al. (2021). This study examined an approach to hybrid machine learning. This study aims to mix native language working techniques and group learning for estimating the aircraft component's unusual failure. These studies are related to the machine learning approach in air transportation; however, this study covers the aviation safety concept by analyzing all perspectives specified in the Bureau of Aircraft Accident Archives (2021), and Plane Crash Info websites (2021).

In this study, the primary causes of the accidents are classified into three categories: human, technical, and terrorism/sabotage. The organizational factors add to the term of the human factors due to its connection. Technical factors are related to maintenance failures in the operational process of aircraft, and terrorism/sabotage is related to the unlawful control of the aircraft. The primary definition of the accidents is derived from the Bureau of Aircraft Accident Archives (2021). Because of the potential severities regarding the primary consequences of accidents, the concept of safety is a term that has significance in the air transport industry (Janic, 2000). The application of machine learning is used to classify most fatal accidents' survivor/non-survivor passengers. The classification includes the factors such as: aircraft (A/C) type, the time period of the accident, total passenger and affected people, flight phase, the duration of the flight, probable cause, and primary definitions. The presented paper improves the literature by classifying survivor/non-survivor passengers. Logistic regression and discriminant analysis are applied to use multivariate statistical analyses for making a comparison. These analyses use machine learning approaches to show the algorithms' robustness. Additionally, they differentiate between the previous papers, the phase of flight, the primary cause, and total passengers determined as the most effective factors according to machine learning and multivariate statistical models for classifying the accidents' survivor/non-survivor passengers.

Materials and Methods

The study includes the 100 accidents with the highest number of deaths. In these 100 accidents, the human, technical, and sabotage/terrorism factors comprise the three common causes of accidents to make an accurate assessment. These 100 accidents include these three basic causes with accurate percentages such as all-time accidents. Additionally, while the 100 accidents with the highest number of fatalities are taken, it has been seen that the accident rates of all time should also be considered. The all-time accidents rate classify as; 75% human factor, 20% technical, and 5% terrorism/sabotage (Plane Crash Info, 2021). The reason why the taken accident number determines as 100 shows that the six selected variables can analyze most accurately to show all the accidents' reasons. Additionally, the high number of deaths in accidents and the use of aircraft with high passenger capacity in these accidents are of great importance in determining the ratio of survivor and non-survivor passengers.

The difference between this study and the other papers is the application of the factors determined by Plane Crash Info (2021) which is a commonly known website for accident analysis. Additionally, machine learning figures out potential factors; aircraft type, distance, the phase of flight, the primary cause, the number of total passengers, and time period play a significant role in evaluating survivor and non-survivor passengers of the most 100 fatal accidents. All these classifications are obtained by the Bureau of Aircraft Accident Archives (2021), and Plane Crash Info websites (2021) as mentioned in the introduction section.

Machine Learning Algorithms

These potential factors are used in several statistical and machine learning (ML) algorithms. The most 100 fatal accident datasets examine the discriminant analysis and logistic regression models in multivariate statistical analysis. In the variable selection method and the cross-validation, the classical statistical techniques are unlikely to estimate the non-linear models that can provide more accurate classification performance in evaluating survivor and non-survivor passengers. ML methods can show more accurate classification performance. ML can define the algorithm that can learn from experience. ML includes three types of learning procedures: supervised, unsupervised, and reinforcement learning. This study focuses primarily on supervised learning algorithms. There isdocumented information on the categorized output in this learning method. Artificial Neural Networks (ANNs) and Decision Trees (DTs) are utilized in this study.

Dimension reduction of feature vector has importance to tune the model complexity according to the statistical learning theory (Bozdogan, 2000; Kocadagli & Langari, 2017). There are many approaches for dimension reduction of feature matrices. For instance, forward selection, backward elimination, stepwise selections, or some transformation techniques such as Principal Component Analysis (PCA) are the dimension reduction methods in the literature. ML algorithms are utilized with k-fold and leave-one-out cross-validation and PCA-based dimension reduction. The principal component analysis provides the weights needed to obtain the new feature that explains the variation best in the dataset. This new variable that includes weights is called the First Principal Component. Moreover, to tune the complexity of the model automatically, the cross-validation methods such as k-fold and leave-one-out are used. The best independent variables specify the most 100 fatal accidents' importance about survivor passengers. ANN and DT models use features obtained from PCA. Before starting the analysis, the components are obtained by using PCA to avoid scaling problems; the dataset is normalized, then the cross-validation type is chosen as k-fold or leave-one-out. Min-max normalization procedure trains the models by using PCA's components as inputs. Min-max normalization formula is given as follows (Inan & Gokmen, 2021):

$$x_i^* = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \quad i = 1,2,\ldots,100 \qquad (1)$$

Classification and Regression Tree Model

DT Classifiers use the Classification and Regression Tree (CART) model. It comprises a univariate binary decision hierarchy. The 'Tree' begins with the "root," and consists of nodes, branches, and leaf nodes. Internal node is expressed as a binary test on a unique variable, with branches demonstrating the consequence of the test; however, each leaf node shows class labels. CART starts by choosing the best variable for dividing the data into two groups at the root branch, which is as homogeneous as possible, and this dividing process repeats for each branch. Ongoing 'purity' calculations are implemented to specify which of the (remaining) properties are best to divide. The Gini index uses CART. Gini index is an algorithm that measures a distribution among affection of specific-field with the result of instance. Gini index is an entropy minimization algorithm that is used for impurity. The nodes are divded according to the smallest Gini index. CART recursively enlarges the tree from the root. Then, the prunes back the large tree (Chong et al., 2005).

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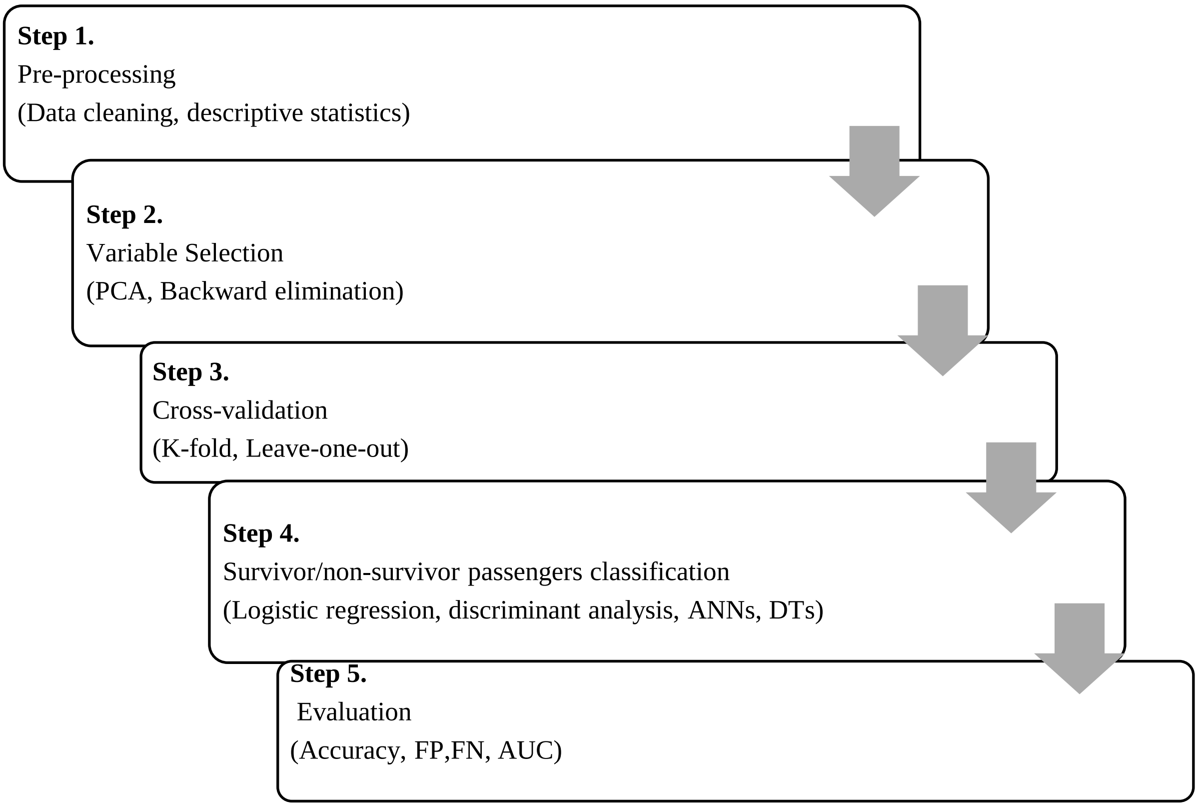
In the training of DTs, the robust models use the variable selection procedure, various kernels such as complex, medium, and simple. ML techniques use ANN, and human brain inspiration creates ANN. The brain forms lots of neurons, and synapses provide the interconnection between the neurons. Perceptrons use ANN's neurons model. This model includes inputs or outputs, and inputs include synaptic weight. In the simplest form, output is a value equal to the sum of the weighted inputs. In other words, activation or transfer function can be applied by a perceptron, like a linear sigmoid; and a hyperbolic tangent function. ANNs include hidden layers. These layers conduct a connection between an input and an output layer. The basic approach used to train networks is backpropagation (Alpaydin, 2014; Burnett and Si, 2017 May; Matlab R, 2020a). ANNs train in stopping criteria of MSE or cross-entropy, and there are different gradient-based algorithms: Scaled Conjugant Gradient (SCG), Gradient Descent with Momentum (GDwM), and Levenberg Marquardt (LM) (Kocadagli, 2015). The framework for accidents survivor/non-survivor passengers classification can see in Figure 1.

Figure 1
The Flowchart that Defines the Methodology



Receiver Operating Characteristic Curve

First, the Receiver Operating Characteristic (ROC) curve (receiver operating characteristic curve) defines a graph to show the classification model performance at all classification thresholds. This curve plots two parameters: True Positive Rate (TPR) and False Positive Rate (FPR). Secondly, AUC is scale-invariant. It measures how the predictions are ranked, rather than their definite values. AUC is a classification threshold invariant. It measures the predictions about a model's quality, irrespective of what is chosen for the classification threshold. The model performance is evaluated by using Area Under Curve (AUC), accuracy ratio, false-positive (FP), and false-negative (FN) rates. These are classified as follows: AUC measures the entire two-dimensional area underneath the entire ROC curve, and it provides an aggregate measure of performance across all possible classification thresholds. Accuracy Ratio is the percentage of correct predictions for a given dataset. The FP rate calculates the ratio between negative events wrongly categorized as positive, and the total number of actual negative events. The FN rate is the probability that a true positive will be missed by the test.

The primary contribution of this study is related to determining the affecting factors of the most fatal 100 accidents: aircraft type, distance, phase of flight, primary cause, number of total passengers, and time period by classifying survivor/non-survivor passengers. The research objective aims to contribute to the literature determining the importance of safety in aviation for classifying the accidents' survivor/non-survivor passengers.

Sample of Data

Determined as one of the three types of safety concepts with its cultural structure, the human factor approach (including organizational factors) includes the identification of the conditions which assist safe behaviors at different levels of the organization. This approach consolidates inside the organization level of the companies as a robust factor has been already developed severely in the technical and management concepts (ICSI, 2021). Safety culture includes the technical factors that provide continuous and sustainable qualities of an experience. It covers the current time period and their physical condition during that time period. They usually include the parameters that direct the experiences which belong to the specific degrees of sensorial details, such as navigation and the related systems (Santos-Reyes & Beard, 2002). The third and the last type of safety culture includes the factor of terrorism/sabotage that covers the intentional intervention during the flight phase. The meaning of sabotage diversifies from abduction, because terrorism accepts hijacking as unlawful control (intervention) of the aircraft (Security and Facilitation, 2020). In the classification of most fatal accidents, only the cause of one accident is diversified from terrorism and sabotage because the cause of the accident covers the intentional action of the pilot defined as only sabotage. Table 1 shows the distribution of these features.

Table 1
The Features for the Distribution

		N	%
Aircraft Type	Airbus	15	15.0
	Boeing	44	44.0
	Other	41	41.0
Distance	Short-Haul Flights	50	50.0
	Medium-Haul Flights	22	22.0
	Long-Haul Flights	28	28.0
The Flight Phase	Flight	33	33.0
	Landing	36	36.0
Time Period	Take-Off	31	31.0
	6-12 hours	32	32.0
	12-18 hours	27	27.0
	18-24 hours	24	24.0
	24-06 hours	17	17.0
Primary Cause	Human Factor	65	65.0
	Technical	25	25.0
	Terrorism/Sabotage	10	10.0
Survivor Numbers	Non-Survivor Passengers	78	78.0
	Survivor Passengers	22	22.0
		Mean±SD	**Med (Min-Max)**
Total Passenger Numbers		200.6±65.1	173 (133-524)

Note. **SD=** Standard Deviation, **Med=** Median, **Min=** Minimum, **Max=** Maximum

The datasets shown in the distribution of the features datasets support the machine learning approach, so machine learning applies to the most fatal 100 accidents. Table 2 shows the selected six variables of this dataset. These variables affect the number of survivors. In the scope of supervised learning, the model training procedure comprises two types of variables: dependent as output and independent as input. The dependent/output variable is the surviving and non-surviving passengers. The independent variables/inputs are the aircraft type, distance, the phase of flight, the primary cause, total passengers, and time period. In summary, Table 2 shows the dependent/output and independent/input variables classification.

Table 2

The Selected Variables

Independent Variables	
Aircraft Type (1:airbus, 2:boeing, 3:other)	Primary Cause (1:Human factor, 2:Technical, 3:Terror/Sabotage)
Distance (1:short haul, 2:medium haul, 3:long haul)	Total Passenger Numbers
Flight Phase (1:flight, 2:landing, 3:take-off)	Time Period (1: 6-12, 2:12-18, 3:18-24, 4:24-06)
Dependent Variable	
Survivor Passenger Number (0/1)	

Findings and Discussions

The findings revealed the importance of the study by adding a discussion to define the practical implications more clearly. These findings also aim to show the contribution to the science of the study. Table 3 shows the performance of logistic regression and discriminant models. Table 4 shows the output of logistic regression which contains odds ratios. Finally, Table 5 shows the classification performance of ANN and SVM models. To assess the importance of independent variables, the normalized importance of independent features reveals the results.

The limitation of this study is the sample size covering the most fatal 100 accidents, and the specific affecting factors as independent variables. Therefore, the analysis of the most fatal 100 accidents can be a reference to determine the causes of all-time aviation accidents with the selected variables as seen in the Bureau of Aircraft Accident Archives (2021), and plane crash info (2021) websites. Additionally, this analysis examines the significant factors that may cause the accident. The findings reveal how this study adds novel contributions to the current body of knowledge regarding aircraft accidents – specifically, Table 2 depicts dependent and independent variables that provide a unique perspective on this issue.

Model Estimation

The analysis considers various multivariate statistical and ML methods to predict robust models that provide high classification accuracy, and low false positive/negative rates for determining survivor and non-survivor passengers on the most 100 fatal accidents. During the model estimation, the methods are trained ten-fold. The methods include: leave-one-out cross-validation, and PCA feature selection procedures. The learning algorithms are written in MATLAB R. (2020a). The model outcomes of all the multivariate statistical and machine learning methods are explained in the following sections.

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Logistic Regression and Discriminant Analysis

This part of the study includes the results of logistic regression and discriminant analysis to show the contribution of independent variables on the survivor/non-survivor passenger classification of the most 100 accidents. The backward Wald variable selection with ten-fold and leave-one-out procedures is used to estimate logistic regression models. AUC, accuracy ratio, false-positive, and false-positive rates assess the performances of estimated models. Table 3 shows the logistic regression and discriminant analysis results. The logistic regression divides into three models, and the discriminants divide into two models as seen in Table 3.

Table 3

The Models' Performance

Method	Models	#Input	NSV	AUC	Acc.	FP	FN	Selected Variables
Logistic Regression Model	**Model 1** Backward No cros-val.	6	3	0.580	0.780	0.064	0.773	Total passenger numbers, Flight phase, Primary cause
	Model 2 Backward with 10- fold	6	3	0.560	0.770	0.064	0.818	Total passenger numbers, Flight phase, Primary cause
	Model 3 Backward with Leave-one-out	6	3	0.560	0.770	0.064	0.818	Total passenger numbers, Flight phase, Primary cause
Discriminant Model	**Model 4** (K-fold)	6	3	0.690	0.720	0.054	0.568	Total passenger numbers, Flight phase, Primary cause
	Model 5 (Leave-one-out)	6	3	0.670	0.710	0.070	0.581	Total passenger numbers, Flight phase, Primary cause

Note. **NSV=**Number of selected variables; **Acc=**Accuracy Ratio, **FP=**False Positive; **FN=**False Negative

A significance level of 0.05 indicates a 5% chance of concluding that an association exists when there is no actual association in the logistic regression model. The selected variables in the five models are found statistically significant ($p<0.05$), and the first three logistic regression models are also suitable interpretations according to Hosmer-Lemeshow test statistics ($p>0.05$). The Hosmer-Lemeshow test is a goodness-of-fit test for logistic regression. Small p-values (under 5%) mean that the model is not a good fit. As can be seen from the results, it provides the assumption of the equality of variance-covariance matrices (Box-M, $p < 0.001$), and the selected variables are found significant (Wilks' Lambda $p<0.001$) in discriminant analysis. The bBox-M test is a multivariate statistical test used to check the equality of multiple variance-covariance matrices. Wilk's lambda tests are related to which variable contributes significance in discriminant function. Table 4 shows that five models consist of total passengers, the phase of flight, and the primary cause. Five models' accuracies find above >70%. The first logistic regression model

(M1) has the highest accuracy (0.780) in addition to the low FP (0.064) and FN (0.773). Table 4 also shows the logistic regression model's odds ratios and *p* values with selected variables. The number of total passengers increases the number of survivor passengers 1.014 times more than non-survivor passengers. The landing phase accidents increase the number of surviving passengers 6.479 times more than in the flight phase. The take-off phase accidents increase the number of survivor passengers 9.674 times more than the flight phase. The accidents that occurred from technical factors have a lower number of survivor passengers by 9.709 (1/0.103) times more than the human factor.

Table 4

Odd Ratios for the Independent Variables

Independent Variables	Total Passenger Numbers	Flight Phase (landing)	Flight Phase (take-off)	Technical Cause	Terrorism/Sabotage Cause
OR (p)	1.014 (0.003)	6.479 (0.049)	9.674 (0.022)	0.103 (0.016)	0.000 (0.998)

ANNs and DTs' Estimation Results with PCA Dimension Reduction

In the ML approach, the variable selection procedure automatically runs during the training of ANNs and DTs. Before the training segment, it sets initial tunings. Classification accuracies, false positives, and FN ratios overtraining, tests, and overall datasets are used to choose the models. This is done to obtain the best performance at the end of the training and variable selection phase. During the variable selection, the PCA is used to reduce dimensions and PCA results show that six parameters are adjusted, with three dimensions having 69.5% variance explanation rate. The first dimension includes the number of total passengers and the primary cause. It is called the capability component (C1), the second dimension includes distance and time period called the geographical component (C2), and the third dimension includes the type of aircraft called the qualification component (C3). The normalized component scores are obtained from PCA. They are input variables in ANNs and DTs. According to ANNs and DTs' results, the best-estimated models give accuracy ratios, false positives, and FN rates to measure performance in Table 5.

Table 5 shows that the models have better performance than logistic regression and discriminant models by considering all the performance criteria. When the machine learning methods evaluate, the best models with selected variables with PCA have a higher performance than the full models with all the independent variables according to the performance measurements.

Table 5

The Classification Performance of ANN and SVM Models

Methods	Procedure	#Input	AUC	Acc.	FP	FN	Selected Variables
ANNs (trainlm, mse)	PCA	3	0.870	0.880	0.116	0.142	C1, C2, C3
	Full Model Feature Selection	6	0.866	0.841	0.020	0.643	All variables in Table 2
DTs (complex tree)	PCA	3	0.900	0.910	0.084	0.118	C1, C2, C3
	Full Model Feature Selection	6	0.820	0.870	0.078	0.304	All variables in Table 2

The ANN model estimates weights to reveal the importance of independent variables for the survivor and non-survivor passengers. According to independent variables' normalized importance over the best full model, the top three variables above 50% normalizing importance are the primary causes. The number of total passengers and the phase of flight supports the logistic regression and discriminant models.

Conclusions and Recommendations

In this study, the causes of aircraft accidents comprise six variables. These variables include aircraft type, distance, the flight phase, the primary cause, total passenger numbers, and time period, which are used to classify survivor/non-survivor passengers. In the literature review, the primary causes of the accidents are categorized by three factors: human, technical, and terrorism/sabotage. These factors define the concept of safety and how the safety concept is affected in most fatal accidents. The statistical and ML models assess potential factors for the six selected variables. The findings show the role in evaluating surviving and non-surviving passenger numbers of the most 100 fatal accidents by using various statistical and ML algorithms. The multivariate statistical analysis examines the most 100 fatal accident datasets. This analysis also examines the variable selection method by applying cross-validation.

The findings support the conclusion that technical factors contributing to aircraft accidents are more costly than human factors; specifically, in accidents with surviving passengers, and in which human factors were the cause, there are typically 9.709 times more surviving passengers than in accidents caused by technical factors. Therefore, the accidents that occurred by technical factors are more hazardous and difficult to recover from than the accidents caused by human factors. Furthermore, the accidents that happened in the phase of flight have decreased the number of survivor passengers 6.479 times more than the landing phase, and 9.674 times more than the take-off phase. Finally, the one unit change in the total passenger numbers has increased the survivor passenger numbers 1.014 times. According to the machine learning results, these parameters are found to be above 50% importance. The algorithms integrated with PCA have better performance than multivariate statistical models. So, the dimensions obtained from PCA called capability, geographical, and qualification have a decisive effect on the surviving passenger numbers. The machine learning algorithms have better performance than the multivariate statistical models in classifying the surviving and non-surviving passengers in

100 most fatal accidents due to having high accuracy and AUC, low FP, and FN. These factors, which are important in the classification of surviving-non-surviving passengers' status, will support aviation experts in their flight planning.

Recommendations

All-time aviation accidents from different perspectives can be analyzed in future research. These studies can classify the flight phases and flight types to determine danger levels. Also, this research can be continued with much more comprehensive accident datasets and utilize various ML approaches such as Support Vector Machines by hybridizing with different variable selection methods (Genetic Algorithms, Particle Swarm Optimization, etc.) to conduct a more detailed analysis.

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