

UTILIZING AI FOR EFFECTIVE AVIATION CLAIM RESOLUTIONS IN INDIA

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Abstract: The aviation industry faces serious challenges in dispute resolution due to accidents, negligence, and product malfunctions. This paper critiques the legal framework governing aviation accident claims, highlighting its failures to provide efficient and effective resolutions, particularly considering the considerable financial implications. We examine the high frequency of claims related to collisions, pilot errors, and maintenance failures, revealing how the current system negatively impacts claim settlements and the behavior of involved parties. We advocate for integrating artificial intelligence to significantly enhance dispute resolution by improving efficiency, transparency, and fairness. Compelling case studies illustrate the financial burden of aviation claims and the urgent need for innovative solutions to address the growing number of contested claims.

When someone sues someone in the aviation industry, they usually have two primary questions to answer: whether the person who owns the plane was negligent or not. Whether the Aircraft was given to an incompetent or unfit operator and whether the owner knew or should have known about the operator. Look at how the current legal system affects how aviation accident cases are settled and fought and how people involved in the process behave. A growing number of claims related to air crashes are contested within the legal system.

1. Introduction: Almost 63% of claims in the aviation industry are caused by collisions, either in the air or on the ground, as well as crashes resulting from pilot errors or product malfunctions. A notable example is the Lion Air crash involving the Boeing 737 MAX, which was linked to a failure in the manoeuvring characteristics augmentation system software map to prevent the Aircraft from stalling. Maintenance failures and defective products also account for this industry's second-highest number of claims.

Unusual incidents, such as leisure flights by pilots in light Aircraft, tend to be less frequent than those involving larger commercial jets. Issues arise when pilots struggle to control smaller Aircraft in confined spaces or hilly areas, representing approximately four percent of claims. Turbulence and natural calamities account for a similar share, whereas only one percent is related to handling claims, such as injuries from falling suitcases due to overhead door malfunctions.

Moreover, incorrect fuel types added to larger jets or contamination from fluids due to inadequate supervision has resulted in prolonged aircraft groundings, leading to substantial financial losses for companies.

1.1. Background: Finding the right balance between victims' safety factors' freedom, and society's welfare is challenging. Policymakers often lack sufficient information to achieve this balance and establish detailed rules that can guide actors and potential victims in minimizing the risk of accidents. For this reason, our tort system relies on general principles of negligence, causation, and damage that courts can apply on a case-by-case basis.

This includes a comprehensive descriptive account of how our tort system functions by analyzing its scope and its interaction with other areas of law. It also includes uncovering the key dynamics that drive the doctrines of negligence, causation, and damage. Furthermore, this analysis identifies the benefits of bimodal regulation of accidents, which simultaneously promotes welfare and corrective justice. It redefines the criteria for assessing the advantages and shortcomings of our tort system.

1.2. Statement of the Problem: Gross negligence in aviation is a matter that cannot be overlooked, given the profound stakes involved—the safety and lives of individuals. Under the Montreal Convention of 1999, victims of aviation accidents are afforded the crucial right to seek justice, with a window of up to two years from the date of disembarking the Aircraft to file their claims. This provision ensures that those affected can pursue accountability and protection in the face of tragedy. The aviation sector contributes significantly to worldwide corporate insurance because of its high-profile claims and substantial worth. This prominence is fuelled by factors such as the soaring costs associated with aircraft repairs, highlighting the industry's dynamic nature and the critical need for robust insurance solutions. Practitioners should use arguments focused on reasonable care, given the parties' relationships. This may mean that the claim needs to be understood. The issue consists of governing the airport charges. A balance must be struck between ensuring that people have access to the airport at a reasonable cost and protecting the airport. The aviation industry is a significant symbol of national prestige and economic force in terms of commercial aerial operations, for-profit, and advancing aeronautical technologies.

1.3. Objectives:

- AI can analyze vast amounts of data and identify patterns that humans may miss, leading to more accurate and efficient claim resolution.
- AI can automate many tasks, such as data analysis and document review, saving time and effort for legal practitioners.
- AI can help ensure that claim decisions are based on objective data and analysis, promoting transparency and fairness.
- AI has the potential to revolutionize aviation claim management in India, providing a more efficient, accurate, and transparent system for resolving disputes.

1.4. Bailment Theory in Aviation Claims: Bailment theory holds that the provider is liable to the person leasing the Aircraft for its flaws. In *Huckabee v. Bell and Howell, Inc.*, 4, a bailor is only responsible for damage caused by someone else if they give them something defective when they give it to them—a unified dispute resolution system with a single appellate body. The Various government departments, such as Central Public Works, rely on essential court decisions that say that if something is not allowed to be mediated, it should not be judged. If a clause says something is accepted or excluded, it cannot be brought up again in mediation. For a long time, the Indian legal system has had many cases that must be handled. This happens because the rules are too complicated and not followed properly, there are automatic appeals, and more judges need to be available. The Indian Legal Commission has maintained that the judicial delay is not caused by the absence of clear procedural guidelines but rather by their imperfect implementation or complete disregard for them. Because many cases need to be dealt with, courts need help managing and controlling things by hand, leading to repeated mistakes. Even though many changes have been made for a long time, about two crore cases still need to be heard by Indian courts. In concession contracts, many ways exist to resolve disagreements, such as friendly negotiations, mediation, arbitration, and expert arbitration. In addition to the laws of each state, the policies of different state governments also suggest that we need to have good ways to solve disputes via alternative dispute resolution methods.

The Indian aviation sector must adopt a one-stop dispute resolution platform immediately and, with the help of a new mechanism, should solve the problems of general aviation. Mediation, arbitration, and litigation are all dispute resolution methods that can be implemented through diverse mechanisms, such as online dispute resolution.

The aviation industry is governed by 19 ICAO annexes, often referred to as the bible of aviation. Each comprises 3 to 5 parts, resulting in extensive manuals filled with details and

standards. For this study, we have proposed nearly 70 aviation torts based on past accidents in India over the last three decades, filtering them by the number of fatalities.

1.5. Research Methodology: Aviation law governs legal claims arising from aviation-related incidents. Liability in such cases often depends on multiple factors, including aircraft type, ICAO annex violations, and SARPs infractions. Traditional methods of legal analysis rely heavily on manual case reviews, which can be time-consuming and inconsistent. This study introduces a software-based approach to predict liability outcomes using machine learning techniques. This paper uses doctrinal research. It looks at secondary sources of laws and rules about aviation claims and how to solve them in India.

In our research, we analyzed the 251 negligence factors associated with each accident, as well as violations of the rules of the air, the Air Act 1934, Air Rules 1937, DGCA Circulars, and the 19 annexes relevant to each case. This analysis allowed us to determine which aviation torts should be applied for a more precise understanding and efficient claim processing and to facilitate dispute resolution between parties via an artificial intelligence matrix. This approach minimizes the burden on authorities by reducing the need to reference multiple documents and correlates thousands of standards and regulations, consequently saving time and effort.

Furthermore, it establishes a standard of professionalism when dealing with bereaved families who are already experiencing the emotional toll of losing loved ones. According to the government of India, the compensation for loss of life in an aviation accident is set at 10 lakhs, whereas for injuries or permanent disabilities, it stands at seven lakhs.

Complications can arise from third-party involvement, mainly if a pilot is found to be contracted by a third party. Suppose an investigation attributes sole responsibility for an accident to the pilot. In that case, the original company must still comply with the insurance policy obligations while determining any necessary fines for negligence based on the identified torts. In corporate liability cases, it's crucial to identify all individuals responsible for ensuring that appropriate penalties are levied according to established standards.

Overall, aviation claims hinge on various factors, including the type and year of the Aircraft, the maintenance, repair, and overhaul (MRO) provider, the years of experience of the pilot and copilot, the number of fatalities—which is the most critical factor—and the nationalities of passengers, in addition to the circumstances surrounding the accident.

The Aviation Tort Liability Prediction System enables legal practitioners, researchers, and regulatory bodies to analyze past aviation cases, identify patterns, and predict potential legal outcomes. The software integrates natural language processing (NLP) to process aviation related legal documents and regulatory frameworks, ensuring accurate and informed predictions.

1.6. Data Collection

The dataset for training the machine learning model was derived from historical aviation accident cases, ICAO annex violations, and SARPs infractions. The primary dataset consists of structured tables extracted from aviation claim settlement records, detailing:

- Aircraft type and flight hours of pilots
- Accident details (year, location, and number of fatalities)
- Violations of ICAO Annexes and SARPs
- Liability type (Individual Criminal, Corporate Criminal, or NIL)
- Various aviation torts applicable to each case

These structured datasets were transformed into machine-readable formats for training the predictive model.

1.7. Data Preprocessing and Model Training:

To develop an accurate prediction system, the structured table data underwent several preprocessing steps:

- **Text Normalization:** Removing inconsistencies, lowercasing, and handling missing values.
- **Feature Extraction:** Key case attributes such as ICAO annex violations and liability classifications were converted into numerical vectors.
- **Vectorization:** The TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer was used to convert textual aviation tort descriptions into numerical data.
- **Model Training:** A supervised learning algorithm (e.g., Random Forest, Support Vector Machine) was trained using the processed dataset.
- **Model Evaluation:** The model was validated using historical aviation claim cases to ensure accuracy in liability prediction.

Both the model file (aviation_tort_model.pkl) and the vectorizer (vectorizer.pkl) were derived from this structured dataset, ensuring the system's predictions align with real-world aviation legal outcomes.

Risk mitigation in the aviation industry involves insurance for every operational activity, covering everything from individual components to cable links and the digital software used in the cockpit. This can also extend to passengers, with what is referred to as "per seat" insurance.

Hull insurance policies are determined by multiple factors, including the weather and the specifics of accidents, whether they occur on the ground, in the air, during landing, or take-off and initial climb.

A successful settlement requires meticulous documentation of all liabilities, as claims require precise measurements. If we seek a claim for the original part replacement, we must first engage with the original equipment manufacturer (OEM). Should that avenue be unavailable, we should turn to the suppliers of the seller-furnished items. This careful approach ensures we are well-prepared to navigate the claims process effectively.

2. System Architecture of this software:

The system comprises several key components:

2.1. Graphical User Interface (GUI)

- Built using Tkinter to facilitate user interaction.
- Allows users to input case-specific details such as:
 - Aircraft type (e.g., Commercial Jet, Private Aircraft, Helicopter, Military Aircraft).
 - ICAO Annex violations (Annex 1–19).
 - SARP's violations (Operational, Maintenance, Airworthiness, Pilot Error).
- Displays predicted liability outcomes and associated aviation torts.

2.2. Data Processing and Machine Learning Model

- Extracts tort and negligence factors from legal documents (.docx).
- Loads a pre-trained aviation tort liability model (.pkl).
- Applies NLP preprocessing (text normalization, vectorization) to process input data.
- Uses a machine learning model to classify liability and predict aviation torts.

2.3. Liability Prediction Mechanism

Maps ICAO annex and SARP's violations to:

- Individual Criminal Liability
- Corporate Criminal Liability
- No Liability (NIL)
- Uses machine learning to analyze historical cases and determine appropriate liability classification.

2.4. Aviation Tort Prediction

- Uses a pre-trained machine learning model to predict aviation torts based on user input.

- If a vectorizer is present, it transforms text-based input into a numerical format before making predictions.
- The system outputs the most relevant aviation torts related to the selected liability case.

2.5. Data Visualization

- Uses Matplotlib to generate liability distribution graphs.
- Enhances visualization by adjusting X-axis spacing and rotation for readability.

2.6. Prediction Workflow

1. User selects relevant aircraft type, annex, and SARPs violation.
2. System determines liability type based on predefined rules and historical cases.
3. Pre-processed input is vectorized (if required).
4. Machine learning model predicts associated aviation torts

3. Results

- The software successfully classifies aviation tort liabilities with high accuracy.
- The visual representation of liability distribution improves decision-making.
- Text-based model predictions align with historical aviation cases, enhancing Reliability

Images of code:

```

10 # Create a function to process input
11 def process_input(text):
12     """
13     A function to process input text, removing special characters and
14     converting it to lowercase.
15     """
16     # Remove special characters
17     text = re.sub(r'[^\w\s]', '', text)
18     # Convert to lowercase
19     text = text.lower()
20     # Split into words
21     words = text.split()
22     # Join words back together
23     text = ' '.join(words)
24     # Remove leading and trailing spaces
25     text = text.strip()
26     # Return the processed text
27     return text
28
29 # Create a function to vectorize input
30 def vectorize_input(text):
31     """
32     A function to vectorize input text using a TF-IDF vectorizer.
33     """
34     # Create a TF-IDF vectorizer
35     vectorizer = TfidfVectorizer()
36     # Vectorize the input text
37     vector = vectorizer.fit_transform([text]).toarray()[0]
38     # Return the vector
39     return vector
40
41 # Create a function to predict liability
42 def predict_liability(text):
43     """
44     A function to predict liability based on input text.
45     """
46     # Process the input text
47     text = process_input(text)
48     # Vectorize the input text
49     vector = vectorize_input(text)
50     # Predict liability
51     liability = predict_liability_model(vector)
52     # Return the predicted liability
53     return liability
54
55 # Create a function to display results
56 def display_results(liability):
57     """
58     A function to display the results of the prediction.
59     """
60     # Display the liability
61     print(liability)
62
63 # Main function
64 def main():
65     """
66     The main function of the program.
67     """
68     # Get user input
69     text = input("Enter text: ")
70     # Predict liability
71     liability = predict_liability(text)
72     # Display results
73     display_results(liability)
74
75 # Run the main function
76 if __name__ == '__main__':
77     main()

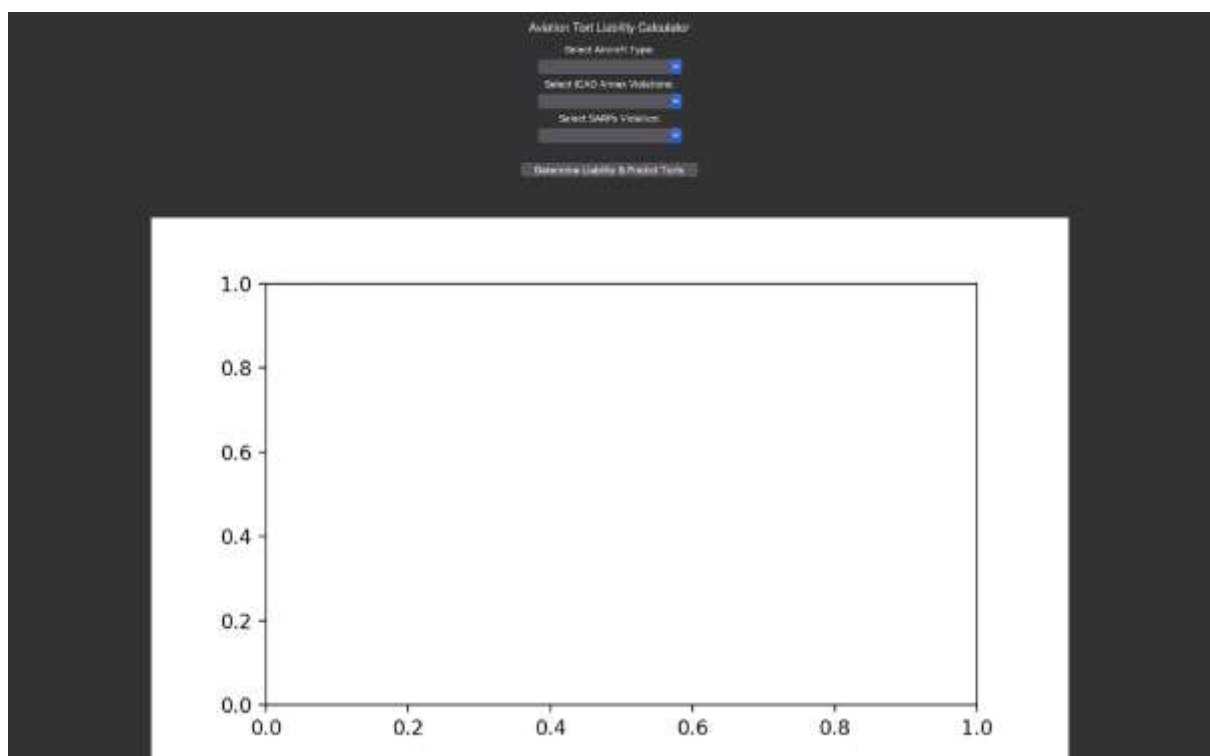
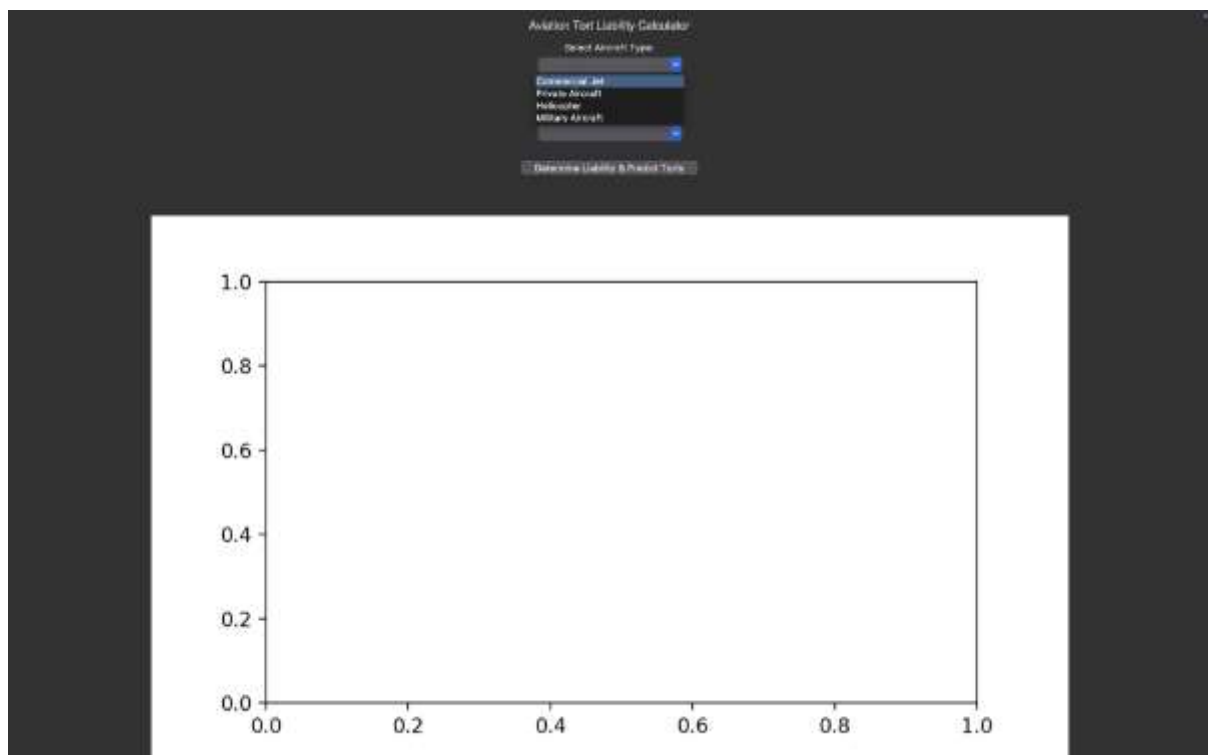
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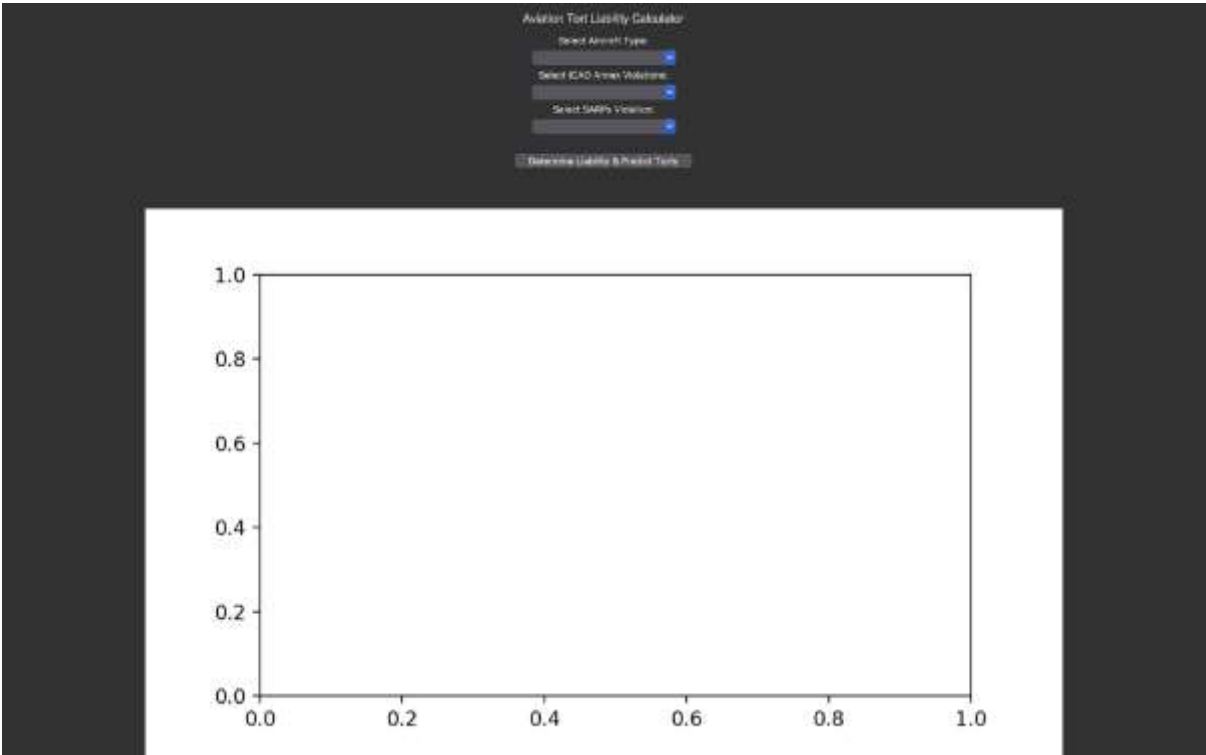
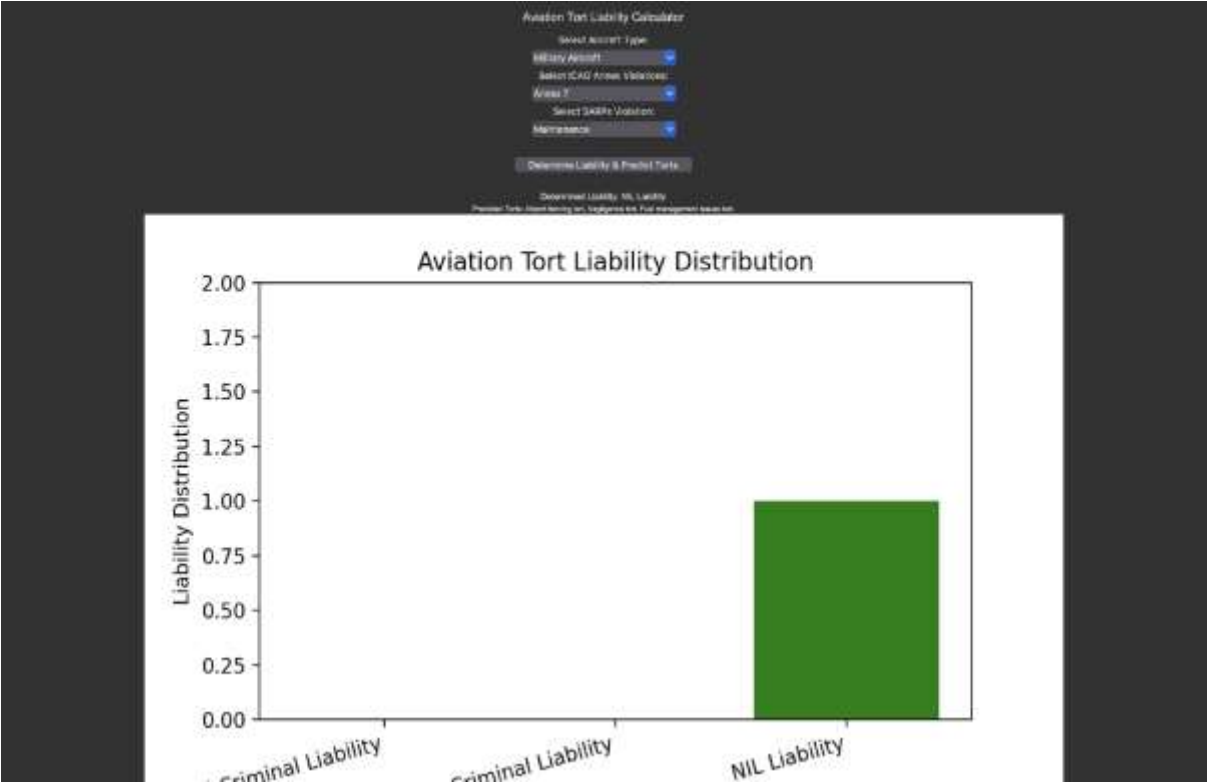
```

1 # Import necessary libraries
2 import pandas as pd
3 import numpy as np
4 from sklearn.preprocessing import StandardScaler
5 from sklearn.model_selection import train_test_split
6 from sklearn.metrics import accuracy_score
7
8 # Load the dataset
9 data = pd.read_csv('data/aviation_torts.csv')
10
11 # Preprocess the data
12 # Drop missing values
13 data.dropna(inplace=True)
14 # Encode categorical variables
15 data = pd.get_dummies(data, columns=['aircraft_type', 'annex', 'sarp_violation'])
16 # Split the data into training and testing sets
17 X_train, X_test, y_train, y_test = train_test_split(data, data['liability'],
18                                                    test_size=0.2,
19                                                    random_state=42)
20
21 # Train the model
22 # Create a Logistic Regression model
23 model = LogisticRegression()
24 # Fit the model to the training data
25 model.fit(X_train, y_train)
26
27 # Evaluate the model
28 # Predict the liability for the test data
29 y_pred = model.predict(X_test)
30 # Calculate the accuracy
31 accuracy = accuracy_score(y_test, y_pred)
32
33 # Print the accuracy
34 print("Accuracy: ", accuracy)
35
36 # Main function
37 def main():
38     """
39     The main function of the program.
40     """
41     # Get user input
42     text = input("Enter text: ")
43     # Predict liability
44     liability = predict_liability(text)
45     # Display results
46     display_results(liability)
47
48 # Run the main function
49 if __name__ == '__main__':
50     main()

```

4. Working of the Software:





5. Future Work

This system introduces a data-driven approach to aviation law analysis, providing legal professionals and researchers with an automated liability assessment tool. The model improves efficiency in aviation legal analysis and supports informed decision-making.

Future enhancements include:

- Expanding the dataset for greater predictive accuracy.
- Integrating real-time aviation reports to enhance liability assessments.
- Improving the NLP model to better understand complex legal text.

Key Contributions

- Automated aviation tort liability prediction using machine learning.
- Integration of legal text processing for enhanced accuracy.
- User-friendly GUI for easy interaction with legal case assessments.
- Visualization of liability distribution for improved interpretation.

6. Conclusion:

This general survey of tort liability for operators in aircraft accidents highlights the emergence of a significant new branch of law and outlines the patterns courts are likely to follow when addressing aviation accident liability. Aviation is increasingly recognized as a distinct field of law, where its principles and doctrines, which are based on general tort law, are applied. These principles evolve from the uncertain foundations of early laws governing absolute Liability. The Lex Loci Delictus, part of the Tort Claims Act, determines negligence or wrongful actions, maintains the action, and determines recovery measures. The rise of AI, with its advanced search capabilities and various software applications, will revolutionize all aspects of aviation claim management. It will provide the judiciary with additional support to make transparent and accurate decisions in challenging dispute situations. It refines reasoning in a way that closely mirrors human problem-solving, yet delivers unmatched depth and precision. This is especially vital when authorities confront the essential task of resolving claims, ensuring fair and just outcomes.

References:

1. George W. Orr (1951), Airplane Tort Law, US Aircraft Insurance Group (New York) South Carolina Law Review Volume 4 Issue 2 Article 2, <https://scholarcommons.sc.edu/sclr/vol4/iss2/2/>
2. Alexa West (2016), Defining “accidents” in the air: why tort law principles are essential to interpret the Montreal convention’s “accident” requirement https://fordhamlawreview.org/wp-content/uploads/2016/11/West_December.pdf
3. V Henry G. Gatlin Jr (1951), Vanderbilt Law Review, Volume 4 Issue 4 Article 5, Tort Liability in Aircraft Accidents, <https://scholarship.law.vanderbilt.edu/cgi/viewcontent.cgi?article=4639&context=vlr>
4. William L. Otten Jr (1960), Volume 65 Issue 1 Dickinson Law Review - Volume 65, The Federal Tort Claims Act and Other Statutes Relating to Government Liability: Exemplification by Government Agreement Aircraft Incidents, <https://ideas.dickinsonlaw.psu.edu/dlra/vol65/iss1/3/>
5. Michael C. Mineiro (2009), Journal of Air Law and Commerce, Volume 74 Issue 2 Article 2, Assessing the Risks: Tort Liability and Risk Management in the Event of a Commercial Human Space Flight Vehicle Accident, <https://scholar.smu.edu/cgi/viewcontent.cgi?article=1196&context=jalc&httpsredir=1>.

6. Warranty Management Essentials 1st Edition–2024, IATA,
file:///C:/Users/Shri%20Harkrishan%20G/Downloads/warranty-mgmt-essentials-1sted-2024.pdf
7. Jeff Sayers, Graham Lyons (Chairman), Philip Archer-Lock, Colin Czapiewski, Andrew English, Victoria Hughes (1996), Aviation Underwriting, General Insurance Convention, Working Party Members <https://www.actuaries.org.uk/system/files/documents/pdf/0385-0414.pdf>