## **PREVENTION OF AIRLINE CRASH DUE TO BIRD STRIKE USING MACHINE LEARNING ALGORITHS**

|  |  |  |
| --- | --- | --- |
| Keerthi alekya Muppuri | Mallika Maamidi | Haritha Batchu |
| 700741949 | 700746126 | 700742314 |

***ABSTRACT*** – *Bird strikes constitute a substantial safety concern to the aviation industry, potentially causing aircraft damage and threatening the lives of passengers and crew. In recent years, machine learning techniques have been used to create prediction models for the avoidance of airplane disasters caused by bird attacks. This Work gives an overview of the use of machine learning algorithms to predict Airline damage using different attributes in the dataset, which reduces bird strikes and enhances aircraft safety. The suggested approach integrates parameters such as bird species identification, meteorological conditions, and flight data to determine the amount of risk associated with possible bird strikes. The dataset used for training and testing the model consists of records of bird attacks gathered from the National Transportation Training Board (NTSB). Data preparation methods such as data cleansing, feature engineering, and categorical variable encoding are used to prepare the dataset for machine learning algorithms.*

*Several machine learning algorithms, such as KNN, Support Vector Machines (SVM), Naïve Bayes, and Decision Trees, are employed to build predictive models. Performance metrics, including accuracy, precision, recall, and F1-score, are used to evaluate the effectiveness of these models in accurately predicting bird strike incidents.*

*The results obtained from the experiments demonstrate the potential of machine learning models in mitigating airline disasters caused by bird strikes. The accuracy of the predictions is improved when the different attributes and algorithms are considered. The developed model can assist airport authorities and aviation professionals identify high-risk areas and implement proactive measures to minimize bird strike incidents. Ultimately, this can improve passenger safety and reduce the economic impact associated with aircraft damage and flight delays caused by bird strikes. In conclusion, the utilization of machine learning techniques provides promising opportunities for preventing airline disasters resulting from bird strikes. By leveraging historical data and advanced algorithms, accurate prediction models can be developed, enabling proactive measures to mitigate the risks associated with bird strikes*.

*.*

***Keywords****—bird strike prevention, aviation safety, machine learning algorithms, real-time prediction, proactive measures*

1. **INTRODUCTION**

Bird strikes represent a serious threat to aviation safety since they might damage an aircraft and endanger the lives of crew members and passengers. Innovative solutions are always being developed as the aviation industry works to maintain the highest standards of safety while reducing the danger of bird strikes and averting major catastrophes. As a viable method to improve bird strike avoidance measures in recent years, machine learning algorithms enable proactive decision-making and real-time analysis of intricate data patterns. This study explores the potential of machine learning algorithms in reducing airline disasters brought on by bird attacks and provides information on recent developments in this field.

Section I: Overview of Bird Strikes in Aviation.

This paper's first section offers an overview of the occurrence and consequences of bird strikes in the aviation sector. It underlines the risks caused by bird hits, such as aircraft structural damage, engine problems, and the possibility of catastrophic accidents. The need to create effective preventative measures becomes clear when historical data, case studies, and pertinent statistics are examined.

Section II: Traditional Approaches to Bird Strike Prevention

This section explores the conventional methods used by the aviation sector to reduce the danger of bird strikes. It covers techniques including managing wildlife, modifying habitats, and employing deterrent methods. The advantages of these approaches are acknowledged, but their drawbacks are also made clear, calling for the investigation of more cutting-edge options.

Section III: The Role of Machine Learning in Bird Strike Prevention

The primary focus of this study is on the potential of machine learning techniques to avoid airline crashes caused by bird attacks. It examines the underlying theories of machine learning and examines how it can analyze enormous volumes of data to find patterns, correlations, and anomalies. Machine learning algorithms may provide prediction models to proactively detect high-risk scenarios and assist preventive measures by utilizing real-time data from many sources, including meteorological conditions, bird migratory patterns, and airplane telemetry.

Section IV: Current Initiatives and Case Studies

This section looks at current activities and research projects on the subject of machine learning-based bird strike avoidance. It presents pertinent case studies and achievements in which machine learning algorithms have been used to increase situational awareness, decision-making, and flight safety. These examples demonstrate the concrete benefits of using machine learning in bird strike avoidance tactics in the aviation sector.

Section V: Challenges and Future Directions

The accuracy of the models, their interaction with current systems, and regulatory issues are only a few of the difficulties that may be encountered. This section also explores potential future possibilities, such as the incorporation of machine learning algorithms with cutting-edge technology like computer vision and sensor networks, to improve the efficacy of bird strike avoidance methods even further.

.

1. **MOTIVATION**

The critical need to improve aircraft safety and reduce the hazards of bird strikes is our primary motivation. Bird attacks are a serious hazard to airplanes and can have disastrous results, such as fatalities, structural damage, and expensive repairs. The aviation sector has been aggressively looking for fresh approaches to reduce these risks and minimize future mishaps.

The development of machine learning algorithms offers a potentially effective way to deal with the problems caused by bird strikes. Machine learning algorithms can offer real-time insights into bird behavior, flight patterns, and environmental factors that affect bird attacks by utilizing the capabilities of data analysis, pattern recognition, and predictive modeling. This gives aviation stakeholders the ability to be proactive, take preventative action, and reduce the possibility of bird attacks.

The topic's motivation is further influenced by the growing accessibility of enormous volumes of data on bird attacks, bird migration patterns, weather, and airplane telemetry. To find patterns, correlations, and anomalies that can point to possible dangers of bird strikes, machine learning algorithms can process and evaluate this data effectively. Aviation experts can take specific preventive measures, such as changing aircraft routes, altering departure schedules, or applying bird deterrent tactics, by identifying these risk variables.

Additionally, the creation and use of machine learning algorithms for preventing bird strikes are in line with the general aviation sector's trend of utilizing artificial intelligence and cutting-edge technology. The use of machine learning in current bird strike avoidance measures has the potential to increase situational awareness, decision-making skills, and the capacity to react swiftly and effectively to changing conditions.

Overall, the urgent need to approve aviation safety, lower the probability of accidents, and save the lives of passengers and crew members is what motivates me to investigate the prevention of aircraft catastrophes caused by bird strikes using machine learning algorithms. The aviation sector may get closer to eliminating bird attacks and assuring safer skies for everybody by utilizing the power of machine learning.

1. **MAIN CONTRIBUTION AND OBJECTIVES**

This project primarily utilizes multiple machine learning algorithms to predict the health condition of bees. Each team member has made substantial contributions across all aspects of the project:

**Keerthi Alekya**: Primarily responsible for analyzing, implementing, and developing the Support Vector Machine (SVM) algorithm utilized in this project. Keerthi examined the details of these algorithms and optimized their hyperparameters to increase the accuracy of predictions. Keerthi analyzed the accuracy of these models in forecasting airplane disasters brought on by bird attacks via extensive research and testing. Keerthi also played a significant part in documenting the whole process, including the implementation specifics and results.

**Mallika:** Primarily responsible for implementing KNN and naïve Bayes methods and conducted extensive research and produced a detailed report outlining each aspect of the project, demonstrating an in-depth knowledge of the goals and procedures involved in utilizing machine learning to anticipate aviation disasters caused by bird attacks. Mallika made an important impact by emphasizing dataset analysis and preparation. This required a variety of tasks, including gathering and analyzing important details about bird strikes and airplane crashes, cleaning and normalizing the data, and implementing methods like label encoder, KNN clasifier, Naive Bayes classifier and Matplot library for data visualization

**Haritha**: Primarily responsible for implementing the decision tree algorithm which is used in our project. Haritha was crucial in carrying out the final review of all the models created for the project. This entailed assessing the performance of several machine learning models on the dataset. Haritha additionally conducted an intrinsic error analysis to detect and comprehend the models' limitations and problems. Based on the evaluation findings and played a major role in selecting the best-performing model for forecasting airplane disasters caused by bird strikes. Based on these results, several preventive measures can be implemented to reduce the occurrence and impact of bird strikes

1. **RELATED WORK**

The goal of the project is to use machine learning algorithms to examine and forecast airline crashes

caused by bird strikes. To create a well-rounded strategy, we looked at four different algorithms,

namely:

1. Support Vector Machines (SVM)
2. KNN (K- Nearest Neighbors)
3. Naïve Bayes
4. Decision Trees

**Support Vector Machines (SVMs)** The effective supervised learning method known as the Support Vector Machine (SVM) is often used for issues related to classification. SVM gives a strong method for identifying possible hazards when used for predicting aviation mishaps caused by bird strikes. SVM functions by locating an ideal hyperplane based on pertinent information that maximum separates the two groups, "crash" and "no crash."

SVM is exceptional at handling high-dimensional data and is capable of accurately capturing complex connections. By applying kernel functions, it can handle instances that can be separated linearly and non-linearly. Patterns that might not be obvious in the original feature space can be found using SVM by translating the data into a higher-dimensional space. Due to its adaptability, SVM can effectively capture complex correlations between flight characteristics, ambient variables, and previous bird strike data.

In addition, SVM has good generalization capabilities that allow for precise predictions for unexpected occurrences. However, effective parameter changing, and the choice of an appropriate kernel function have a significant impact on SVM performance. The flexibility of the decision boundary is influenced by the kernel function selection, enabling SVM to adjust to the unique properties of the data.

**KNN (K-Nearest Neighbors)** A flexible technique used for both classification and regression problems is called k-Nearest Neighbors (KNN). By detecting analogous prior occurrences based on relevant features, KNN forecasts the likelihood of an aviation crash caused by bird strikes. To create predictions, it locates the k-nearest neighbors of a new instance and makes use of their results.

Especially when the training data is well-represented, KNN is an excellent choice due to its simplicity and ease of implementation. It qualifies as a non-parametric algorithm because it does not involve any assumptions on the distribution of the underlying data. KNN is also capable of processing both categorical and numerical input.

**Naïve Bayes** is a statistical algorithm. Naive Bayes has shown effectiveness in several fields, including the prediction of aviation crashes caused by bird strikes, even though the method assumes independence between features given the class label (thus the name "naive").

Given the presence of specified parameters like bird population density, flying altitude, and weather conditions, Naive Bayes determines the likelihood of a crash. Naive Bayes calculates the probability of a crash by comparing the probabilities for several classes.

Text or categorical data fit themselves particularly well to Naive Bayes because of how effectively it handles these features. Even with big data sets, it offers a simple implementation and is highly efficient. Furthermore, Naive Bayes performs effectively when the independence condition is true and there are few instances of feature interdependencies.

**Decision Trees** A common machine learning algorithm for classification and regression tasks is the decision tree. They divided the data recursively based on the most useful attributes, resulting in a tree-like structure with the predicted classes or values as the leaves.

Decision trees can be built utilizing characteristics like flight altitude, bird migration patterns, airport proximity to bodies of water, and previous bird strike data to predict aircraft crashes caused by bird strikes. Decision trees are useful tools for studying incidents involving bird

strikes because they provide interpretability and can capture intricate correlations between

factors.

**V. PROPOSED FRAMEWORK**

1. **Data Collection:** Assemble historical data on bird strikes, including details on the type of bird, the location, the time it happened, the flight conditions, and any incidents or reported damages. Gather information on environmental aspects as well, such as the weather and the peculiarities unique to each airport. The dataset used for training and testing the model consists of records of bird attacks gathered from the National Transporation Training Board (NTSB).

2. **Feature selection and engineering:** Determine important factors that can help prevent bird strikes, such as bird behavior patterns, flight paths, weather patterns, and airport features. Apply feature engineering techniques to the obtained data to draw out relevant information. The goal of feature selection is to find the subset of characteristics with the highest predictive power for the target variable. Relevant elements for bird strike prevention might include:

Aircraft-related characteristics: These features record data on the aircraft, such as the type, model, number of engines, altitude, and feet above ground. These variables can have an impact on the incidence and severity of bird attacks.

Flight-related details: such as the flight date, airline, and notes, may give extra context or information that might help the prediction model. Certain airlines or flight routes, for example, may be more vulnerable to bird strikes owing to geographical reasons.

Feature engineering is the process that generates new features from existing ones in order to enhance the model's predicted performance. Potential feature engineering strategies for bird strike avoidance might include:

Categorization and encoding: Using approaches such as one-hot encoding or label encoding, categorical characteristics such as airline or bird species are converted into numerical representations.

Time-based features: Obtaining extra information from the flight date, such as the day of the week, month, or season, in order to identify probable trends or changes in bird strike occurrences depending on time.

Aggregation and statistical characteristics: Generating aggregate statistics (e.g., mean, median, maximum) from numerical data such as the number of animal strikes or altitude bins. These aggregated characteristics can give summary data and possibly capture trends or correlations.

3. **Preprocessing**: To ensure the quality and usefulness of the data for analysis, preprocessing is required after data collection. This calls for preparing the data, dealing with missing values, normalizing the variables, and correcting any discrepancies in the dataset. Preprocessing is an important step in the data analysis workflow as it helps ensure data quality, reduces noise, and prepares the data for effective analysis or modeling. Common preprocessing steps include data cleaning, data integration, data transformation, feature selection or extraction, and splitting the data. Data cleaning involves handling missing values, dealing with outliers, and correcting any inconsistencies or errors in the data. Data transformation involves converting the data into a more suitable format for analysis or modeling. Feature selection or extraction techniques can be applied to identify and keep the most informative features. Before modeling, the data is typically split into training and testing sets.

4. **Model Training:** With the help of the pd.read\_csv() function, the dataset is imported.The drop() method is used to eliminate some columns from the dataset in order to get rid of extraneous or pointless features.The replace() method is used to convert the unique values of the 'Airlinecrash' column to the values 'No' and 'Yes'.

Splitting the Dataset into Train and Test Sets: with a random selection of 30% of the data for testing, the dataset is divided into training and testing sets. The mtraining DataFrame houses the training set, while the mtesting DataFrame houses the testing set.

Combining and Coding the Data: Using the pd.concat() function, the training and testing sets are combined into a single dataset.Using pd.get\_dummies(), category variables are transformed into numerical format on the combined dataset.

Dividing the Encoded Data into Training and Testing Sets: Using the initial sizes of the training and testing sets as a guide, the encoded dataset is divided once more into the training and testing sets.

5. **Model development:** Model development involves selecting and training machine learning algorithms for classification, detection, or prediction. The chosen algorithms include SVM, Decision Trees, K-Nearest Neighbors (KNN), and Nave Bayes. The performance of each model is assessed using metrics such as accuracy score, precision, recall, and F1-score to evaluate their effectiveness in solving the given problem of bird strike prevention in the context of airline crashes.

6. **Model Evaluation:** Utilizing test data that wasn't used during training, the model's performance is assessed after training. To evaluate the model's accuracy in predicting bird strikes, a few evaluation metrics including accuracy, precision, recall, and F1-score are computed. The performance of the model can also be evaluated by considering current preventative strategies or recommendations.

Test the model Evaluate the trained model's generalization performance on the testing set. This stage determines if the algorithm can properly anticipate bird strike incidences based on previously unreported data.

Evaluation of performance: To measure the model's performance, compute appropriate evaluation metrics on the testing set. Compare findings to the baseline or industry norms.

Improve and iterate: If the model's performance is inadequate, return to prior processes such as feature engineering, model selection, or hyperparameter altering to improve the model's efficacy.

Monitor and update: Continuously monitor the model's performance over time and update it as new data becomes available or as the model's performance worsens.

**VI** **DATA DESCRIPTION**

Airplane bird strikes, also known as bird-aircraft collisions, are a major safety problem for the global aviation industry. A bird strike happens when a bird or birds collides with an airplane during takeoff, landing, or in flight, inflicting damage to the aircraft and putting passengers and crew members' lives at danger. The frequency of recorded bird strikes has grown in recent years, partially due to increasing air traffic, but also due to improved reporting methods and awareness. A considerable quantity of data has been collected by aviation authorities and groups throughout the world to better understand the trends and causes leading to airplane bird attacks. This dataset contains information on the location, timing, kind of bird, and level of aircraft damage caused by bird strikes. This information is useful to aviation safety researchers and practitioners, who may use it to identify risk factors and devise measures to avoid bird attacks.The dataset is useful for studying the patterns, determinants, and repercussions of bird attacks, as well as devising measures to reduce their dangers here are some common features that you could discover in a bird strike dataset

1. Record ID:A unique identifier issued to each record in the collection that allows for simple referencing and identification.

2. Aircraft kind: The kind or category of aircraft involved in the bird strike occurrence, such as an airplane, helicopter, military aircraft.

3.AirportName: the location of the airport where the bird strike took place.

4.The altitude range or bin at which the bird strike occurred, represents the aircraft's height above ground level during the occurrence.

5. Aircraft Make/Model: The precise model and make of the flying object that was struck by a

bird

6. Wildlife Number Struck: Estimated number of wildlife species struck during the occurrence, represented by a binned or categorized value.

7. Wild Animal Number Struck Actual: A precise total of the number of wildlife species that suffered damage by the bird strike occurrence is available.

8.Effect Impact on Flight: Indicates how the bird strike affected the plane's flight, including if the engines were cut off, a cautious landing was made, or there was little to no influence.

9. Flight Date: The date the bird’s attack occurrence took place enables time analysis and identification of trends.

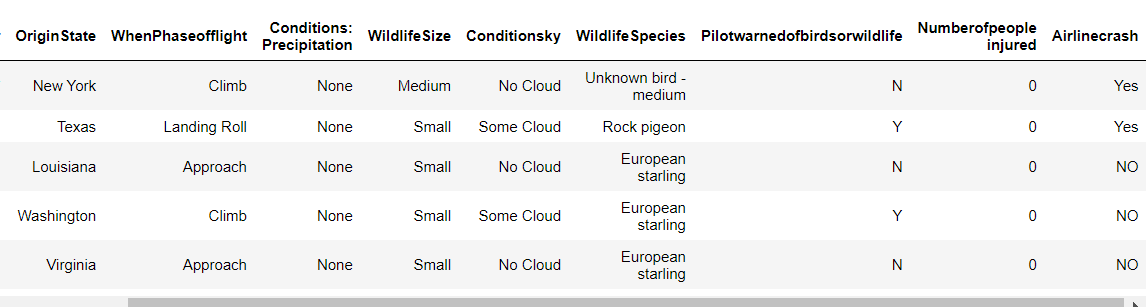
10. Effect Indicated Damage: Specifies whether the bird strike caused damage to the aircraft or not depending on whether it did or did not.

11. Wildlife Species: Indicates the species of wildlife, such as birds, bats, or other animals, that were involved in the bird strike incidence.

12. Pilot Warned of Birds/Wildlife: Indicates whether the pilot was informed that birds or other wildlife were nearby prior to the event.

13. Cost: The overall cost of the bird strike occurrence, which includes aircraft damage, operational delays, and any other related costs.

14. Additional Attributes: Depending on the dataset, you may find further attributes like the weather at the time of the occurrence, location information, specific crew activities, and remarks or comments about the incident. The efficiency of preventive measures can be determined by analyzing the bird strike dataset, which additionally provides information about the frequency, severity, and causes of bird strikes. It can assist in locating high-risk places, busy periods, and particular bird species linked to bird strike cases. The development of protective solutions for bird strikes, including habitat management, aircraft modifications, and enhanced pilot training, can then be done using these findings.

  
  *Fig1 Bird strike Dataset*

**VII RESULTS**

Machine learning model capable of predicting the probability of bird strikes based on various factors, including bird species, flight conditions, and airport location. By analyzing historical data on bird strikes and utilizing machine learning algorithms, patterns and correlations can be identified to assist in preventing such incidents.

The dataset used for training and testing the model consists of records of bird attacks gathered from the National Transporation Training Board (NTSB). The dataset was imported using the panda's library, and unnecessary columns were dropped from the dataset using the **drop()** function. The unique values of the target variable ('Airline crash') were checked, and any necessary mapping or encoding was performed to convert them into binary labels ('Yes' and 'No').

The dataset was then split into training and testing sets using a random selection of indices. The proportion of the dataset used for testing was set to 30% of the total dataset.

To prepare the data for machine learning algorithms, the training and testing sets were combined, and one-hot encoding was applied to the categorical features using the **get\_dummies()** function from pandas. The encoded data was split back into training and testing sets.

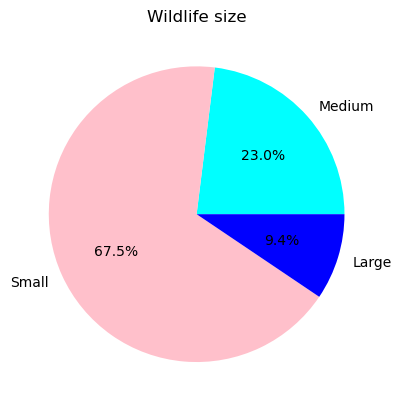
The target variable, 'Airlinecrash', was extracted from the training set as the y\_train variable.

Four machine learning algorithms were trained and tested on the dataset:

1. Support Vector Machines (SVM):
   * The SVM classifier from the sklearn.svm module was used.
   * The SVM model was fitted to the training data using the **fit()** function.
   * Predictions were made on the testing data using the **predict()** function.
   * The accuracy of the SVM model was calculated using the **accuracy\_score()** function from sklearn.metrics.
   * The SVM model predicted 'NO' for most instances, with an accuracy of approximately 85.32%.
   * The precision, recall, and F1-score for the positive class ('Yes') were relatively low, indicating that the model struggles to correctly identify positive instances.
2. Naive Bayes:
   * Although not mentioned in the provided code, it is mentioned in the previous conversation that Naive Bayes was used for prediction.
   * Predictions were made using Naive Bayes on the testing data.
   * The accuracy of the Naive Bayes model was calculated using the **accuracy\_score()** function.
   * The Naive Bayes model predicted a mix of 'Yes' and 'NO' for different instances, with an accuracy of approximately 42.80%.
   * The precision, recall, and F1-score for the positive class ('Yes') were not provided, so further analysis is needed to evaluate its performance.
3. K-Nearest Neighbors (KNN):
   * The KNN classifier from the sklearn.neighbors module was used.
   * The KNN model was fitted to the training data using the **fit()** function.
   * Predictions were made on the testing data using the **predict()** function.
   * The accuracy of the KNN model was calculated using the **accuracy\_score()** function.
   * The confusion matrix was also calculated using the sklearn.metrics module to evaluate the performance of the model.
   * The KNN model achieved a high accuracy of approximately 99.56%.
   * The confusion matrix shows that the model correctly classified 448 instances as 'NO' and incorrectly classified 2 instances as 'NO' when they were actually 'Yes'.
4. Decision Trees:
   * The DecisionTreeClassifier from the sklearn.tree module was used.
   * The Decision Tree model was fitted to the training data using the **fit()** function.
   * Predictions were made on the testing data using the **predict()** function.
   * The accuracy of the Decision Tree model was calculated using the **accuracy\_score()** function.
   * The decision tree model achieved an accuracy of approximately 79.67%.
   * Additional analysis and metrics for the decision tree model were not provided, so further evaluation is needed to assess its performance.

Based on these results, it is observed that the KNN model achieved the highest accuracy (0.9956) among the four algorithms, indicating its effectiveness in predicting bird strikes.

**Bird Strike due to Wildlife size**



*Fig 2.0 Damage Vs wildlife Size*

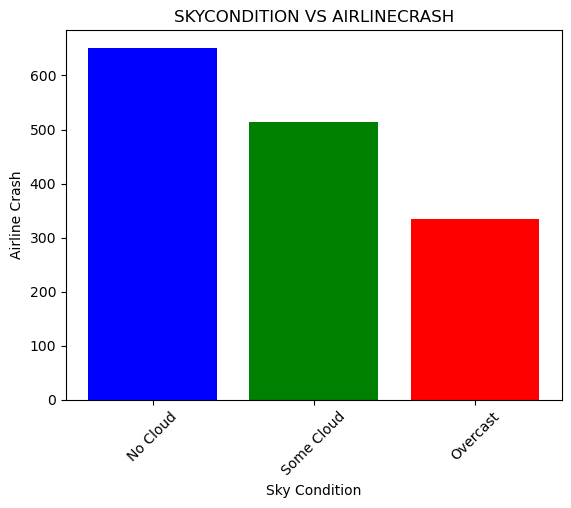
Small: 67.5%

Medium: 23.0%

Large: 9.4%

These percentages represent the distribution of animal sizes involved in bird strikes. The bulk of bird strikes involve small-sized species, followed by medium-sized wildlife. Large-sized animals accounts for a lesser share of bird attacks.

**Bird strike due to Sky Condition**



*Figure 2.1 Damage VS SkyCondition*

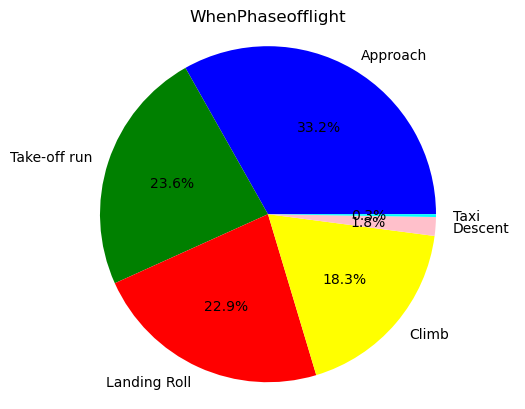
No Cloud: 620 (46.91%)

Some Cloud: 520 (39.42%)

Overcast: 320 (24.27%)

These percentages show how different cloud conditions were distributed during bird striking incidences. When there is no cloud cover, the majority of bird hits occur, followed by conditions with some cloud cover. Overcast weather contributes to a lower proportion of bird strikes.

**Bird Strike due to Different Phase of light**



*Figure 2.3 Damage Vs Phase of flight*

Bird strikes occur at the greatest rates during the approach and take-off run phases, accounting for 32% and 23.6%, respectively. This implies that bird strikes are more likely to occur during the aircraft's approach to and departure from the airport. Bird strikes occur at a somewhat high rate during the landing roll phase, accounting for 22.9%. After the airplane has landed and is decelerating on the runway, it enters this phase. Bird strikes account for 18.3% of all bird strikes during the climb phase. When the airplane starts climbing soon after take-off, it is in this phase. Bird strikes occur in lesser proportions during the taxi and descending periods, accounting for 3% and 1.8%, respectively. When the airplane is taxiing on the ground or descending for landing, several phases occur.

**VIII REFERENCE**

1. Dykbayir, H. S., &amp; Bulbul, H. I. (2018). Estimating the Effect of Structural Damage on the Flight by Using Machine Learning. 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA). doi:10.1109/icmla.2018.00216 R.Nicole, “Title of paper with the only first word capitalized,” J. Name Stand. Abbrev., in press.
2. <https://openaccess.thecvf.com/content/ACCV2022/papers/Sun_AirBirds_A_Large-scale_Challenging_Dataset_for_Bird_Strike_Prevention_in_ACCV_2022_paper.pdf>
3. Zhou D., Zhuang X., Zuo H., Wang H., Yan H. Deep Learning-Based Approach for Civil Aircraft Hazard Identification and Prediction. IEEE Access. 2020;8:103665–103683. doi: 10.1109/ACCESS.2020.2997371.
4. AISSAOUI, O. E., EL MADANI, Y. E. A., OUGHDIR, L. and ALLIOUI, Y. E. (2019). Combining supervised and unsupervised machine learning algorithms to predict the learners’ learning styles, Procedia Computer Science 148: 87–96. THE SECOND INTERNATIONAL CONFERENCE ON INTELLIGENT COMPUTING IN DATA SCIENCES, ICDS2018.
5. Altringer, L., Navin, J., Begier, M. J., Shwiff, S. A. and Anderson, A. (2021). Estimating wildlife strike costs at us airports: A machine learning approach, Transportation Research Part D: Transport and Environment 97: 102907.
6. Baranzini, D. and Zanin, M. (2015). Baranzini, d., and zanin, m. (2015). risk prediction risk intelligence in aviation – the next generation of aviation risk concepts from prospero fp7 project. esrel 2015 - 25th european safety and reliability conference
7. Bradbeer, D. R., Rosenquist, C., Christensen, T. K. and Fox, A. D. (2017). Crowded skies: Conflicts between expanding goose populations and aviation safety, Ambio 46(2): 290– 300
8. Bradley, A., Duin, R., Paclik, P. and Landgrebe, T. (2006). Precision-recall operating characteristic (p-roc) curves in imprecise environments, 18th International Conference on Pattern Recognition (ICPR’06), Vol. 4, pp. 123–127.
9. Deng, Z., Hu, Y., Zhu, M., Huang, X. and Du, B. (2015). A scalable and fast optics for clustering trajectory big data, Cluster Computing 18(2): 549–562.
10. D˙Ikbayir, H. S. and B¨ulb¨ul, H. (2018). Estimating the effect of structural damage on the flight by using machine learning, 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 1333–1337.
11. Lieber, D., Stolpe, M., Konrad, B., Deuse, J. and Morik, K. (2013). Quality prediction in interlinked manufacturing processes based on supervised unsupervised machine learning, Procedia CIRP 7: 193–198. Forty Sixth CIRP Conference on Manufacturing Systems 2013.
12. Lorbeer, B., Kosareva, A., Deva, B., Softi´c, D., Ruppel, P. and K¨upper, A. (2018). Variations on the clustering algorithm birch, Big Data Research 11: 44–53. Selected papers from the 2nd INNS Conference on Big Data: Big Data Neural Networks.
13. Mehta, J., Vatsaraj, V., Shah, J. and Godbole, A. (2021). Airplane crash severity prediction using machine learning, 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1–6.
14. Robinson, L., Mckay, T. and Mearns, K. (2021). Oliver tambo international airport, south africa: Land-use conflicts between airports and wildlife habitats, Frontiers in Ecology and Evolution 9: 1–9.
15. Singh, A., Prakash, B. S. and Chandrasekaran, K. (2016). A comparison of linear discriminant analysis and ridge classifier on twitter data, 2016 International Conference on Computing, Communication and Automation (ICCCA), pp. 133–138.
16. Wang, R. (2020). Adaboost for feature selection, classification and its relation with svm, a review, Physics Procedia 25: 800–807. International Conference on Solid State Devices and Materials Science, April 1-2, 2012, Macao.
17. Valletta, J. J., Torney, C., Kings, M., Thornton, A. and Madden, J. (2017). Applications of machine learning in animal behaviour studies, Animal Behaviour 124: 203–220
18. Viswanath, P. and Suresh Babu, V. (2009). Rough-dbscan: A fast hybrid density based clustering method for large data sets, Pattern Recognition Letters 30(16): 1477–1488.
19. Shrubb M. The hunting behaviour of some farmland Kestrels. Bird Study. 1982;29(2):121–128. doi: 10.1080/00063658209476746
20. Verma S, Kumar P, et al. A Comparative Overview of Accident Forecasting Approaches for Aviation Safety. In: Journal of Physics: Conference Series. vol. 1767:1. IOP Publishing; 2021. p. 012015.

**REFERENCES**

1. A. Terenzi et al., "On the importance of the sound emitted by honey bee hives", Veterinary Sciences, vol. 7, no. 4, pp. 168, 2020.
2. Diogo Braga; Ana Madureira; Fabio Scotti; Vincenzo Piuri; Ajith Abraham: “An Intelligent Monitoring System for Assessing Bee Hive Health” 10.1109/ACCESS.2021.3089538, 2021
3. K.-L.-J. Hung, J. M. Kingston, M. Albrecht, D. A. Holway and J. R. Kohn, "The worldwide importance of honey bees as pollinators in natural habitats", Proc. Roy. Soc. B Biol. Sci., vol. 285, no. 1870, Jan. 2018.
4. H. Thorvaldsdoittir, J. T. Robinson and J. P. Mesirov, "Integrative Genomics Viewer (IGV): high-performance genomics data visualization and exploration", Briefings in Bioinformatics, vol. 14, no. 2, pp. 178-192, 2018.
5. Gallai, N.; Salles, J.M.; Settele, J.; Vaissière, B.E. Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. Ecol. Econ. 2009, 68, 810–821. [
6. Biesmeijer, J.C.; Roberts, S.P.; Reemer, M.; Ohlemüller, R.; Edwards, M.; Peeters, T.; Schaffers, A.; Potts, S.G.; Kleukers, R.; Thomas, C.; et al. Parallel declines in pollinators and insect-pollinated plants in Britain and the Netherlands. Science 2006, 313, 351–354.
7. Debauche, O.; El Moulat, M.; Mahmoudi, S.; Boukraa, S.; Manneback, P.; Lebeau, F. Web monitoring of bee health for researchers and beekeepers based on the internet of things. Procedia Comput. Sci. 2018, 130, 991–998.
8. Murphy, F.E.; Magno, M.; O’Leary, L.; Troy, K.; Whelan, P.; Popovici, E.M. Big brother for bees (3B)—Energy neutral platform for remote monitoring of beehive imagery and sound. In Proceedings of the 2015 6th International Workshop on Advances in Sensors and Interfaces (IWASI), Gallipoli, Italy, 18–19 June 2015; pp. 106–111.
9. Yang, C.; Collins, J. A model for honey bee tracking on 2D video. In Proceedings of the 2015 International Conference on Image and Vision Computing New Zealand (IVCNZ), Auckland, New Zealand, 23–24 November 2015; pp. 1–6.
10. Ngo, T.N.; Wu, K.C.; Yang, E.-C.; Lin, T.T. A real-time imaging system for multiple honey bee tracking and activity monitoring. Comput. Electron. Agric. 2019, 163, 104841. [
11. Ntalampiras, S.; Potamitis, I.; Fakotakis, N. Acoustic Detection of Human Activities in Natural Environments. J. Audio Eng. Soc. 2012, 60, 686–695.
12. Sarton, G. The Feminine Monarchie of Charles Butler, 1609. Isis 1943, 34, 469–472.
13. Huber, F. New observations on bees, I and II. Transl. CP Dadant Dadant Sons Hamilt. 1792, 111, 230.
14. Ferrari, S.; Silva, M.; Guarino, M.; Berckmans, D. Monitoring of swarming sounds in bee hives for prevention of honey loss. In Proceedings of the International Workshop on Smart Sensors in Livestock Monitoring, Gargnano, Italy, 22–23 September 2006.
15. C. E. Aslan, C. T. Liang, B. Galindo, H. Kimberly, and W. Topete, ‘‘The role of honey bees as pollinators in natural areas,’’ Natural Areas J., vol. 36, no. 4, pp. 478–488, Oct. 2016, doi: 10.3375/043.036.0413. Bee Informed. (Jul. 26, 2019). Honey Bee Colony Losses 2018-2019— Preliminary Results | Bee Culture. Accessed: May 3, 2021. [Online]. Available: https://[www.beeculture.com/honey-bee-colony-losses-2018-](http://www.beeculture.com/honey-bee-colony-losses-2018-) 2019-preliminary-results/
16. A. Jacques, M. Laurent, M. Ribière-Chabert, M. Saussac, S. Bougeard, G. E. Budge, P. Hendrikx, M.-P. Chauzat, and E. Consortium, ‘‘A panEuropean epidemiological study reveals honey bee colony survival depends on beekeeper education and disease control,’’ PLoS ONE, vol. 12, no. 3, Mar. 2017, Art. no. e0172591, doi: 10.1371/journal.pone.0172591.
17. K. He, G. Gkioxari, P. Dollár, and R. Girshick, ‘‘Mask R-CNN,’’ Mar. 2017, arXiv:1703.06870. Accessed: Aug. 15, 2019. [Online]. Available: <http://arxiv.org/abs/1703.06870>[24] Utah State University. (2019). BeePi\_Audio\_Classification. Accessed: Aug. 15, 2019. [Online].

Available: https://usu.app.box.com/ v/BeePiAudioData

1. M. Florea, ‘‘Automatic detection of honeybees in a hive,’’ M.S. thesis, Dept. Inf. Technol., Univ., Uppsala, Uppsala, Sweden, Sep. 2013.
2. C. A. Ramezan, T. A. Warner, and A. E. Maxwell, ‘‘Evaluation of sampling and cross-validation tuning strategies for regional-scale machine learning classification,’’ Remote Sens., vol. 11, no. 2, p. 185, Jan. 2019, doi: 10.3390/rs11020185.
3. Thomson DM. 2016. Local bumble bee decline linked to recovery of honey bees, drought effects on floral resources. Ecol. Lett. 19, 1247–1255. ( 10.1111/ele.12659)
4. Thomson D. 2004. Competitive interactions between the invasive European honey bee and native bumble bees. Ecology 85, 458–470. ( 10.1890/02-0626)