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Explainable Swin Transformer Framework for Aircraft Bird Strike Risk Prediction Using SHAP-Based Feature Analysis

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ABSTRACT: Aircraft bird strike risk prediction is important because it prevents catastrophic engine failures, structural damage, and loss of life during low-altitude flights. In this paper, a Swin Transformer (ST) with Shapley Additive explanations (SHAP) based feature analysis is proposed for aircraft bird strike risk prediction. Data preprocessing transforms raw, noisy multi-source aviation and ecological records into clean inputs for predictive models. It handles missing radar tracks, standardizes diverse weather metrics, and encodes cyclical time features, ensuring Deep Learning (DL) algorithms accurately forecast bird strike risks. STs are applied in bird strike risk prediction and airport safety frameworks primarily for high-accuracy small-object detection and real-time visual monitoring of avian hazards. SHAP interprets complex DL models used in aircraft bird strike risk prediction by quantifying the individual impact of environmental, temporal, and operational features on collision probability. The performance analysis is carried out using python software and assesses the model's performance using key metrics such as precision, recall, F1-score, confusion matrix, and ROC-AUC. The proposed ST-SHAP uses two classes, they are no damage and caused damage. The proposed ST-SHAP achieves high accuracy of 96% and better convergence speed. The proposed method outperforms conventional techniques, contributing a robust and reliable tool for aircraft bird strike risk prediction.

Keywords: Swim Transformer (ST), Shapley Additive explanations (SHAP), aircraft bird strike risk prediction, Data Preprocessing.

1. Introduction

Predicting the times of most bird strike risk can be difficult. Instead of forecasting exposure to bird movement or the number of birds in the air, which is more directly related to exposure to the danger, the conventional approach for predicting bird strike risk relies examining the dates of previous bird strikes [1,2]. Aircraft striking birds and other wildlife accounts for over $1.2 billion in yearly damage. Bird strikes can cause significant damage to aircraft and even result in the loss of life [3]. A bird strike costs more than just the damage to the aircraft. Costs beyond the aircraft damage can include operational costs associated with shutting down a runway, loss of business to competitors, inspection requirements, and other related expenses [4]. Beyond the cost to operations is the liability to the airport operator. The liability of airport operators and managers in the occurrence of a bird attack drives the need for wildlife mitigation efforts [5,6].

The most significant liability lies with the airport manager, specifically whether they applied the required mitigation techniques by an applicable wildlife management plan. Static, signature-based rules and rigid taxonomies are the methods of conventional aircraft bird strike risk prediction [7]. Due to lacks execution context, fails to adapt to polymorphic payloads, and results in high false-positive rates, the traditional method struggles with modern threats. To allow security systems to automatically learn complex, non-linear patterns from massive volumes of bird strikes while minimizing false positives and latency, DL techniques are used for aircraft bird strike risk prediction. While DL models natively eliminate the need for manual feature engineering, optimization techniques ensure these networks remain fast, accurate, and lightweight enough to stop evolving aircraft bird strike threats in real time.

Table 1: *Comparison of Existing Techniques*

Method	Convergence speed	Reliability	Response time
Convolutional Neural Network (CNN) [8]	Low	High	High
CNN-YOLO [9]	Low	Low	High
Long Short -Term Memory-Recurrent Neural Network (LSTM-RNN) [10]	High	Low	Low
ST-SHAP	High	High	Low

Table 1 shows the comparison of existing techniques such as CNN, CNN-YOLO and LSTM-RNN. These techniques have some disadvantages like low convergence speed, less reliability and High response time. To avoid these issues, an ST-SHAP is proposed for aircraft bird strike risk prediction. The contribution of the paper is as follows,

- Data preprocessing is used to clean raw airport, weather, and flight data. It fixes missing values, removes noise, scales numbers, and converts text into a standard format.
- ST-SHAP is proposed for aircraft bird strike risk prediction to build a high-accuracy, spatially aware risk model while making its black-box predictions fully transparent and interpretable for aviation safety management.

2. Recent Works

Bird movement prediction using LSTM networks have been presented in [7] to avoid bird attacks with low elevation aircraft. Using LSTM networks to predict bird movement helps lower aviation bird-strike risks, but it has major downsides. These include high data needs, slow training times, difficulty scaling to full flocks, and a tendency to overfit on noisy wildlife tracking data. CNN is presented in [8] for aviation safety, which improve aviation safety by automating maintenance visual inspections, predicting accident severity, and analysing pilot cognitive states or incident text data with high accuracy. Due to the limited interpretability of black-box models, difficulty in capturing long-term sequential flight data, and high sensitivity to rare failure samples are the drawbacks of CNN in aircraft bird strike risk prediction. The hybrid CNN-YOLO have been proposed in [9] for aircraft bird strike risk prediction. The combination of convolutional spatial feature extraction with YOLO's fast object detection is a hybrid CNN-YOLO model for aircraft bird strike prediction. High computational overhead from merging architectures, poor small-target detection when birds are distant, and high false-positive rates from complex airfield backgrounds are major issues of CNN-YOLO. To overcome these drawbacks, an ST-SHAP is proposed in this paper for aircraft bird strike risk prediction.

3. Proposed Work Explanation

The proposed block diagram of ST-SHAP for aircraft bird strike risk prediction is represented in figure 1. The process begins with input data, which immediately undergoes a rigorous preprocessing stage designed to clean the data by removing noise, removing outliers, and handling both invalid and missing values. Once cleaned, the data transitions into data visualization to analyse trends and patterns, followed by feature selection to isolate the most relevant attributes for modelling. Next, the dataset enters the train and test splitting phase, partitioning the data to ensure robust model evaluation. The core architectural component is the ST, which processes the split data sequentially across four main stages. It starts with a Patch Merging step that groups pixels into patches, followed by Layer 1 containing a Linear Embedding layer and two Swin Transformer Blocks. Layers 2, 3, and 4 continue processing the feature maps through subsequent Patch Merging steps and progressive stacks of Swin Transformer Blocks (scaled by 2, 6, and 2 repetitions, respectively) before generating a final Output.

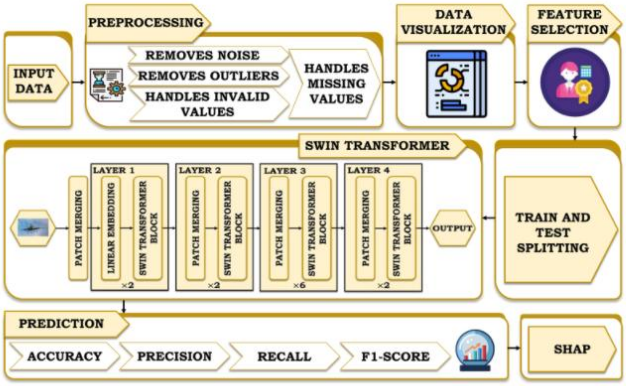

Figure 1: *Proposed block diagram of ST-SHAP for aircraft bird strike risk prediction*

The output is routed to the prediction phase, where the technique's effectiveness is rigorously evaluated using standard classification metrics: accuracy, precision, recall, and F1-Score. Finally, the process concludes with SHAP, a model-agnostic explainable AI tool used to interpret individual predictions and explain which visual features most heavily influenced the network's decisions.

3.1. Modelling of Data preprocessing

The unstructured data is transformed into clean and standardized formats in data preprocessing, which is suitable for DL. It is reducing noise through techniques like resizing, normalization, and filtering, improves system performance by enhancing data quality. These methods adjust pixel brightness and contrast to improve image quality for rendering.

$$g(x) = \alpha f(x) + \beta \tag{1}$$

Gamma correction performs non-linear adjustments to individual pixel values, essential for capturing, displaying, or printing images correctly,

$$V_{out} = AV_{in}^{\gamma} \tag{2}$$

Where V_{in} is input pixel value (0-1), V_{out} is output, and γ is the gamma factor. COA-SRP turn cleaned data into the shortest, fastest, or cheapest paths while avoiding real-world roadblocks.

3.2. Modelling of Data Visualization

The process of turning raw numbers into clear pictures like charts and graphs is named as data visualization. To calculate key values, map coordinates, and show trends so people can understand information quickly, data visualization uses math formulas.

Mathematical expression for mean (average) to check data centre:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

Mathematical expression for min-max feature scaling:

$$x_{normalized} = \frac{x_i - \min(X_{train})}{\max(X_{train}) - \min(X_{train})} \tag{3}$$

Crucially, the min and max values are calculated only from the training data (X_{train}). The same parameters are then used to transform the test data.

Choose variables for the X and Y axes and convert data points to pixel coordinates on a screen. Linear scaling equation for pixel position is derived as:

$$P = \frac{x - x_{Min}}{x_{Max} - x_{Min}} \times pixelwidth \tag{4}$$

Instead of scanning through thousands of rows in a spreadsheet, visualization tools convert data into intuitive shapes and colours, making systemic flaws immediately apparent.

3.3. Mathematical modelling of ST

STs improve bird strike risk mitigation by powering high-precision small object detection in camera and radar monitoring. By utilizing hierarchical feature upsampling and custom shifted window sizes, these vision transformers excel at spotting sparse, distant birds that threaten low-altitude and air-taxi flight paths. Figure 2 shows the architecture of ST classifier.

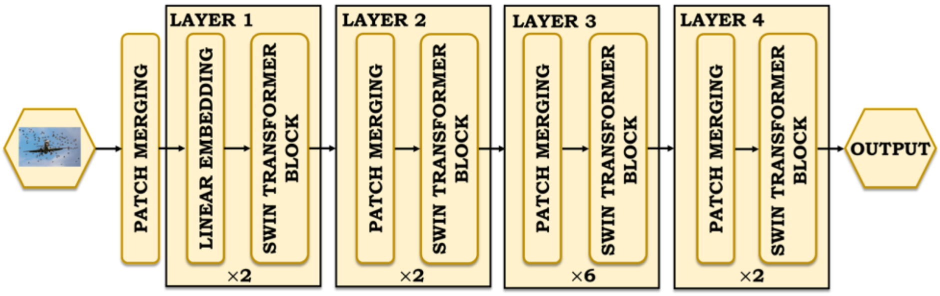

Figure 2: *Architecture of ST Classifier*

3.4.1 Steps involved in ST Classifier:

Step 1: Images are resized, normalized and pre-processed.

Step 2: Self-attention is computed only within local windows. The windows configuration shifts, allowing interaction between patches from different windows in the previous layer.

Step 3: To create a hierarchical structure, 2×2 neighboring patches are concatenated, reducing the resolution by $2\times$ while doubling the channel depth to 2C, acting as a down sampling layer.

Step 4: Com puts self-attention with relative position bias. The attention mechanism in ST includes a relative position bias $B \in R^{M^2 \times M^2}$ for each head.

$$Attention\ (Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d}} + B\right)V \tag{5}$$

Where Q is the query, k is the key, and V is the value matrices, key dimension is denoted by d, and size of the window is designated by M.

Step 5: Create ST Block structure. Each block consists of a norm layer, attention, a residual connection, an MLP (feed forward network), and another residual connection.

$$\hat{z}^l = W - \frac{MSA}{SW} - MSA\left(LN(z^{l-1})\right) + z^{l-1} \tag{6}$$

$$z^l = MLP\left(LN(\hat{z}^l)\right) + \hat{z}^l \tag{7}$$

Where z^l is the output of block l and LN is layer normalization.

Step 6: For an input of size $\frac{H}{2^k} \times \frac{W}{2^k} \times C_k$, merging 2×2 adjacent patches reduce spatial resolution while increasing channels

Step 7: Predicted output is produced by ST Classifier.

The ST classifier achieves linear computational complexity, high accuracy, reduced memory usage, and ability to capture both local and global dependencies.

3.5. Modelling of SHAP

SHAP uses cooperative game theory to explain machine learning models. It calculates each feature's marginal contribution across all possible feature subsets (coalitions), weighted by combinatorial coefficients, to assign a unique fair payout value (Shapley value) to every feature. Figure 3 shows the SHAP feature analysis.

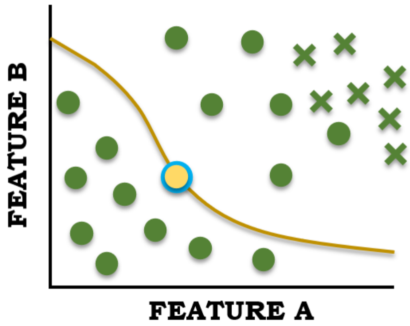

Figure 3: *SHAP feature analysis*

The exact SHAP value for feature is computed as:

$$\phi_i(v) = \sum_S \frac{|S|!(|F|-|S|-1)!}{|F|!}\left(v(S \cup |i|) - v(S)\right) \quad (8)$$

Where, F is the set of all input features, S is the subset of features not containing feature i, $v(S)$ is the model's expected prediction outcome when conditioned only on feature subset S. $v(S \cup |i|) - v(S)$ is the marginal contribution of adding feature. $\frac{|S|!(|F|-|S|-1)!}{|F|!}$ is the weighting factor representing the number of permutations.

4. Results and Discussion

The ST-SHAP is proposed for aircraft bird strike risk prediction, which is evaluated using python software. The name of dataset used for simulation is Bird Strikes in Aviation: Aircraft Collisions, which is taken from Kaggle. The number of features used for simulation is 26, they are 'Record ID', 'Aircraft Type', 'Airport Name', 'Altitude Bin', 'Make Model', 'Number Struck', 'Number Struck Actual', 'Effect', 'Flight Date', 'Damage', 'Engines', 'Operator', 'Origin State', 'Flight Phase', 'Conditions Precipitation', 'Remains Collected?', 'Remarks', 'Wildlife Size', 'Conditions Sky', 'Wildlife Species', 'Pilot Warned', 'Cost', 'Altitude', 'People Injured', 'IsAircraftLarge?', 'Remains Sent to Smithsonian', The classes named as no damage and caused damage are used for simulation and the percentage of class no damage is 90% and caused damage is 10%.

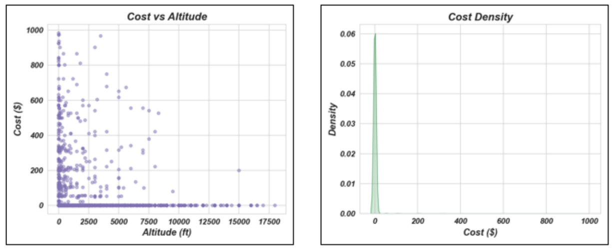

Figure 4: *Cost vs altitude and cost density*

Figure 4 shows the Cost vs altitude and cost density. Cost vs Altitude displays the relationship between cost in dollars and altitude in feet. The heaviest concentration of data points sits directly on the baseline where the cost is $0, extending all the way up to an altitude of nearly 18,000 feet. For data points where a cost is incurred, the values are clustered heavily at lower altitudes under 5,000 feet, with some individual costs reaching up to $1,000. As altitude increases past 7,500 feet, higher costs become extremely rare, and the overall variability in cost sharply decreases. Cost Density illustrates the distribution and frequency of the cost values independently of altitude. It features an extremely sharp, narrow green peak concentrated entirely near $0, reaching a density value of 0.06. The line drops to zero almost immediately after and remains flat across the rest of the horizontal axis up to $1,000. This confirms mathematically that a dominant percentage of the entire dataset consists of entries with zero or near-zero costs.

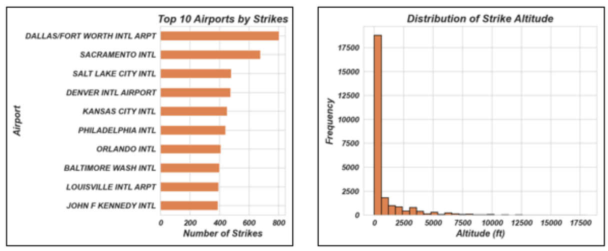

Figure 5: *Top 10 airports by strikes and distribution of strike altitude*

Figure 5 shows the Top 10 airports by strikes and distribution of strike altitude. The top ten airports by their total number of strikes, showing that Dallas/Fort worth international airport experiences the highest frequency with approximately 800 incidents, followed closely by Sacramento International Airport, while John F. Kennedy International Airport has the fewest among the top ten at around 380 strikes. The right histogram illustrates the altitude distribution of these strikes, showing a heavily right-skewed pattern where the vast majority of incidents occur near ground level between 0 and 1,000 feet.

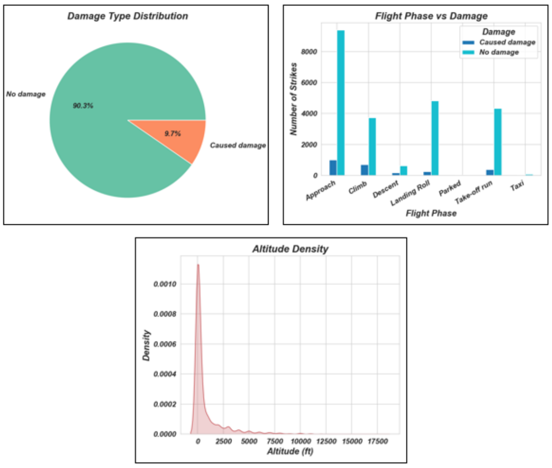

Figure 6: *Damage type distribution, Flight phases vs damage and altitude density*

Damage type distribution, Flight phases vs damage and altitude density are demonstrated in figure 6. In damage type distribution, the 91.3% of incidents cause in class no damage, while only 8.7% cause actual damage to the aircraft. In flight phases vs damage, number of strikes in approach for no damage is 8800 and caused damage is 900. The number of strikes in climb for no damage is 3800 and caused damage is 700. Finally, the altitude density plot illustrates that wildlife strikes are heavily concentrated near the ground, with the likelihood of a strike dropping sharply as altitude increases and becoming nearly non-existent above 5,000 feet.

Table 2: *Classification report*

Classes	Precision	Recall	F1-Score	support
No damage	0.73	0.42	0.53	491
Caused damage	0.94	0.98	0.96	4595
Accuracy			0.93	5086
Weighted avg	0.92	0.93	0.92	5086

Table 2 shows the classification report, which includes two classes, they are no damage and caused damage. The precision of class no damage is 0.73 and caused damage is 0.94. The recall value of class no damage is 0.42 and caused damage is 0.98 and the F1-Score of class no damage is 0.53 and attack is 0.96.

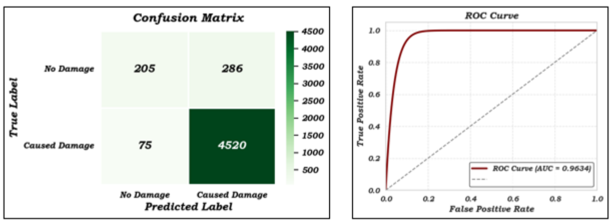

Figure 7: *Confusion matrix and ROC Curve*

Figure 7 shows the confusion matrix and ROC curve. he Confusion Matrix evaluates the model's predictions against the actual data across two categories: "No Damage" and "Caused Damage." It shows that out of the actual "No Damage" instances, the model correctly predicted 205 cases but misclassified 286 cases as "Caused Damage". For the actual "Caused Damage" instances, it correctly identified 4,520 cases while missing 75 cases that were incorrectly labelled as "No Damage". In ROC Curve, the AUC value of proposed ST-SHAP is 0.9634, which shows the reliability of the proposed system.

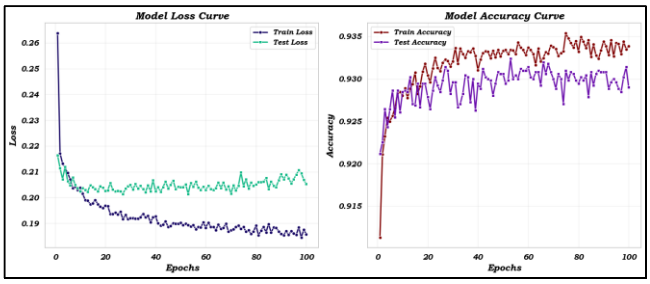

Figure 8: *Accuracy and loss of proposed ST-SHAP*

The accuracy and loss of proposed ST-SHAP are represented in figure 8. The accuracy of proposed ST-SHAP is 93% and the loss of proposed ST-SHAP is 20%, which demonstrates the effectiveness of proposed system.

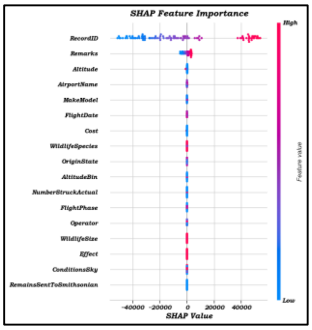

Figure 9: *SHAP Feature importance*

Figure 11 shows the SHAP feature importance. The SHAP value is mentioned in x axis and features are represented in y axis. The features like RemainsSentToSmithsonian at the bottom have almost no impact and the feature Record ID is the most important predictor.

Table 3: *Feature Wise Missing Value Analysis*

No	Feature	Value
1	Record ID	28477.855357
2	Remarks	2155.839749
3	Altitude	136.523511
4	Airport Name	63.836455
5	Make Model	38.609808
6	Flight Date	33.182753
7	Cost	30.943595
8	Wildlife Species	25.030298
9	Origin State	8.248696
10	Altitude in	2.451934
11	NumberStruckActual	1.887316
12	Flight Phase	1.488443
13	Operator	1.421001
14	Wildlife Size	0.710053
15	Effect	0.704022
16	Conditions Sky	0.022088
17	RemainsSentToSmithsonian	0.012358

Table 3 shows the feature wise missing value analysis. The features are listed in descending order, starting with "Record ID" at the highest value of 28,477.855357, followed by "Remarks" at 2,155.839749. A sharp decline occurs after these top two entries, with "Altitude" dropping to 136.523511, followed closely by aircraft and flight details such as Airport name, make model, Flight Date, and Cost, which range from roughly 63 down to 30. The remaining features gradually decrease from around 25 down to approximately 1.42. Finally, variables related to the post-incident outcome, such as "Wildlife Size," "Effect," "Conditions Sky," and "Remains Sent to Smithsonian," hold the lowest values, all finishing well under 1.0.

Table 4: *Comparison of response time*

Method	Response time
CNN [8]	0.3s
CNN-YOLO [9]	0.5s
LSTM-RNN [10]	0.4s
Proposed ST-SHAP	0.1s

Table 4 shows the comparison of response time. The response time of proposed ST-SHAP is 0.1s lower response time (faster inference latency) in a Swin Transformer classification model enables real-time edge deployment, reduced compute costs, and instant decision-making in live video streams or medical diagnostics. By using shifted local windows instead of global attention, Swin achieves linear computational scaling.

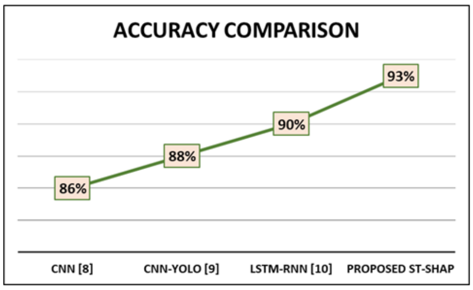

Figure. 12: *Accuracy Comparison*

Figure 12 shows the accuracy comparison. The accuracy of proposed ST-SHAP is 93%. Combining the Swin Transformer with SHAP provides a high-performance, transparent framework for predicting aircraft bird strike risks. It merges superior multi-scale spatial modeling of environmental and radar data with reliable, human-interpretable feature attribution for critical aviation safety decisions.

5. Conclusion

In this paper, a hybrid ST-SHAP has been proposed for aircraft bird strike risk prediction. The performance analysis is carried out using python software. ST-SHAP are effective at identifying, classifying, and mitigating aircraft bird strike risk, achieving 93% accuracy. Utilizing optimized feature sets allows for efficient, real-time detection without requiring massive, computationally expensive models. The developed method is compared with existing methods like CNN, CNN-YOLO and LSTM-RNN in terms of precision, recall and F1-Score. The DL models, ST-SHAP offer high accuracy of 93%, and less computational time of 0.1s in aircraft bird strike risk prediction. Future work focuses on advancing real-time artificial intelligence, integrating high-frequency millimetre-wave on-board radar, and refining spatiotemporal probabilistic models to transition from broad forecasts to actionable, automated airport operational planning.

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