PREDICTION DAMAGE FACTOR CLASSIFICATION OF AIRPORT PAVEMENT USING MACHINE LEARNING

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Abstract

Airport pavements experience continuous stress from operating large aircraft, compromising their structural integrity. Maintaining pavement resilience is crucial for ensuring flight safety. The Damage Factor (DF) is a crucial metric for evaluating the cumulative effect of aircraft loads on surface conditions. Accurate damage assessment and prediction are crucial for strategic maintenance planning and operational stability. This research examines the capacity of advanced mathematical methodologies, particularly machine learning, to identify and predict damage determinants. The researchers created sophisticated models that utilize extensive datasets, encompassing historical pavement performance records, aircraft movements, meteorological data, and material characteristics. The study aimed to enhance prediction capabilities using advanced algorithms, including random forest, logistic regression approaches linear SVM, tree and ensemble models. The findings indicated that the Majority Voting (MV) (random forest, decision tree and logistic regression) model attained the highest test accuracy of 81.82%, and ROC AUC value 0.8461, validating its robust capacity to accurately discern data patterns. Conversely, the naïve Bayes model exhibited markedly inferior performance, with a test accuracy of only 52.27%, underscoring its limited applicability to the dataset compared to alternative methodologies. The results reveal that the exceptional performance of the (MV) classification effectively identify underlying patterns in airport pavement deterioration data. This allows for extrapolation to a substantial training set under novel and unforeseen conditions.

Keywords*: Aircraft traffic, Algorithms, Classification learning, Damage factor, Machine learning.*

1. INTRODUCTION

Airports are crucial components of urban transportation and aviation infrastructure. Safety and comfort are paramount in airport operations; therefore, runway conditions must be consistently evaluated during maintenance to prevent and rectify damage. Damage to airport pavement substantially affects the safety of aircraft take-off and landing. Consequently, regular assessment of airport pavement degradation is essential for guaranteeing the safety of aircraft take-off and landing (Zhang et al., 2023; Prahara & Rachma, 2020). The Damage Factor (DF) quantifies the degree of pavement deterioration in airport pavements caused by different aircraft weight loads. Damage Factor is determined by empirical models, including the multi-layered flexible design methodology, which considers pavement quality, airplane loads, and climatic variables (Fatikasari et al., 2022). The intricacy of contemporary aircraft and heightened air traffic has necessitated using machine learning (ML) in pavement analysis. Machine learning can precisely forecast outcomes via damage factor analysis, as it accommodates vast datasets and discerns patterns and interactions that may be imprecise with other models. Airport managers and designers must thoroughly understand pavement deterioration to ensure safe and efficient operations (Barua et al., 2021).

This study aims to enhance predictive accuracy of airport pavement conditions and improve maintenance strategies. By examining important structural factors such as pavement thickness, in conjunction with historical performance and environmental data, the model facilitates a more accurate assessment of cumulative damage and enhances the efficacy of finite element analysis for rigid pavements (Barua & Zou, 2022; Ashtiani, Paniagua, et al., 2022).

This work established machine learning and data augmentation approaches to forecast the stiffness modulus of the asphalt concrete layer of an airport pavement, utilizing data pertaining to the airport's state. The predictive model may estimate the stiffness modulus for unmeasured runway sites via a shallow neural network trained with back-calculation results and data augmentation methods. In parallel, the US Federal Aviation Administration (FAA) commenced research on the Serviceability Level (SL) to establish dependable methodologies for constructing durable airport pavements. This extensive index evaluates a pavement's appropriateness for aircraft utilization (Ashtiani, Murrell, et al., 2022). Diverse machine learning methodologies have been employed to assess and forecast the severity of aviation incidents. The methods encompass artificial neural networks, support vector machines, random forests, gradient boosting classifiers, nearest neighbour classifiers, and logistic regression (Rosadi et al., 2024; Kaidi et al., 2023). Through the analysis of patterns and trends, airlines can identify potential risks and operational issues before they escalate on the airport runway. Advanced analytical tools enable airlines to implement preventive measures instead of merely reacting to events after they occur (Sen et al., 2022; Song & Luo, 2024).

2. LITERATURE REVIEW

The Pavement is the paramount airport infrastructure, as it must guarantee sufficient operability irrespective of traffic and weather conditions. Consequently, employing the most suitable and dependable investigative methods to evaluate structural integrity is imperative. The structural evaluation of airport pavements yields critical insights into their anticipated performance and assesses their present technical condition and remaining operational lifespan. *T.T. İnan et al.* applied a Multinomial Logistic Regression model to classify aircraft damage, using Principal Component Analysis (PCA) to generate features that effectively capture variations within the dataset. The study reported a testing accuracy of 0.581 for Model 4 with Recursive Feature Elimination (RFE) (İnan, 2023). *M. Krestenitis et al.* utilized the Contrastive Language-Image Pre-training (CLIP) model to detect three defect types of cracks, joints, and tire marks and classify damage severity into low, medium, and high levels. The model leveraged natural language labels for direct estimation of damage severity, providing high-level semantic outputs that enhance comprehensive runway condition assessment (Krestenitis et al., 2024). *W. Zeiada et al.* employed the Gaussian Process Exponential Regression (GPR) model to analyze and predict the occurrence of transverse cracks in flexible pavements. Using extensive datasets from the LTPP program, their study identified a positive deviation in transverse crack frequency and achieved an R-squared value of 70% (Zeiada et al., 2024). *T. A. Parsons et al.* employed machine learning techniques to analyze maintenance and qualification records, aiming to identify problem types that airport owners prioritized for investment key indicators of factors contributing to pavement underperformance. The study sought to validate the assumption that three main components accurately represent airport pavement suitability. Initial results demonstrated the potential of Linear Discriminant Analysis (LDA) in detecting issues within funding requests and work order documentation. However, the SF1391 model included numerous non-paving projects, limiting its ability to isolate specific pavement-related problems (Parsons & Pullen, 2023). *J. Bae, S. G. Yum et al* developed a neural network–based machine learning model to classify aircraft damage by analyzing causes of financial losses derived from insurance claim payout ratios and risk occurrence timing. The study utilized data from 625 transportation infrastructure construction projects and reported classification accuracies of 74.1%, 69.4%, and 71.8% for the training, cross-validation, and test sets, respectively (Bae et al., 2021). *H.W. Park et al* conducted the transfer function is the fundamental paradigm for designing software that correlates mechanically computed pavement damage with actual on-site damage. A Pavement Condition Index (PCI) model, which accounts for environmental and traffic loads, was created as a transfer function for concrete airport pavement design software (Park et al., 2023). *Y. Zhang et al.* examined void formation beneath concrete slabs, a common form of damage in airport pavements, and employed a signal-wise cascade deep network (SWC-Net) for void detection. The model was trained using a combination of real and simulated GPR signals, with FDTD simulations enriching the dataset by representing diverse field conditions. The study reported that SWC-Net outperformed image-based deep learning approaches in identifying subsurface voids (Zhang et al., 2024). *V. Perri et al.* applied the You Only Look Once (YOLO) model within a three-stage framework: analyzing orthophotos of pavement sections using a custom crack-detection model, extracting crack geometry through skeletonization and semantic mask analysis, and automating PCI calculation for faster, more consistent assessments. The dataset was built through detailed manual labeling on a computer-vision platform such as Roboflow, focusing on longitudinal and transverse cracks to ensure high-quality training data. The study reported average length-measurement errors of ±3.70% for longitudinal cracks and ±3.65% for transverse cracks, with width-measurement errors of ±4.24% and ±4.09%, respectively. The automated PCI values differed from field inspections by only ±1.33%. Additionally, 80% image overlap in both directions was used to achieve high-resolution, gap-free orthophotos (Perri et al., 2025). Moreover, pavement radar detection was used to assess the surface-layer thickness of the southern runway and verify the actual depth of the cement concrete pavement.

3. METHODOLOGY

3.1. Export and preprocess the dataset

The dataset utilized to ascertain the pavement damage classification factor was constructed by extracting essential aircraft operational features and pavement-related information, subsequently structuring them into an Excel file form 2014 -2024 for systematic analysis. The dataset comprises variables including *Aircraft Classification Mass, Engine Type, Number of Engines, Speed, Surface Type, and Phase of Flight*, chosen for their direct impact on pavement loads and deteriorating mechanisms. Each record documents the interplay between aircraft configuration and operational factors that influence stress distribution across pavement layers. Following data cleansing and encoding, the Excel dataset was utilized as the input for training three machine learning algorithms. These models were utilized to categorize pavement sections according to their vulnerability to damage, facilitating the recognition of trends and key components that contribute to pavement deterioration under diverse aircraft operations. This methodology offers a data-driven basis for assessing damage factors and improving airport pavement management techniques.

Airport pavement damage data are categorized into two groups: damaged and no damaged. To predict whether a given combination of factors will cause pavement damage, the value of the damage factor (0 or 1) serves as the target variable. All other columns, including aircraft type, speed, weather, and surface type, serve as characteristics (independent variables) that can affect the damage factor. An example of the sample used in this study is provided in **Error! Reference source not found.** Several datasets were used to evaluate the prediction accuracy of the classification model. Our dataset consists of 1007 points. To train and evaluate our model, we split the data into 900 “no damage” and 106 “damage” and then to balanced 106 “damage” and 106 “no damage” to training and testing sets. 84 of the data was used for training and 22 for testing or evaluation.

Tabel 1. Training Dataset Samples.

AIRCRAFT	NUMBER OF ENGINES	TYPE OF ENGINE	SPEED	SURFACE TYPE	DAMAGE FACTOR VALUE	CONDITION DAMAGE FACTOR
EMB-120	2	C	170	ASPH-F	0	NO DAMAGE
MISC-MAX	2	C	140	TURF-G	1	DAMAGE
B-777-200	2	D	160	TURF-G	0	NO DAMAGE
FALC-2000	2	D	170	TURF-G	1	DAMAGE
A-320	2	D	140	CONC	1	DAMAGE
B-737-300	2	D	250	CONC	0	NO DAMAGE
B-737-800	2	D	120	ASPH-F	0	NO DAMAGE
B-737-800	2	D	120	CONC-G	0	NO DAMAGE
B-757-200	2	D	190	CONC	1	DAMAGE
B-737-400	2	D	190	TURF	0	NO DAMAGE
PA-34 SENECA	2	C	150	CONC-G	0	NO DAMAGE
EMB-170	2	A	170	CONC	0	NO DAMAGE
B-737-300	2	D	132	TURF	0	NO DAMAGE
B-737-700	2	D	120	CONC	0	NO DAMAGE
CRJ100/200	2	D	210	ASPH-G	0	NO DAMAGE
EMB-170	2	D	170	ASPH-G	0	NO DAMAGE
B-737-700	2	D	140	ASPH-E	0	NO DAMAGE
A-319	2	D	160	CONC-G	0	NO DAMAGE
PA-44 SEMINOLE	2	D	120	TURF-G	0	NO DAMAGE
A-321	2	C	170	CONC	1	DAMAGE

The training of the above-mentioned dataset was conducted using Python programming Language in the Google Colab environment. The testing results obtained are explained in detail in the results section.

3.2. Indicators for model evaluation

The classification learner, comprising ensemble trees, decision trees, support vector machines (SVMs), and several basic classifiers, is an invaluable resource in Python. Moreover, it enables *Supervised learning* involves utilizing a training dataset comprising input instances and corresponding desired outputs to construct a function (or model) aimed at accurately predicting the unknown target output of future instances. The defining feature of supervised learning is the presence of an instructor and the training input-output dataset.

The task of predicting continuous target variables is referred to as regression. If the objective is to forecast discrete target variables, the task is classified as classification.

Unsupervised learning: it begins with a training dataset including input instances, aiming to partition the training examples into clusters such that the data inside each cluster exhibits a high degree of closeness. In unsupervised learning, data labels are not accessible, in contrast to supervised learning. The source-trained model is applicable for predicting trajectories on a novel dataset. It additionally offers an interactive training and comparison interface for several machine learning categorization models. This program streamlines the selection and training of a classification model by directing users through the necessary options and tasks in the workflow, as depicted in **Error! Reference source not found.**.

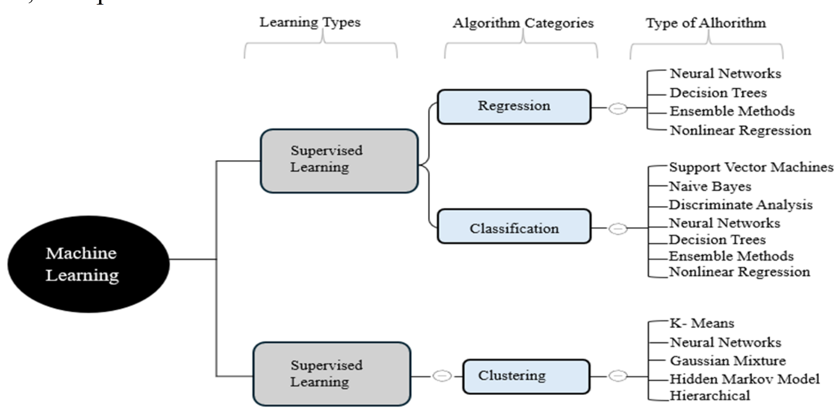

Figure 1. Categories of Machine Learning with frequently utilized algorithms.

Additionally, Model performance measures are employed to assess the efficacy of models, especially within machine learning, statistics, and predictive modeling. Research utilizes these metrics to assess the extent to which a model identifies patterns in data and the accuracy of its predictions. The selection of evaluation metrics depends on the classification model, the problem domain, and the class or output model. The formulas for its calculation are provided below.

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \tag{1}$$

Where TN aims for True Negative, TP is True Positive, FP is False Positive, and FN is False Negative.

Following the establishment of the accuracy value for prediction, the precision will be assessed in the data categorization. The subsequent equation will ascertain the precision's correctness: 2. Besides calculating the Recall and F1 score, Equations (3) and (4) were employed.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Where TP is True Positive, FP is False Positive.

$$Recall = \frac{TP}{TP+Fn} \tag{3}$$

Where TP is True Positive, FN is False Negative.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

4. RESULTS AND DISCUSSIONS

This study predicts the Damage Factor (DF) of airport pavements using machine learning, where the response variable is automatically selected as the column with the fewest unique entries and classified into two outcomes: damage (1) or no damage (0). The predicted results depend on multiple input attributes including pavement type, weather conditions, and aircraft-related information and are visually represented in the Parallel Coordinates Plot shown in **Error! Reference source not found.**

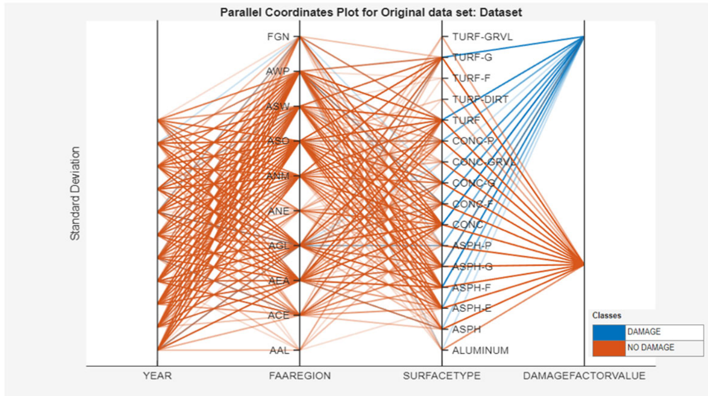

Figure 2. Parallel Coordinates Plot for the Original dataset.

Error! Reference source not found. presents the confusion matrix illustrating the classification performance of the evaluated Hard Voting Ensemble, which combines predictions from the Decision Tree, Random Forest, and Logistic Regression models through majority voting, demonstrates a balanced and strong performance in the pavement damage classification task. The model correctly identified 16 images of no damage (label 0) and 20 images of damage (Predicted1). However, it misclassified 6 no-damage images as damage and 2 damage images as no damage achieving accuracy 81.82% and 82.91% (Precision), 81.82%(Recall), and 81.67% for (F1-score) Overall, the ensemble achieved a good trade-off between both classes, effectively reducing misclassifications compared to several individual models, indicating that combining diverse classifiers enhanced its overall predictive reliability for detecting airport pavement damage. **Error! Reference source not found.**. illustrates that the evaluation of machine learning model hard majority voting models reveals a distinct hierarchy according to testing accuracy.

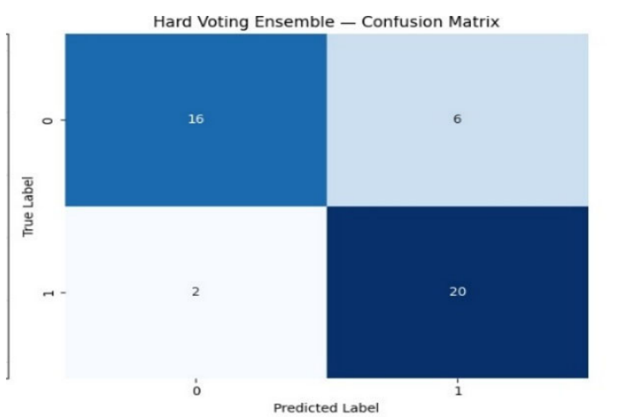

Figure 3. Confusion Matrix by majority voting model accuracy.

Tabel 2. Evaluation Results of the Hard Voting Ensemble Classifier on the Test Dataset.

No. Model	Test Accuracy	Precision	Recall	F1 Score
Majority voting (random forest, decision tree, and logistic regression)	81.82%	82.91%	81.82%	81.67%

Additionally, **Error! Reference source not found.** presents the confusion matrixes illustrating the classification performance of the evaluated machine learning models. The Logistic Regression model correctly classified 16 no-damage images and 13 damage images, while it misclassified 6 damaged pavements as undamaged and 9 undamaged pavements as damaged. The Random Forest model performed slightly better, correctly predicting 14 no-damage and 20 damage cases, but misclassifying 8 no-damage as damage and 2 damage cases as no-damage. The Decision Tree showed similar results, with 15 no-damage and 20 damage samples correctly identified, and 7 and 2 misclassifications for no-damage and damage cases, respectively. The Naive Bayes classifier strongly favored the damage class, correctly identifying all 22 damage samples but misclassifying nearly all no-damage samples (21) as damage, recognizing only 1 no-damage case correctly. The Linear SVM achieved 14 correct predictions for no-damage and 14 for damage but misclassified 8 no-damage and 8 damaged images. The Efficient Linear SGD model matched the Logistic Regression's performance, with 16 correct no-damage and 13 correct damage predictions, while misclassifying 6 no-damage and 9 damage samples. Finally, the SVM (RBF) model correctly classified 17 no-damage and 10 damage samples but incorrectly labeled 5 no-damage and 12 damage images.

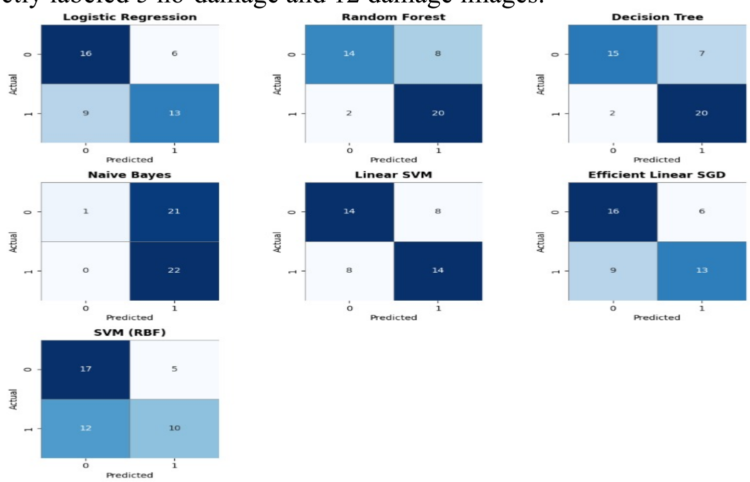

Figure 4. Confusion Matrices for different model's classifiers It shows the number of Actual (top left) and Predicted (lower middle).

The Receiver Operating Characteristic (ROC) curve depicted in the figure demonstrates the efficacy of the Hard Voting Ensemble models classifier in differentiating between crack and non-crack images. **Error! Reference source not found.** depicts the ROC curve, which compares the True Positive Rate versus the False Positive Rate across several categorization criteria. The curve illustrates the model's capacity to accurately identify fractured surfaces while reducing false positives. An AUC score of 0.85 signifies robust discriminative capacity, indicating that the Hard Voting Ensemble model proficiently distinguishes between positive and negative classes. An AUC of 1.0 indicates exceptional performance, whereas a value of 0.5 denotes random guessing; hence, an AUC of 0.85 demonstrates that the Hard Voting Ensemble models attain a high degree of prediction accuracy and reliability.

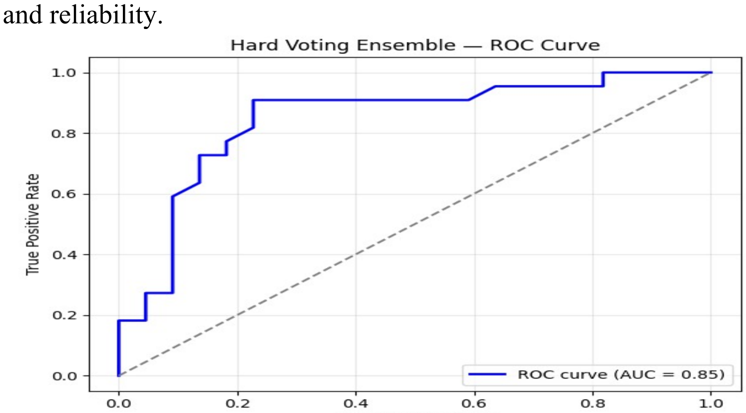

Figure 5. Receiver operating characteristic (ROC) curve for the model Decision Tree

Error! Reference source not found. depicts the Precision-Recall (PR) curve, demonstrating the trade-off between precision (the proportion of accurately predicted positive instances among all predicted positives) and recall (the proportion of accurately predicted positive instances among all actual positives) for the hard voting ensemble classifier. This curve is very beneficial for assessing model efficacy on imbalanced datasets. The curve illustrates the inverse relationship between precision and recall, demonstrating the model's capacity to sustain accuracy while identifying a greater number of positive samples. The area under the curve (PR AUC) value of 0.83 signifies that the hard voting ensemble models exhibit proficient performance in discerning pavement conditions, achieving an optimal equilibrium between precision and recall. This outcome indicates that the model effectively reduces false positives while accurately identifying pavement damage, hence affirming its reliability and robustness in the classification procedure.

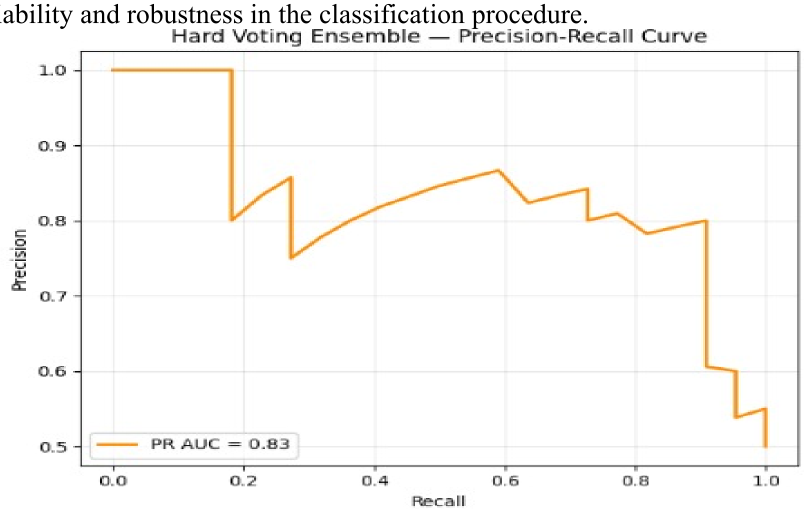

Figure 6. Validation Precision-Recall Curve.

This comparative investigation illustrates that employing several machine learning classifiers, such as tree-based, ensemble, neural network, and support vector machine models, improves the accuracy and reliability of predicting airport pavement deterioration variables. The results indicate that various models identify distinct data patterns, and combining their complementing advantages via ensemble approaches enhances predictive performance, especially for real-time forecasting applications. The study offers significant insights for creating effective prediction algorithms that enhance proactive airport pavement management and deterioration prevention measures.

Error! Reference source not found. illustrates that the evaluation of machine learning models reveals a distinct hierarchy according to testing accuracy. The Decision Tree model attained an accuracy of 79.54%, with a maximum precision of 81.15%, a recall of 79.54%, and an F1-score of 82.23%, indicating robust and balanced predictive performance. The Random Forest model achieved an accuracy of 77.27%, with a precision of 79.46%, a recall of 77.27%, and an F1-score of 87.08%, demonstrating strong and reliable performance. The assessment of various classification methods demonstrates significant discrepancies in their prediction efficacy. The Logistic Regression model attained an accuracy of 65.90%, a precision of 66.21%, a recall of 65.90%, and an F1-score of 65.80%, reflecting a balanced but moderate performance. The Efficient Linear SGD model achieved an accuracy of 65.90% and somewhat surpassed Logistic Regression with an F1-score of 68.07%, indicating superior overall equilibrium between precision and recall. The Linear SVM produced a somewhat lower accuracy of 63.63%, with constant precision and recall values of 63.63%, and an F1-score of 66.01%, indicating performance akin to Logistic Regression but slightly less accurate. The SVM utilizing the RBF kernel exhibited suboptimal performance, achieving an accuracy of 62.36%, precision of 62.64%, recall of 60.36%, and a markedly deficient F1-score of 37.10%, suggesting inadequate generalization of the nonlinear kernel for this dataset. The Naive Bayes model exhibited the poorest performance, attaining merely 52.27% accuracy, despite a comparatively high precision of 75.58%. Its low recall of 38.19% and F1-score of 57.85% underscore significant misclassifications.

Tabel 3 . Recall, F1-score, and Precision are machine learning algorithms.

Machine Learning Model	Testing Accuracy	Precision (%)	Recall (%)	F1- Score (%)
Decision Tree	79.54%	81.15%	79.54%	82.23%
Random Forest	77.27%	79.46%	77.27%	87.08%
Logistic regression	65.90%	66.21%	65.90%	65.80%
Efficient Linear SGD	65.90%	66.21%	65.90%	68.07%
Linear SVM	63.63%	63.63%	63.63%	66.01%
SVM (RBF)	62.36%	62.64%	60.36%	37.19%
Naive Bayes	52.27%	75.58%	38.19%	57.85%

5. CONCLUSION

This research illustrates notable progress in forecasting airport pavement degradation by amalgamating various data sources, such as pavement type, meteorological conditions, and aircraft attributes, employing multiple machine learning models to clarify the intricate nonlinear correlations among damage determinants. The suggested methodology facilitates real-time prediction and assessment of airport pavement degradation variables, providing a thorough and dependable decision-support tool for design and risk management authorities across diverse temporal and spatial contexts. This approach enhances the usability and accuracy of pavement condition assessments by prioritizing model interpretability and integrating machine learning outputs with powerful visualization tools and contemporary software. The results shows that the Majority Voting (MV) ensemble which combines Random Forest, Decision Tree, and Logistic Regression achieved the highest prediction accuracy of 81.82% and a ROC AUC of 0.8461, demonstrating superior performance in estimating airport pavement damage factors. Individually, the Decision Tree and Random Forest models also performed well, with accuracies of 79.54% and 77.27%, respectively, whereas Logistic Regression, Efficient Linear SGD, and Linear SVM produced moderate accuracies between 63.63%–65.90%, and SVM (RBF) and Naive Bayes showed the weakest results, at 62.36% and 52.27%. Overall, ensemble and tree-based methods consistently outperformed linear and probabilistic classifiers, confirming their robustness and greater suitability for airport pavement deterioration prediction.

The research advises planners to perform monthly inspections to avert damage to airport pavements. This research possesses the capacity to enhance multiple domains. Advanced machine learning methods effectively solve airport pavement issues, overcoming the limitations of classic damage factor prediction techniques. Future research in damage factor assessment can be enhanced by systematically comparing various predictive models and assessing the impact of data standardization, especially when amalgamating disparate data sources. This study presents a thorough framework illustrating that sophisticated machine learning methods improve prediction accuracy and facilitate proactive decision-making for the mitigation of airport pavement degradation.

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