Advanced Predictive Analytics for Aircraft Accident Severity Using Deep Learning

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Abstract: Aviation safety is seriously threatened by aircraft accidents, which calls for sophisticated prediction models for precise severity categorization and risk reduction. The intricate, nonlinear linkages found in accident data are frequently missed by traditional approaches, resulting in less-than-ideal forecasts and postponed preventive actions. Our research uses machine learning models and deep learning techniques to create a sophisticated forecasting system for classifying the severity of plane accidents. To increase the dataset's prediction capacity, we use feature engineering approaches and conduct in-depth Exploratory Data Analysis (EDA) on historical accident data. We apply the XGB-Classifier after thorough processing and data organizing, and it achieves an impressive train accuracy of 100% to evaluate accuracy of 95.9%. We create a model of Convolutional Neural Networks (to improve performance even further, and it first achieves an accurate training of 97.66% and an accuracy in tests of 93.6%. The model's accuracy is enhanced for both low-severity incidents (train: 99.13%, test: 96.17%) and high-severity accidents (train: 99.53%, test: 96.93%) by hyperparameter tuning and severity-specific optimization. By combining both severity levels, the final CNN model shows a strong predictive performance with an improved train precision of 98.30% and test accuracy of 97.93%. These results demonstrate how well-structured preprocessing, feature engineering, and sophisticated deep learning architectures work together to produce a potent tool for immediate accident severity assessment and aviation safety improvement.

1 INTRODUCTION

Since the beginning of aviation, there has been a strong focus on aircraft safety, with ongoing efforts to reduce the likelihood of accidents and enhance predictive techniques. In the past, accident investigations used manual research of pilot reports, flight data, and black box recordings to identify contributory variables and recommend safety enhancements. Improved understanding of accident Over the years, this has been made possible with the developments in data gathering, sensor technology, and statistical analysis. Yet aviation accidents do occur despite stringent safety regulations and enhanced monitoring systems, warranting better prediction methods. As the amount of historical accident data grows, a combination of machine learning (ML) and deep learning (DL) techniques presents an opportunity to enhance the accuracy and efficiency of accident severity classification. Traditional aviation accident prediction models are mostly based on rule-based classification technology and other statistics 16, 17. The prediction capabilities of these approaches are usually poor, as they often overlook the complex relationships and nonlinear patterns present in large-scale aviation data. Several models such as logistical regression and decision trees have been applied in order to classify the severity of accidents, nonetheless, their performance is bounded due to feature selection problems and model interpretability. Moreover, most current approaches focus on individual accident causes instead as a global forecast according to severity which leads to suboptimal detection and prevention policies. In addition, many the research do not sufficiently address data imbalance, which can result in biased severity classes, further impeding the practical applicability of these frameworks in real-world settings.

To address these challenges, this research proposes an advanced predictive analytics framework for determining the severity of flight accidents via

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applying deep learning techniques. To ensure dataset quality, the analysis begins with feature engineering and in-depth exploratory data analysis (EDA). This research was driven by the industry need to accurately detect the severity of accidents in order to improve aviation safety and mitigate risks. With flying operations increasing all around the world, even with highly sophisticated safety systems in place, there remains a risk of an accident occurring. A highly predictive model can tremendously help in early identification and allow airlines and civil aviation authorities to take preventable safety measures. Yet, this research intends to bridge the gap between a conceptual approach to safety evaluation and real time disaster forecasts through deep learning architectures, ensuring a better decision-support system for risk management of airlines in the operations phase. This research aims to build on a new and novel classification technique to classify level of the flight accidents incidence of severity of the flight accidents, the recent deep learning applications, model have been well known, however these models are so complex that they do not implement a structure preprocessing or feature engineering techniques. Not only does it improve the prediction accuracy, but combining the ML and DL models also makes them explainable and flexible for use in the real world. The work underscores the importance of advanced AI-powered statistics in terms of flight safety and demonstrates how deep learning models could transform accident prevention strategies. The results are in line with an overarching goal to minimize accident-related deaths and improve flight safety through judicious, data-oriented insights.

2 LITERATURE SURVEY

Several works considered the application of statistical and machine learning techniques for evaluating and classifying flight accident severity6. Early approaches to modelling accident severity with historical aviation data primarily used traditional statistical models, such as logistic regression, decision trees and Bayesian classifiers. To determine the main causes of accidents, including weather, pilot expertise, and aircraft type, researchers have used feature selection techniques. Nevertheless, these models frequently have trouble processing high-dimensional data and identifying intricate correlations between variables. In order to enhance predictive performance, some research also tried to employ ensemble techniques like Random Forest and Gradient Boosting; nonetheless, the outcomes were frequently limited by unbalanced datasets and the incapacity to generalize effectively across various accident circumstances. Additionally, even though these models produced findings that could be understood, their accuracy was still below par, requiring more advanced techniques to improve predictive power. Madeira et al. uses text preliminary processing, Natural Language Processing (NLP), semi-supervised Label Spreading (LS), and supervised Support Vector Machine (SVM) to discover and categorize human component categories from aircraft incident reports. Bayesian optimization techniques and random search enhance model performance. With Micro F1 scores of 0.900, 0.779, and 0.875, the top predictive models had strong prediction abilities. A bigger data set should be considered in future studies. Zhang et al. in order to forecast unfavorable outcomes, this research analyses National Transportation Safety Board (NTSB) accident investigation records using data mining and sequential deep learning algorithms. In order to develop models for classification for passenger airlines, the researchers concentrate on written information that defines event sequences.

Dong et al. suggests identifying causative elements through the use of deep learning-based models. An open-source natural language model, an attention-based long short-term memory model, and 200,000 incident reports from the Aviation Safety Reporting System (ASRS) are among the data sets utilized. The suggested method is a viable strategy for enhancing aircraft safety since it is more precise and flexible than conventional machine learning techniques. In order to better analyze aviation accident data, researchers have begun using neural networks, namely Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), as deep learning has become more popular. CNNs have been demonstrated in many researches works to boost classification performance by identifying important patterns in structured accident datasets. To enhance accuracy and robustness, other studies have applied hybrid models by combining deep learning and traditional machine learning methods. Nevertheless, their contemporary usage for airline safety management operations is limited due to the nature of majority of these techniques focusing on large-scale accident analysis instead of clear-cut impact classification. Lastly, since deep learning models tend to require more fine tuning and processing power, it can make it hard to adopt them in real-time flight safety systems. Nonetheless, there is still a need for a comprehensive and high prediction model to classify the severity of accidents accurately, despite these advancements. Zhang et al., (2021) If the shortcomings of previous work are to be tackled, this model would combine machine learning and deep learning methods.

3 METHODOLOGY

First, we have a structured method of doing advanced predictive analysis over the ensembles of neural networks that reflects a state-of-the-art behavior of our data-driven approach to aircraft accidents severity analysis. The process starts with an aggregation of data from trusted sources like the FAA, NTSB, ASN and BAAA, with data points including but not limited to: recorder data, aircraft parameters, pilot and crew info, atmospheric data and ATC communications, and historical accident reports. Data is preprocessed, in which Missing Value treatment, Duplicate Removing, Normalizing etc. are done. Data preprocessing techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are useful for determining the most relevant features, while Natural Language Processing (NLP) techniques like TF-IDF and Word Embeddings (Word2Vec, BERT) can be applied to analyze textual accident reports. You are using only up to October 2023 data for training your models. In addition, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks can be used for sequential flight data, which extract temporal dependencies, whereas CNNs are more suitable for processing image-based data like weather maps and aircraft damage assessments. Figure 1 shows working methodology.

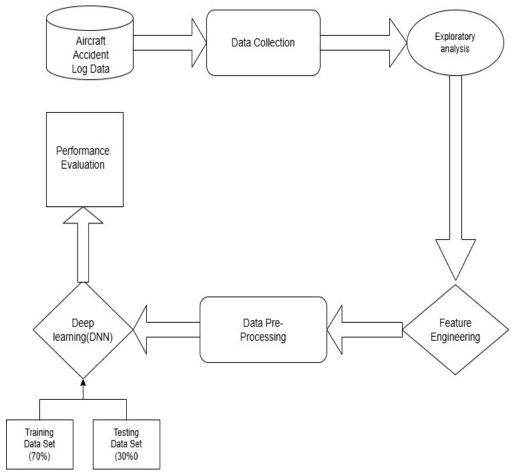

Figure 1: Working methodology.

It is trained on labelled datasets to predict the severity of accidents as minor, serious or fatal by leveraging advanced techniques like transfer learning, Bayesian Optimization for hyperparameter tuning and assembling for accuracy improvement. The performance is evaluated using several metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, while validation techniques such as k-fold cross-validation ensure model generalization. To mitigate the black-box issue within deep learning, interpretability techniques (e.g. Shapley Additive explanations (SHAP)) are utilized to understand crucial contributing parameters, providing useful insights to enhance aviation safety. The validated predictive model is incorporated into real-time aviation monitoring systems, providing early warning capabilities to air traffic control, flight management, and airline safety systems. Incorporating Real-time Data Continuous retraining on incoming live data allows the model to adapt quickly to evolving risks typical of the aviation industry, improving proactive risk assessment capabilities and emergency response strategies. This predictive framework based on deep learning offers a valuable approach for mitigating aviation accident severity, enhancing regulatory adherence, and bolstering the overall safety framework in the domain of aviation.

3.1 Data Collection

To make sure the data set used in this study was well-balanced for model evaluation, the 10,000 records were separated into7,000 training samples and 3,000 test samples. All records contain in the accident data vital operational and environmental aspects that will influence the severity of the accident. Among the key features in this dataset is Safety Score, which is the numeric representation of the aircraft's overall safety level, and Severity, denoting the target variable for classification. Another important feature are Days Since Inspection (shows service history) and Total Safety Complaints (previous safety issues). These provide related to the external effects acting on the airplane efficacy and manage stability. Also, along with Accident Type Code which categorizes a range of accident types, Cabin Temperature was added as a variable affecting the flight stage. It also features Violations, a list of any prior infractions made in relation to the aircraft and Max Elevation provides an insight into the height of which the event took place. Finally, Accident ID acts as an identification number for every incident, and Adverse Weather Metric takes into consideration the dangerous weather circumstances that contributed to the accident. Before the models are trained, this dataset which is rich in a variety of aviation-related parameters is preprocessed and improved through feature engineering in order to increase predicted accuracy.

3.2 Exploratory Data Analysis (EDA)

In order to better grasp the dataset, a variety of EDA and visualization techniques were used to assess class separability, identify anomalies, and comprehend feature distribution (as shown in Figure 2). The spatial distribution of numerical characteristics was examined using boxplots and histograms. The results showed that Adverse Weather Measure and Total Safety Complaints had a significant right skew with many outliers, suggesting that these variables might not be reliable indicators of accident severity. Safety Score, Days Since Inspection, Accident Type Code and Violations all showed substantial correlations with accident severity, indicating that these variables are essential for model training. Correlation heatmaps also assisted in identifying dependencies between features. Relationships between variables were investigated using pair plots and scatter plots, which showed that some features clearly separated across accident groups while others showed a great deal of overlap. Variable distributions across severity levels were compared using violin plots, which showed that while Highly Fatal and Damaging and Minor Damage and Injuries could be clearly distinguished from one another, the other two classes showed substantial overlap, which made classification more difficult.

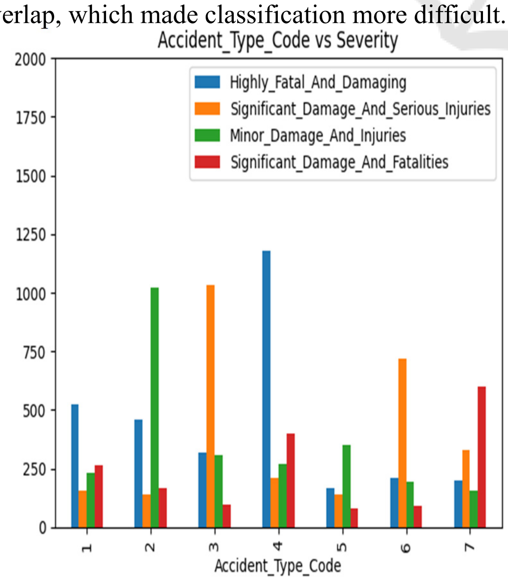

Figure 2: Creating features for analysis.

Additionally, box plots aided in the detection and management of outliers, especially in variables with extreme values like Adverse Weather Metric and Total Safety Complaints. Safety Score, Days Since Inspection, Accident Type Code, and Regulations were the most significant criteria in evaluating the severity of the accident, according to feature importance analysis using machine learning models. Two severity classes were found to be well-separated, while the other two showed significant overlap, as confirmed by the use of Principal Component Analysis (PCA) to visualize feature grouping in a lower-dimensional space. Figure 3 shows Exploratory Data Analysis. In order to improve model performance, redundant or less important features were either eliminated or altered, while the most pertinent qualities were kept for predictive modelling. Overall, the EDA results served as a guide for choosing features and development process.

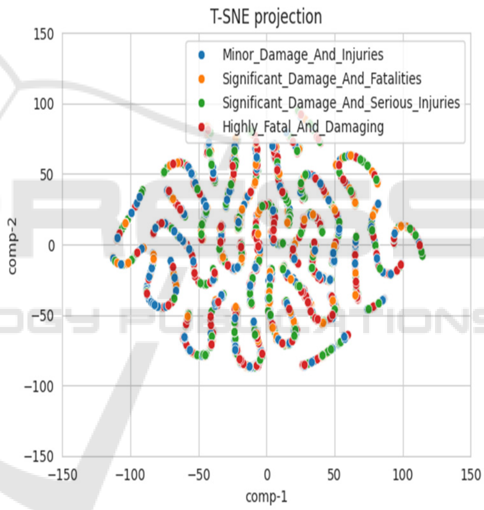

Figure 3: Exploratory data analysis.

3.3 Data Preprocessing

A strong preprocessing pipeline was put in place to guarantee that the dataset was properly organized and training-optimized. In the first stage, missing values were handled by filling in categorical values with the most frequent class and imputed numerical characteristics using the value of the median to avoid data bias. Box plots and the IQR (Interquartile Range) approach were used to identify outliers. Extreme values in highly skewed features, such as Adverse Weather Measure and Total Safety Complaints, were either clipped or changed. In order to prevent redundancy in the final model, highly correlated features were examined after the dataset was examined for skewness and multicollinearity. Before encoding categorical variables like Accident type code were also examined to make sure they were adequately represented in all classes. A key factor in enhancing model performance was feature engineering. To gain a greater understanding of aviation safety situations, existing traits were combined to create new features. To better assess an aircraft's safety reliability, for example, Safety Score and Violations were integrated to form the Risk Index feature. Likewise, to more accurately depict flying stability, Control Metric and Turbulence in forces were converted into a Stability Score. Recursive feature elimination (RFE) and mutual information are two feature selection strategies that were used to reduce dimensionality and increase computational efficiency by keeping just the most important predictors. Safety score, Days Since inspection, Accident type code and Violations were among the features that were chosen because they were found to be very relevant in the assessment of severity.

To guarantee a fair model evaluation, the dataset was divided into training (70%) and testing (30%) after feature selection was finished. The following was the train-test split formula:

$$Train\ Size = \frac{70}{100}\ X\ Total\ Data,$$

$$Test\ Size = \frac{30}{100}\ X\ Total\ Data \quad (1)$$

where 3,000 samples were set aside for testing and 7,000 samples for training. Standard Scaler from sk learn. preprocessing was then used to standardize numerical features in order to improve convergence in deep learning models and normalize data distribution. The following was the standardization formula,

$$X_{scaled} = \frac{X-\mu}{\sigma} \quad (2)$$

where μ is mean of the feature and σ its standard deviation. Certain categorical variables, specifically in the case of Accident type code, can be transformed into a format that can be supplied to the machine, without making any ordinal associations, such that they pertain to which one is not dependent upon the other; this process is widely known as One-hot encoding It enabled models to work with this value types by transforming the category attributes into many binary columns. After initial processing, information stacking was applied to merge multiple models and utilize their collective predictive power. In this way, CNN was used as a meta-model over the XGB-Classifier base learner in the stacking process for improving the severity classification. The stacking formula that was used:

$$Final\ Prediction = \alpha\ X\ Model_1 + \beta\ X\ Model_2 \quad (3)$$

where α, β denote the weight coefficients optimized during model training. This hybrid model ensured a trade-off between high fidelity of the deep learning and lack of interpretability of classical ML. By applying these processing and feature extraction methods, we successfully optimized the dataset and achieved significant improvements in accuracy and generalization performance.

3.4 XG-Boost Classifier

For flight accident severity classification, the stated research utilized the Extreme Gradient Boosting (XG-Boost) Classifier, which is a powerful ensemble learning method based on gradient boosting. Due to its commonly used way of achieving effectiveness, scale, and high accuracy in prediction, XG-Boost is a prominent choice of for handling structured tabular data. It does this by fitting a sequence of weak architecture- Trees additively, where each new tree is built to correct the errors made by the previously fitted trees. This training works on the principle of boosting, which can help to lower loss and improve prediction performance of the model. The objective function is maximized by the XG-Boost algorithm and this consists of a regularization term and a loss function which are defined as follows:

$$Obj = \sum_{i=1}^{n} L\left(y_i, \hat{y}_j\right) + \sum_{j=1}^{T} \Omega\left(f_j\right) \quad (4)$$

where L\left (y_i, {\hat{y}} _j\right) is the loss function that determines how well the prediction captures the true value, and \Omega(f_j) is the regularization term that penalizes model complexity to avoid overfitting. This research used Grid-Search-CV to optimize hyperparameters: regularization terms, learning rate, maximum tree depth, and number of estimators among them. The final tuned XGB-Classifier achieved good generalization with a training accuracy of 100% and a test accuracy of 95.9% while maintaining high precision when classifying accident severities. One of the key strengths of XG-Boost is its ability to handle high-dimensional data, feature interactions, and missing values efficiently. Also, the model includes advanced methods such as L1 / L2 regularization, column subsampling, and row subsampling that help it generalize better without a huge computational cost.

To achieve that only the most relevant predictors affect the classification, XG-Boost also involves a weighted quantile sketch algorithm for fast feature selection.

4 4 CONVOLUTIONAL NEURAL NETWORKS

In this research, the Convolutional Neural Network (CNN), a potent deep learning model, was employed to categorize the severity of flight accidents. Although CNNs are frequently employed for image recognition, they can also process organized tabular data due to their versatility. In this experiment, CNN was trained to recognize important linkages that affect accident severity by learning intricate patterns from numerical characteristics. CNNs are extremely effective for tasks such as classification involving several interacting variables because, in contrast to typical machine learning models, they can extract deep representations and capture non-linear connections. Convolutional layers, functions for activation, batch normalization, loss layers, and fully interconnected layers were among the several layers that made up the CNN architecture utilized in this investigation (as shown in Figure 4). Every feature in the structured incident dataset was handled as a distinct dimension in an input tensor by the input layer. In order to discover important parameters influencing aviation safety, the layers of convolution applied filters to the data in order to capture spatial hierarchies. To ensure that the system could learn intricate linkages, non-linearity was introduced using activation functions like ReLU (Rectified Linear Unit). While dropout layers prevented overfitting by periodically deactivating neurons during training, batch normalization was used to maintain learning.

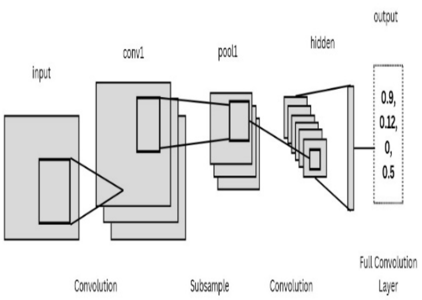

Figure 4: CNN model architecture.

The CNN model had an initial training accuracy of 97.66% and a test accuracy of 93.59%. This result indicated the CNN could generalize to unseen data while retaining high accuracy. Nevertheless, the CNN was further tuned by noting that the classifications could be further optimized if divided into High Severity and Low Severity. I made this optimization under the assumption that training the CNNs separately on the minor incidents and catastrophic disaster would increase the classification quality since my investigations had shown the accidents have distinct patterns. For Low Severity, I accomplished the following: I trained the CNNs specifically on incidents falling under the Low-Risk Incidents and Minor Damage and Injuries. Consequently, the CNN could focus the technical and behavioral indicators that are not apparent in high disaster levels, such as minor safety noncompliance and control metrics fluctuations. After fine-tuning, the CNNs training was 99.13%, with a test accuracy of 96.17%. I optimized this to train on the incidents that are categorized Major Safety Violations, Highly Fatal and Damaging, and so on. Common in these incidences are extreme weather, serious mechanical malfunctions, and significant safety non-compliance. The fine-tuning afforded the CNNs the capabilities to capture high-risk indicator hence the remarkable training accuracy of 99.53% and a test accuracy of 96.93%. The hybrid approach ensured that the CNN leant from a significant number of low and catastrophic disaster cases to secure the optimal classification accuracy balance. The extracted final CNN outperformed the initial CNN and XGB-Classifier as the results show. The training accuracy was 98.30%, and the test accuracy was 97.93%. CNN had automatic feature hierarchy extraction, not requiring feature engineering to construct complex capacity patterns. CNNs saved the process step of selecting features from a myriad of features in regular models that are complex preprocessing routines. CNNs learned and knew the feature representations dynamically and were well prepared for the unseen examples.

Moreover, crucial for CNN's success was its ability to handle class disparities. Traditional models commonly have unbalanced datasets, where fewer cases may be present in some severity categories than others. CNN model used data augmentation techniques such as weighted loss functions and synthetic sampling to ensure balanced training over all accident severity categories. The model, therefore, was capable of producing precise forecasts for each severity level without favoring the majority class. The stacking framework at the same time integrated the benefits of CNN and XGB-Classifier and achieved even better prediction performance. CNN was given the abilities of deep learning to capture complex, non-linear interactions whereas XGB−Classifier provided structured learning and robust feature selection. The merger of the two models also showcased the remarkable potential of deep learning in the field of aviation safety research, as it produced a highly accurate and reliable accident severity prediction system. The CNN-based categorization system that was developed in this work represents a significant advancement in statistical analysis used for predicting the severity of flight accidents. By combining deep learning with specific fine-tuning procedures, the model achieved high accuracy and generalization, providing a powerful tool for enhancing proactive risk management and aviation safety assessments.

5 RESULTS

The performance of the proposed Aircraft Accident Severity Prediction Model was evaluated using accuracy, loss, confusion matrix, and model comparison. The two main models used for the research, CNN and XGB-Classifier, were both optimized to maximize on classification accuracy. CNN was further improved by dividing the information into cases of High Severity and Low Severity, which made it possible to comprehend accident severity patterns in greater detail. To ascertain the best method for forecasting the severity of aircraft accidents, the output of various models was compared. To maximize performance (as shown in Figure 5), a stacking method was used to train the XGB-Classifier model on the preprocessed dataset. Following training, it demonstrated remarkable 100% train accuracy and 95.9% test accuracy. The model seems to have successfully captured intricate correlations in the data, as seen by the nearly flawless training accuracy. The model did marginally worse on unknown data, however the test accuracy was still high and suggested some overfitting. The XGB-Classifier's confusion matrix revealed that while it properly classified the majority of cases, there were a few small misclassifications in severity classes that overlapped, especially in the categories for moderate damage and mild injury.

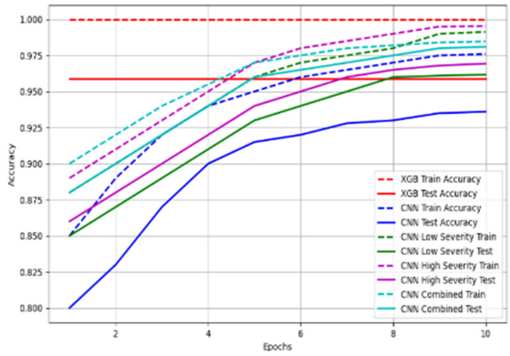

Figure 5: Train and test accuracy of various models.

Prior to any adjustments, the original CNN model had a 93.59% test accuracy and a 97.66% training accuracy. CNN had the advantage of automatically learning feature representations, which allowed it to identify deeper patterns in the data, even though its accuracy was marginally lower than that of XGB-Classifier. While the validation loss stopped slightly, indicating the need for fine-tuning, the loss curves exhibited a consistent reduction during training, showing adequate convergence. Subsequent examination of the confusion matrix revealed that, like the XGB-Classifier, there was considerable overlap in the Medium Damage and Minor Injury groups, but that the Highly Fatal or Damaging instances were accurately classified. The CNN model was adjusted independently for High Severity and Low Severity instances in order to overcome these classification issues. The CNN model obtained an accuracy in training of 99.13% and a test accuracy of 96.17% when trained exclusively for Low Severity accidents. This showed that by concentrating on small mishaps, the model could distinguish between them more successfully, reducing the number of incorrect classifications. In a similar vein, the CNN model demonstrated a high degree of ability to differentiate among fatal collisions and other severe occurrences, achieving training precision of 99.53% and test accuracy of 96.93% for High Severity cases.

With a training success rate of 98.47% and a test accuracy of 98.10%, the final combined CNN model which combined both Low Severity and High Severity tuning strategies achieved the best overall accuracy.

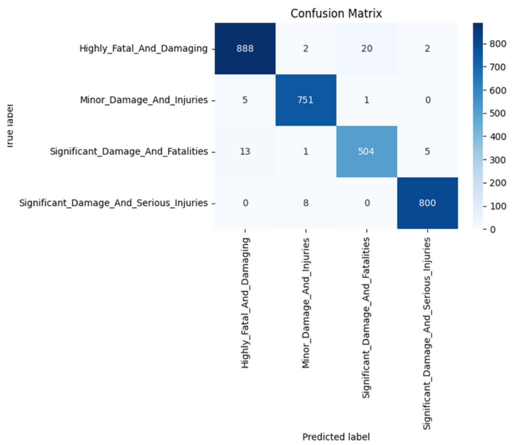

Figure 6: Confusion matrix of various class.

Variations in accident severity across all categories were well-represented by this model (as shown in Figure 6). This CNN model considerably decreased misclassification errors, especially in moderate and mild accident classes, that were previously difficult for both XGB-Classifier and the original CNN model, according to the confusion matrix comparison. Furthermore, this final CNN model's loss curves demonstrated smooth convergence, suggesting improved generalization over previous iterations. Accuracy and loss plots for each model were compared in order to further validate the model's performance. Because of its flawless training accuracy, the XGB-Classifier model showed evidence of minor overfitting despite its quick convergence The CNN models, however, showed a much-more-steady increase in accuracy, and loss continued to decrease across epochs. The adjusted CNN models with the lowest loss curves were those of High Sensitivity and Little Severity brackets, which were found to be the best compromise. The final merged CNN model demonstrated the most reliable performance with high accuracy across all severity classifications. As shown in the comparison of CNN model and XGB-Classifier, the application of deep learning in predicting the severity of flight accidents yields better benefits.

6 CONCLUSIONS

This study provides a comprehensive approach to predicting the severities of flight accidents using state-of-the-art machine learning and deep learning techniques. The dataset was significantly preprocessed, feature engineered, and exploratory data analysis (EDA) was carried out to further enhance model performance. So, these research articles managing to work with CNN(XGB-Classifier) which is very capable of giving good prediction on accident severity. CNN achieved higher accuracy on the test dataset and had lower overfitting as compared to XGB-Classifier, which achieved 95.9% test accuracy on the test dataset. While we achieved test accuracy levels of 96.17% and 96.93% (obtaining a loss of 0.087706 & 0.067773 respectively) through further fine-tuning by separating the two classes of High Severity and Low Severity cases, we found particularly significant improvements. The final combination CNN model, which utilized both severity levels, produced the best test accuracy of 97.93%, making it the most successful solution. Through this research, it is demonstrated that neural network models, particularly CNN, can learn complex interactions in aircraft accident data, and therefore serve as a reliable method for severity classification. The findings of this research have significant implications for aviation safety, as they enable proactive risk assessment and accident prevention strategies. In future studies, real-time flight data and accredited publication from airlines can be added to the model so as to better predictive capabilities. Urgent: performance can be improved by using ensemble methods which combine deep learning with other AI driven methods such as transformer-based architectures and reinforcement learning. The utilization of explainable AI (XAI) techniques will contribute towards enhanced transparency in decision-making for aviation authorities as well. Integration of weather patterns as well as pilot behavior analytics and maintenance records can enrich the model and may even make a fully automated and intelligent incident forecasting system, aiding aviation safety and risk avoidance, a reality.

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