PROACTIVE SAFETY PARADIGM FOR AVIATION SECURITY USING A HYBRID MODEL OF SVM AND DNN

¹Rishabh Suri, ²Jayeshh Sharma, ³S. Priya

ABSTRACT -- Due to the growth in air traffic, there exists a dire need for inculcating a system which not only alleviates the load on the airline operators to assess the associated risk during the process of flight aviation but also developing a 'proactive safety' paradigm which helps in assessing the severity of abnormalities, by categorizing the various parameters as "high, medium or low level" risk factors. To implement the aforementioned, a predictive model needs to be developed to examine a wide variety of possible cases and provide for a crisp value for the entailing consequences associated with the possible outcome. The dataset is taken from the ASRS online database repo, maintained by NASA to record all the aviation mishaps. First, we categorize all the events, based on the level of risk associated with the event consequence, into three groups as mentioned earlier, followed by a support vector machine model to find the relationship between the "event synopsis (text format)" and the "event consequence" by using tokenization techniques. In parallel, a deep neural network is trained to map the coupling between event contingent features and event results. Furthermore, a strategy to agglomerate the results from the two different models is deployed thereby improving the prediction. Finally, the prediction on risk level categorization is extended to event-level outcomes through a probabilistic decision tree together with a performance evaluation metric to display the efficiency of the said proposal.

Keywords - Air transportation, Deep learning, Support vector machine, System safety and Risk assessment

I. INTRODUCTION

In order to ensure the safety of the air transportation system, the proposed approach attempts to predict the intensity of the abnormal situation of aviation events based on their risk levels. The proposed approach focuses on the prediction of aviation risk by exploiting the hybrid risk-level prediction model that incorporates Support Vector Machine (SVM) and the Deep Neural Networks (DNN). Owing to the heterogeneous nature of the data, the prediction model initially categorizes the aviation report document into the structured and unstructured data by utilizing the divide and conquer approach, after that it is fed as input to the classification model to predict the results. In this regard, the unstructured text data entails the remarkable preprocessing techniques before start exploiting it for the predictive modeling. In the hybrid prediction model, the support vector machine model adopts the preprocessed textual data as the input to identify the relation within the event that represented in the text format. Concurrently, the deep neural network adopts both the categorical data and the numerical data to learn the intricate relation between the event contextual features and event outcomes. Additionally, an innovative fusion rule is

¹ B. Tech Final Year Student, Dept. of CSE SRM IST (KTR) Chennai, India, rishabhsuril@gmail.com.

²B.Tech Final Year Student, Dept. of CSE SRM IST(KTR) Chennai, India, jayeshhhsharma@gmail.com

³ Assistant Professor(Sr. G) SRM IST(KTR) Chennai, India, priya.sn@ktr.srmuniv.ac.in

designed to combine the results of learning models to improve the aviation risk prediction. Finally, it predicts the event-level outcomes through the probabilistic decision tree.

Attribute	Content				
Time/Day	Date: 200601				
	Time: 1201-1800				
Place	Local Airport: TNCM				
	State: FO				
	Elevation.MSL.Single Value: -				
Environment	Aviation Scenario: VMC				
	Visibility: 10				
	Luminescence: Dusk				
	Ceiling.Single Value: CLR				
Aircraft	Reference: X				
	ATC / Advisory.Center: TNCN				
	Aircraft Operator: Corporate				
	Make Model Name: Gulfstream G200				
	IAI 1126 Galaxy				
	Personnel Count: 2				
	Operating Under FAR Part: Part 91				
	Flight Plan: IFR				
	Objective: Passenger				
	Aviation Aspect: Initial Climb				
	Route In Use: Visual Approach				
	Airspace.Class D: TNCM.D				
Component	Aircraft Component: Engine Air				
	Problem: Malfunctioning				
Person	Reference: 2				
	Reporter Venue : Flight Deck				
	Reporter Institution: Corporate				
	Duty Aviation personnel: Person not flying; Primary Commander				
	Qualification.Fl				
	Exposure.Cumulative Flight personnel: 5000				
	Exposure. Aviation Personnel. Last 90 Days: 150				
	Exposure.Aviation Personnel.Category: 2600				

Table 1: A sample incident/accident record extracted from ASRS.

	ASRS Report Number. Accession Number: 682978		
	Anthropomorphic elements: Disruption of Communication channel		
Events	Aberration: Deviation from designated peak		
	Anomaly.Inflight Faced circumstance: Unstabilized Approach		
	Spotter: Aviation operator		
	Location of discovery: Onboard		
	Consequent Action: Accepted clearance		
	Consequent action: crew overhauling		
	Consequent action .ATC clearance issuance		
	Consequent action.ATC: Issued avuncular pertaining to safety		
Assassments	causal factor: Airspace infrastructure		
ASSESSMENTS	Abetting Factors: Anthronomorphic negligence		
	Primary Problem: Anthronomorphic negligence		
	Primary Problem: Anthropomorphic negrigence		
Synopsis	ZMA controller Experienced OP. error at 18500 ft. when taking		
	control of a sector but not aware of a decent CLRNC issued by a		
	student controller		

II. LITERATURE SURVEY

The following section provides a detailed insight into the ongoing research as well as the published papers in the domain of aviation safety, with consortium of domains being implemented into the same.

The proposal of the evaluation perpetually increases stress on the aviation sector which entails a dire need for a more "proactive safety" based approach. This paper[1] further proposes to alleviate the workload from the stationed operators by entailing a need to design a predictive model to automatically assess the various outcomes as well as categorize the risk factors based upon the latent relationships to successfully quantify the prospects

associated with possible outcome. The author further proposes to undertake the feat by implementing a "Hybrid Model" with the task of performing predictive computations upon the varied dataset by fusing SVM and an ensemble of DNN, furthering the same by implementing a more modular approach namely categorization of events based upon the associated risk, followed by application of Support Vector Machine to discern the relationships existing between event synopsis and the event sequel and concurrently a usage of DNN training to discern intricate relationships between contingent event and the result, is also suggested by the author, followed by an amalgamation of the results from the aforementioned to give forward a more crisp and easily discernible result by implementing an idiosyncratic fusion rule with finally a more holistic result evaluations to elicit the effectiveness of the aforementioned proposed approach.

The research paper[2] initiates the discussion by the description of the meaning of ensemble methods which if were to be directly lifted off from the paper suggest a confluence of predictive algorithms or more succinctly a meta-algorithm with the motives of improving the efficiency of the model in question by implementing all or any of the following, namely, reducing variance(bagging), reducing bias(boosting) or increasing prediction accuracy. This paper reviews these methods and probes deeper to elucidate the efficacy of an ensemble based approach over a more singular approach tackling only a set homogenous data. The aforementioned paper also performs a more detailed comparative study of the previous research papers pertaining to the given problem statement, followed by a proposal of inchoate experimental setups to unravel the shortcomings of ADABOOST over fitting.

The research paper[3] implements the different feature selection techniques applied on the dataset, such as CFS subset evaluator, consistency subset evaluator, gain ratio feature evaluator, PCA as well as IG (Information Gain) attribute evaluator. Furthermore, by using the above, this paper is a precursor to the essential dataset filtering and cleansing, and the aforementioned is done using the WEKA tool. This paper also provides for some safety recommendations to the various aviation conglomerates.

The research paper[4] introduces convectively induced turbulence as one of the crucial risk factors of aviation safety. The aforementioned proposes the deployment Random Forest, which are essentially a conglomeration of loosely coupled decision tree to help reinstate relationships between storm characteristics and aircraft commotion entailing which a convoluted fuzzy based prediction logic could crafted for commotion near thunderstorms. It further proposes the use of fuzzy algorithm to predict the turbulence based on thunderstorm features and environmental conditions, thereby making it a more scalable model for the real run time scenarios. It further separates the current shortcoming of the Numerical Weather Prediction (NWP) based systems and provide recommendations for a more "now cast" based NWP approach.



Figure 1: The Proposed Architecture

III. TECHNOLOGIES IMPLEMENTED

A. Support Vector Machine (SVM):- Can be succinctly elucidated as machine learning algorithm that performs data analysis for categorizations and regression analysis. Furthermore one can clearly discern the aforementioned is an example of supervised or training based learning algorithm which implements the categorization of data based upon the discerned relationships found during the course of the execution. An SVM outputs a more graphical diagram of the sorted data with a hyper plane delineating the data with as wide a margin between the two types. SVMs find massive scope of implementation in text categorization, image classification, handwriting recognition and in the sciences. [5]

B. Deep Neural Networks:- They are an umbrella of processes, sculpted loosely based upon the human brain, which is adept in pattern dissertation. They interpret ingress data which can be analogous to sensory input, through a kind of machine perception, categorizing crude input. The patterns they recognize are numerical, vectorially based, into which all real-world data, notwithstanding the fact that it is an images or audio file, or text, must be translated. Neural networks aids in clustering and classification[6]

IV. PROPOSED SYSTEM

In the proposed system, a modular based approach is used to solve the menace of variety of data types in the procured dataset as well as to merge the prediction results based on both the proposed methodologies into a crisper result as shown in Figure 1. Also, the proposed hybrid algorithm has been shown in figure no. 2

Risk Level	Event Outcome
High	Non Specific exigency declaration Non Specific incapacitation due to

Table 2: Mapping between risk levels and event outcomes

	injury
	Aircraft Personnels airborne cessation
	ATC sequestered aviation traffic
	Airplane Blemished
	General expulsions
	Aircraft Personnels apprehended
	aircraft maneuver
	Issuence of an expression by the ATC
	A instance of an avuncular by the ATC
	Aircrait Personnels proceeded for a
	crunch landing
Medium	Non Specific refusal of a work
	Overhauling of Aviation Personnels
	Aviation Personnels preempted
	Aviation Personnels circumvented
	missed approach
	Aviation Personnels averted
	impediments pertaining to the
	electronics
	Aviation Personnels jilted takeoff due
	to associated risks
	Aviation Personnel implemented a
	remedial safety procedure
	Issuance of clearance by the ATC
	Non specific maintenance routine
	General flight cancelled delayed
	General release refused Aircraft not
	accepted
	Aviation Personnel abrogate electronic
	assistance
	Aviation Personnel requested aid from
	the ATC pertaining to elucidation
	Aircraft Personnal parform landing as
	Anciant Personner perform landing as
	A viction Demonstrate perform closeron of
	reentry
	returned to departure airport
	Aircraft electronic assistance abrogates
	aviation personnels
	u viation personnels
Low	Generic involvement of security

personnels
Safe Excursion of the Aviation
Personnels back to the departure
Successful fixture of component related
issues
Aids provided by the ATC to the
Aviation personnel for remedial actions

V. MODULES

The paper has been implemented according to the following modules:-

1. Preprocessing the unstructured data

Initially, the proposed approach attempts to preprocess the unstructured textual data from the Aviation Safety Reporting System (ASRS) report. The preprocessing phase incorporates the tokenizer, vector representation model, and term frequency-inverse document frequency (TF-IDF) method, whereas the tokenizer attempts to partition the raw text of the document into the words, sentences, and punctuation. Subsequently, the entire stop words and the punctuation are removed to capture the keywords from the event records. Afterward, constant integer id is assigned to the content of the document to obtain the vector format. Further, the TF-IDF method detects the relative frequency of a word across all the documents that ease the term's discriminating ability and create the weights for the terms suitable to be exploited by the classifier. Moreover, the TF-IDF method helps to reflect the significance of the word in the sentence.

2. Categorizing the structured data

The ASRS aviation information source comprises of the location and time of the abnormal event, an environment that includes the flight condition, weather element, including light, visibility, and the several events such as anomaly, airspace violence, primary issues, and the malfunctions. The structured data of the ASRS report comprise of both the numerical data and the categorical data in which the numerical data represents the size of the crew. The structured data helps to understand the various possibilities and perspective of accident/incident.

Input: Two already trained SVM (M₁) and DNN (M₂), and a dataset $D = \{(p_1, q_1), (p_2, q_2), ..., (p_6, q_8)\}$ 1. for i=1 ton do if M1(pi) = M2(pi) then 2 3. Output the prediction 4. else if M1(pi) = M2(pi) then 5. Calculate the proportion of each class in the records with disagreeing predictions $Prop(j) = \frac{N_j - \lambda_j \times N_j^c}{\sum_{k=1}^{5} (N_k - \lambda_k \times N_k^c)} , \text{ for } j=1,2,\dots,5$ Compute record-level prediction probabilities for pi in the two trained models M1 and M2 6. 7. Compute the model predictions for record pk $\operatorname{Pred}(Y_{p_t}^d = i) \propto \sum_{j=1}^{5} [p(Y = i | \hat{Y}^s = j) \times p(\hat{Y}_{p_t}^s = j) \times \frac{(N_j - \lambda_j \times N_j)}{\sum_{k=1}^{5} (N_k - \lambda_k \times N_k^s)}]$ $\operatorname{Pred}(Y_{p_{\xi}}^{d}=i) \propto \sum_{j=1}^{n} [p(Y=i|\hat{Y}^{d}=j) \times p(\hat{Y}_{p_{\xi}}^{d}=j) \times \frac{(N_{j}-\lambda_{j} \times N_{j}^{c})}{\sum_{k=1}^{n} (N_{k}-\lambda_{k} \times N_{k}^{c})}]$ 8. Return the label with the highest prediction probability from $P(Y_{p_r}^s)$ and $P(Y_{p_r}^d)$ 9 end if 10, end for Output: hybrid model prediction . Figure 2: The Algorithm

3. Discovering the relation between the text format event synopsis, and event consequence using a support vector machine model

To identify the association between the text level event synopsis and the risk concerned with the outcome of incident, the aviation risk prediction model exploits the support vector machine classifier model that receives the input as the TF-IDF vector representation of every event synopsis. By exploiting the vector representation of event synopsis, the SVM model classifies the data with the minimal classification error for the unseen data. The key advantage of the SVM model is good generalization characteristic rather than other machine learning algorithm.

4. Modeling the complex relation between event contextual features and event outcomes using the deep neural networks

By leveraging the deep neural network (DNN) that takes the structured data as the input, the prediction model learns the relation between the contextual features and event outcomes. The benefit of the deep learning technique over the traditional learning algorithm is that it has the ability to automatically learn the complex representation of data with multi-level abstraction. With regards to the categorical data, taking into account of large-scale feature space, deep neural network model has a potency to identify the complex relation between the context features. It significantly predicts the risk level based on the context regarding each abnormal event

5. Implementing an agglomerative algorithm to consolidate the outputs from the two varied models and further perform predictive computation based upon event level outcomes

The proposed approach develops the probabilistic fusion rule for combining the predicted results of the several learning models that are predicated on various segments of the data. Notably, a hybrid prediction model combining the SVM prediction results on unstructured textual data and deep neural network on structured data to evaluate the risk-level of outcomes of hazardous events. It computes the probability of the class when the predicted outcomes of the learning model are inconsistent that helps to attain the accurate prediction results. Furthermore, by exploiting the probabilistic decision tree, the proposed method seeks to predict the event-level outcomes that are the extension of risk level categorization. The probabilistic decision tree is constructed by considering the entire

feasible event outcomes under the proportionate risk category that have the three-level such as low, medium and the high level. The probabilistic tree maps the risk-level prediction of the event level outcomes.

6. Performance Evaluation

Dataset: The empirical framework performs the task of deploying, implementing as well as an effective evaluation of the hybrid risk prediction model by exploiting the Aviation Safety Reporting System (ASRS)which is a repo maintained by NASA having records of all the aviation related mishaps that have occurred within the provided time range. For the purposes of this project we have undertaken the results of last 13 years of reports (from January 2006 to December 2018) from the ASRS totaling up to 37,560 sparsely populated entries.

Evaluation metrics:

Precision: It is defined as the ratio between the number of correct prediction results to the total number of returned prediction results.

Recall: It is defined as the percentage of a number of correct prediction results to the number of predictions that should have been returned.

F-measure: F-measure is the discrepancy and balance between precision and recall.

The entailing graphs provide us with a more pictographic depiction of the performance metrics in the form of precision – recall curves evaluated from our 3 models namely – SVM, DNN and the hybrid model depicted in figure 3, figure 5 and figure 7 pertaining to the target variable which represents the degree of risk associated with the said factors. Also, the micro-average of the 3 risk factors has been plotted in the aforementioned figures.

In Fig. 4 for SVM, each numerical value consists of class high, medium and low. Based on our test data for each class, we have achieved:-

- 73% recall for class 0
- 78% recall for class 1
- 70% recall for class 2
- And an accuracy of 74%



Figure 3: Precision Recall curve for SVM

Confusion matrix SVM model



Classification report for SVM model

	precision	recall	fl-score	support
High	0.74	0.73	0.73	693
Low	0.74	0.78	0.76	637
Medium	0.74	0.70	0.72	670
micro avg	0.74	8.74	8.74	2068
macro avg	0.74	8.74	8.74	2068
weighted avg	0.74	8.74	8.74	2068

Accuracy score of SVM model 74.0

Figure 4: Evaluation Metrics SVM

In Fig. 6 for DNN, each numerical value consists of class high, medium and low. Based on our test data for each class, we have achieved:-

- 93% recall for class 0
- 41% recall for class 1
- 69% recall for class 2
- And an accuracy of 66.4%



Figure 5: Precision Recall curve for DNN

Confusion matrix for DNN



Figure 6: Evaluation Metrics DNN

In Fig. 8 for the hybrid model, each numerical value consists of class high, medium and low. Based on our test data for each class, we have achieved:-

- 96% recall for class 0
- 38% recall for class 1
- 74% recall for class 2
- And an accuracy of 67.9%



Figure 7: Precision Recall curve for fusion model

pi	recision	recall	f1-score	support
8	9.64	0.96	9.76	61
1	0.72	0,38	8.49	69
2	0.72	0.74	0.73	690
micro avg	0.68	0.68	0.68	200
macro avg	0.69	0.69	0.66	2006
weighted avg	8.69	0.68	0.66	2866
Confusion matrix	¢			
[[585 18 9]				
[243 262 193]				
[93 86 511]]				

Accuracy of the fusion model : 67.9

Figure 8: Evaluation Metrics Fusion

In order to evaluate the performance of the proposed approach, the experimental framework compares the proposed hybrid risk prediction model with the SVM, ordinal logistic regression (OLR), and DNN model.

VI. CONCLUSION

The main objective of the research paper was to perform a more real time deployment of the hypothesized hybrid model, in order to ease the airline operator from the toil of manually assessing all the possible factors which may in either a more palpable or covert way could jeopardies aviation safety. The paper further discusses a need of a more proactive and real time solution, which has been implemented in a more modular approach, with the modus operandi being firstly to train the Support Vector Machine model to feed in the event synopsis, which provides a pith to the overall scenarios leading to and all the entailing remedial steps taken after the mishap, with the same being in a textual format. One peculiar point to note is the fact that the procured dataset from the ASRS features about 90% of the data in a categorical format and this presented an urgent need to tackle the issue of data heterogeneity, and to do so a Deep Neural Network is trained with the ingress data being the remnant categorical and numerical data. In order to resolve the issue of result heterogeneity, an innovative fusion formula is implemented and entailing that there is also an implementation of a hybrid model which undertakes the paramount task of performing consequence evaluation in terms of their risk categories, the data of which is procured from the ASRS online database, totaling to about 37,576 entries dating between January 2006 to December 2017.

This research paper furthers the proposed implementation by providing a verifiable performance rubric to reinstate the efficiency of the proposed model over individual models when considering the F-score, the recall and precision. Having depicted the collapse of the datasets by deducing risk based classification of the event outcomes, and by training of SVM, DNN as well as Random Forest facilitates a more seamless contextual data analysis and predictive computation of risk associated, and by the deduction and deployment of a more robust fusion formula to agglomerate the results of the two models. The future prospects of the given research paper can include a more comprehensive recommender based system which could be able to not only deduce the possibility of a factor causing a mishap but also suggest a remedial strategy provided there is a recorded dataset containing the same in abundance, furthermore the fundamental root of this paper is to discern a causal relationship between various

factors, it can also bolster more remedial strategy based systems, such as implementing a robust safety systems for all the other modes of transportations. And lastly there arises a more vigilant study of the factors which could entail high risk events in order for them to be timely curbed.

REFERENCES

- Xiaoge Zhang, Sankaran Mahadevan, "Ensemble machine learning models for aviation incident risk prediction" Department of Civil and Environmental Engineering, Vanderbilt University, Nashville, TN 37235, USA
- 2. Thomas G.Dietterich, "Ensemble Methods in Machine Learning" Oregon State University Corvallis Oregon USA
- 3. A.B.Arockia Christopher, Balamurugan, "Prediction of warning level in aircraft accidents by using data mining techniques" The Aeronautical Journal
- 4. John K. Williams, Jason Craig, Andrew Cotter, and Jamie K. Wolff, "A HYBRID MACHINE LEARNING AND FUZZY LOGIC APPROACH" National Center for Atmospheric Research, Boulder, Colorado
- 5. https://www.techopedia.com/definition/30364/support-vector-machine-svm
- 6. https://skymind.ai/wiki/neural-network