Review

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Review

Machine Learning-Based Aircraft Conflict Prediction: A Systematic Literature Review

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Abstract: Over the last few decades, there is a remarkable increase in air traffic worldwide; however, despite of rapid technological development and improved airport infrastructure, there is still an increasing number of aviation accidents and fatalities. In order to meet safety demands of Air Traffic Control (ATC), Machine Learning (ML) based aircraft conflict detection techniques are focused to predict events before they come to reality. This research presents a systematic literature review (SLR) about the applications of ML techniques in safety prediction of ATC system. Initially, the existing aircraft conflict prediction models are classified into three broad categories; logical, geometric and probabilistic. A formal process of SLR is then conducted which is initiated with preprocessing and effective searching. A series of filtering called title, abstract and objective-based are then applied to extract the most relevant articles. Detailed and critical reviews of selected articles are performed to identify challenges which are segregated into dataset, model and evaluation techniques, furthermore, the optimal solutions for each are proposed. Finally the matrices to map the identified challenged with their proposed solutions are constructed. This research serves as a foundation for future research and towards integration of ML based safety prediction techniques into modern ATC system.

Keywords: aircraft conflict prediction; machine learning; safety; air traffic control

1. Introduction

Air traffic control (ATC) is a ground-based service which provides supervision to an aircraft within controlled airspace. Around the world, the basic objective of ATC systems is to maintain safe separate between aircrafts to avoid collisions, to manage and increase an efficient flow of air traffic, and to provide help and support information to pilot. From takeoff till landing, aircraft pilots maintain communication with air traffic controllers who provide necessary guidance and recommendations within its assigned area of airspace about flight, ascent and descent paths and relevant information about weather conditions as shown in Figure 1(a). When an aircraft flies to the airspace boundary, its control is delegated to the next controller through the process of handover. This process continues until aircraft's control is handed over to the controller of destination airport.

The ATC system is becoming more complex with the continuous growth of air traffic and the evolution of aircrafts with different operational attributes. The International Civil Aviation Organization (ICAO) is a specialist bureau of the United Nations constituted in 1944 is now a consortium of 193 nations is and it defines international safety, environmental and operating standards for civil aviation [34]. According to the safety report released by ICAO in 2023, the number of flight departures for scheduled commercial operations increased by approximately 11 per cent with around 25 million departures in 2021, as compare to around 22.5 million in 2020. It shows a big increase in number of aircrafts.

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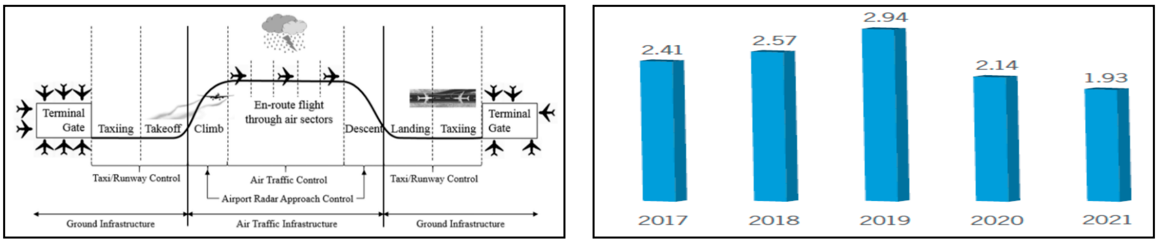

(a) (b)

Figure 1. (**a**) Description of ATC Working; (**b**) Global Accident Rate Trend.

Further, ATC is a safety critical system that can result in injury or loss of life if it fails or malfunctions in order to avoid casualties or loss of life, and to prevent environmental and financial damages. Figure 1(b), published in ICAO current safety report, shows over the previous five years there exist the global accident rate trend (per million departures), with 2021 having an accident rate of 1.93 accidents per million departures, a decrease of 9.8 percent from the previous year [34]. The highest count with 114 accidents was recorded within this period in 2019. However, the number of accidents significantly decreased in both 2020 and 2021; but it is worth noting that during these two years there was a significant decrease in traffic of passengers and flights due to measures placed by governments aimed at minimizing the spread of COVID-19. The number of fatal accidents per year remained the same in 2020 and 2021 which shows that the risks associated with aviation, related to, or in direct support of the operation of aircraft, remained constant and are not controlled to an acceptable level.

Furthermore, ATC is a challenging system which is influenced by many external factors such as political, legislative, economic, technological change, weather, cultural norms and vendors. It is required to provide constant monitoring in order to establish highest levels of aircraft safety. Moreover, the manual safety systems implemented at many airports of the world are time consuming and lack the ability to make efficient intime decisions about flight [11]. Many problems and challenges are faced by them such as air traffic congestion, flight safety failures, increased delays and higher costs [12]. The safety of aviation industry for all stakeholders cannot be ensured without a formal process.

Aviation safety is concerned with the knowledge and practice of risk management in aviation. The primary objective is prevention of aircraft accidents and incidents which is achieved through training of air travel personnel, research, guidance to passengers and the general public, as well as improvements in aircraft and aviation infrastructure design. However, the complexity of airspace is increasing rapidly due to higher number of emerging aircrafts such as drones and unmanned aircraft those need to be accommodated along with scheduled flights. In order to ensure flight safety, collision detection techniques are widely used which computes the time impact by identifying intersection points of two or more object. One such system is Traffic Alert and Collision Avoidance System (TCAS) which gives information to the pilot about the nearby aircraft and it serves as a safeguard against mid-air collisions [35]. TCAS is a reactive system as it detects collision at runtime but nowadays aviation industry is transitioning from a reactive risk management strategy to proactive risk management in order to forecast a safety risk before occurring. Therefore, the basic objective aviation service providers of aviation safety is defined as to attain the capability to predict unsafe events and to prepare counter strategies for risk mitigation whenever risks are encountered.

Machine Learning (ML) is an effective technique that uses mathematical models of data in order to make computer learn without direct human instructions and it also allows a computer system to learn continuously based on its experience. The algorithms used in ML are based on statistical methods and are applied to make classifications or predictions which subsequently enhance effective decision making process [33]. ML is rapidly gaining importance in various fields of life such as data science, medical diagnostics, computer vision, internet search engines, voice recognition, spam email detection, statistical data analysis etc.

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There are several ***applications of ML in ATC*** to automate its operations, lower expenses, provide safety, and improve customer experience. Following are few of them.

- predict congestion in air traffic and recommend alternative routes to minimize delays through analyzing aircraft real-time flight data, weather conditions and other contributing factors.
- compute accurate quantity of fuel required for the complete flight through identifying and processing flight data such as route lengths and altitudes, aircraft type and weight, weather, etc.
- predict probable maintenance faults before they occur, detect potential issues using data from in-service aircraft.
- provide optimal dynamic sector configuration by analyzing data on traffic volume, weather conditions, terrain, and other factors and then determining the most efficient sector boundaries.

The main component in ML is models which learn from given data and gives solution to a problem. There exist a large number of ML models used in domain of ATC which are applied depending on the diverse nature of tasks to be solved. The three broad classifications of ML models for ATC system which are found in literature are; Logical, Geometric and Probabilistic Models as shown in Figure 2.

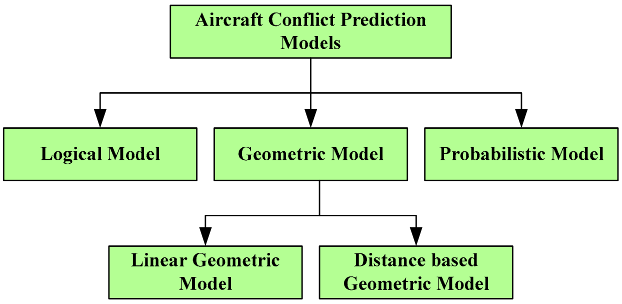

Figure 2. Classification of Aircraft Conflict Prediction Models.

1.1. Logical Models

The type of ML models which can be easily transformed into human understandable rules those are easily assembled in a tree structure, also known as a feature tree. Decision trees are specialized form of feature trees in which leaves are labelled with classes. In ATC system logical models are used in [15,17,26].

1.2. Geometric Models

Geometric models also referred as feature learning is a ML model that integrates computer vision in order to solve visual tasks and works on the principle of similarity by focusing instance space's geometry. Features are described as points in two (x and y axis) or three (x, y and z axis) dimensional space and even non-intrinsic features are also modeled in a geometric manner. The primary benefit of geometric models is that they provide effective visualization within two or three dimensional space. Geometric models are categorized into two types.

1.2.1. Linear Geometric Models

Linear models are the category of geometric model that is developed in instance space directly, by using concepts of geometric such as lines or planes in order to partition the instance space. There are a variety of linear models applied for the tasks of prediction, including classification, probability estimation and regression. In ATC system linear models like the least-squares method (a mathematical regression analysis) is used in [2], Support Vector Machine (which best segregates two or more classes using a hyper-plane) is used in [25].

1.2.2. Distance Based Geometric Models

Distance based models are the category of geometric model that shows similarity between instances by using distance as metric such as Euclidean, Minkowski, Manhattan, and Mahalanobis. In this technique the most similar training instance which has smallest distance from instance to be classified is retrieved from memory and training instance class is assigned to the new instance. In ATC system few basic distance based models are k-nearest neighbor (calculating the cluster means and reassigning points to clusters) is used in [22] and Hierarchical clustering, algorithm that builds hierarchy of clusters is used in [26].

1.3. Probabilistic Models

A probability model is a category of ML model which works on the theory of probability as future events predictions is associated with randomness. In this model the variables we know about is denoted as instance's feature values and the target variables we are interested in is denoted as instance's class. A well-defined but unknown probability distribution is applied with the assumption that there exists some underlying random process which generates the values of these variables. Naive Bayes is a widely used Probabilistic model whereas in ATC system Probabilistic models like Bayes theorem is used in [4,7,8,11,12,20].

In this research a comprehensive systematic literature review (SLR) is conducted on aircraft conflict prediction by using Machine Learning techniques. There exist some SLR regarding various dimensions of ATC system which are summarized in Table 1. In Table 1 we cover the objectives and problems addressed in existing surveys of ATC. However, main contributions of this research are as follows:

a. a critical review is performed to analyse the problems in state-of-the-art techniques aircraft conflict prediction.
b. challenges are identified in three perspectives namely dataset, model and evaluation techniques.
c. the optimal solutions are proposed and identified challenges are mapped with them to form a matrix.

This paper is structured as follows: in Section 2 details of SLR are discussed and Section 3 provides identified challenges. The Optimal solution of each identified challenge is described in Section 4 and Section 6 provides conclusions.

Table 1. Current ATC surveys.

Ref	Year	Objective	Problems Addressed
[25]	2020	stochastic modeling applications in aviation	demand and capacity management
			management of air traffic congestion
[26]	2022	employment of AI techniques for improvement of ATM capability	history of AI techniques
			structure of AI techniques
			advantages of AI methods
			applications to several representative ATM tasks
[27]	2022	applications of Deep Reinforcement Learning (DRL) in conflict resolution	basics of conflict resolution
			construction of DRL
			practical demonstration of DRL in conflict resolution
[28]	2023	Deep Learning (DL) applications for Air Traffic Management (ATM)	solutions are categorized based on DL techniques
			future recommendations based on the ATM solutions
			open challenges identified for DL applications and ATM solutions

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[29]	2022	benefits of AI within aviation/ATM domain	Working of general and ATM eXplainable Artificial Intelligence (XAI)
			exploring need of XAI
			existing solutions and their limitations
			formulate the findings into a conceptual framework
[30]	2020	reviews 4D track prediction technology	classification of existing prediction techniques
			combination methods with aircraft track data
			techniques of data mining used
			applicable scope of each method
[31]	2021	survey of aircraft tracking systems	categorize existing techniques according to their approaches
			development of real-time DL-based Aircraft Tracking system
[32]	2020	review of existing Conflict Resolution methods for manned and unmanned aircrafts	taxonomy to categories CR algorithms
			working of tactical and distributed framework
			overview of four CR algorithms
			testing of manned and unmanned scenarios

2. Systematic Literature Review

A systematic literature review examines data and findings of other authors relative to a specified research question or questions. A systematic literature review is just one research methodology that can be used to do this. Systematic reviews (SRs) identify, collate, and systematically summarize empirical evidence from two or more primary research studies. The following activities are performed to conduct SLR in this research as shown in Figure 3.

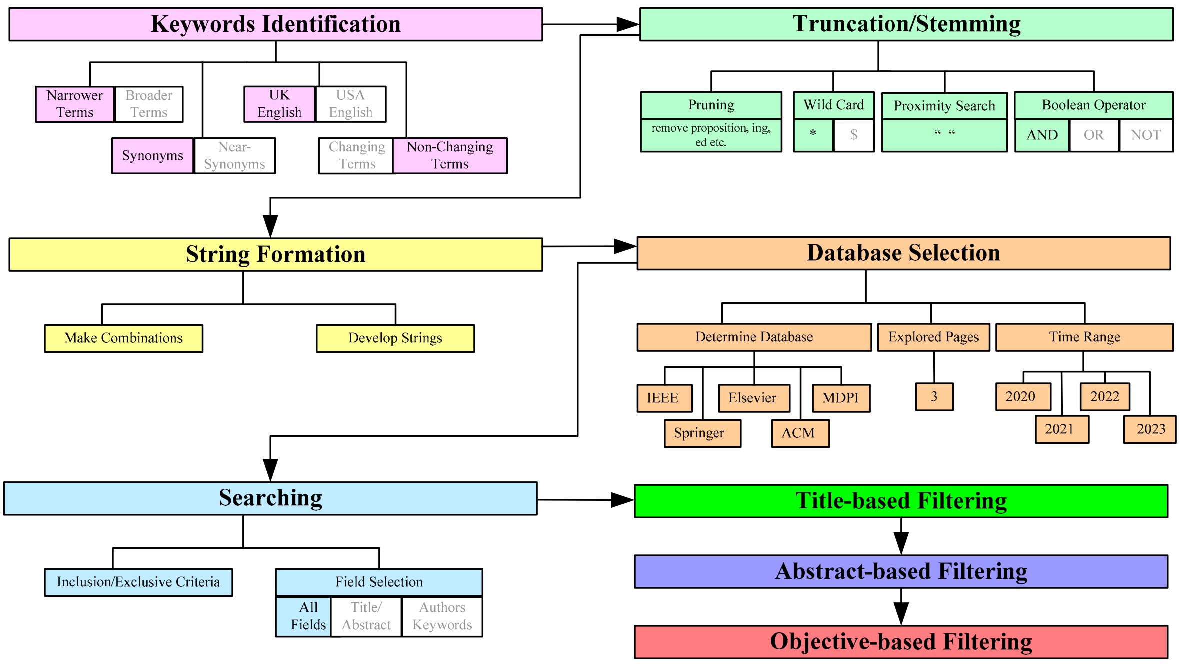

Figure 3. The Overview of SLR in this Research.

2.1. Keywords Identification

The terms to be searched are called keywords. There is a need to take account of all selected keywords. In criteria defined for this activity is shown in Table 2.

Table 2. Keywords Identification for the problem.

Safety	Prediction	of	Air Traffic	Control
conflict-free	forecast		aviation	manage
collision less	envisage		aircraft	administer
non-contention	detect		flight	governance

2.1.1. Broader/Narrower Terms

A keyword is termed as narrow if it is concrete while it is broader if a keyword can be further narrow down into some other narrow keywords. For example, "Electronic gadget" is a broad term and cell phone, tablet computers and ipads, earthquakes, floods, hurricanes are its narrower terms. In this research we have selected narrow keywords as shown in Table 1. For “safety”, “prediction” and “control” whereas “air traffic” can be narrow down as “airport”, “airspace”, “terminal”, “apron” areas etc but we have focused only on terms related to “air traffic”.

2.1.2. Synonyms/Near-Synonyms

There should be a relevancy between selected synonyms, such as workers, employees, personnel. In this survey three synonyms are identified for each keyword which are selected on close relevance as shown in Table 1.

2.1.3. UK/US English

These are two variations in spellings of a keyword. For instance, in UK English we spell “colour” and we write “color” in USA. We have focused on UK English because it is a standard for technical write ups like research articles.

2.1.4. Terminology Change over Time

Some keywords get changed with the passage of time. For instance, "Bipolar disorder" is earlier referred to as "Manic depression". There is no such word in our research problem

2.2. Truncation

Truncation also called as stemming is a process of inserting the stem of a keyword and a truncation symbol so that we can retrieve other forms of the keyword. Table 3 shows the results of truncation on identified keywords.

Table 3. Steps of Truncation on one of the string.

Safe~~ty~~	Predict	~~of~~	Air Traffic	Control
Safe	Predict		Air Traffic	Control
Safe*	Predict*		Air Traffic	Control

2.2.1. Pruning

It is the process in which certain words like propositions, ‘ing’, ‘ed’ are trimmed from the keywords. For example, “safety” will become “safe” etc.

2.2.2. Wild Card

Wildcard is a character that signifies specific meaning to the search engine. For example: “safe*” will retrieve “safety”, “safely”, “safest” etc. where * is a wild card. In this research wildcards are used on selected for effective search of relevant research articles.

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2.2.3. Proximity Searching

By enclosing words into double quotation indicates searches for that exact phrase, for instance "Air Traffic".

2.2.4. Boolean Operators

In searching a database, the Boolean operators AND, OR and NOT are applied to combine terms. We first search for individual keyword and then move to the search history and combine the results using Boolean operators. In this research AND operator is used to fetch all relevant researches containing all keywords a shown in Figure 4.

Figure 4. Application of Boolean Operator in Search Clause.

2.3. Strings Formation

After defining keywords next step is the formation of substrings. Table 4 shows the strings which are formed by making combinations of the keywords.

Table 4. List of strings developed from selected keywords.

Safe	Predict	Air Traffic	Control
safe	forecast	Air Traffic	control
safe	envisage	Air Traffic	control
safe	detect	Air Traffic	control
conflict	predict	Air Traffic	control
conflict	forecast	Air Traffic	control
conflict	envisage	Air Traffic	control
conflict	detect	Air Traffic	control
…..	…..	…..	…..
…..	…..	…..	…..
contention	detect	flight	detection

2.4. Databases Selection

The selection of databases to be searched is an important step for collection of relevant research articles. This activity comprises of following steps.

2.4.1. Determine Databases

The following highly-ranked five databases are searched in this research.

- IEEE
- Elsevier
- Springer
- ACM

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- mdpi

2.4.2. Explored Pages

For each input string first three pages of each database is searched.

2.4.3. Time Range

Three folders are created in Zotero for downloading researches of years 2020, 2021, 2022, 2023.

2.5. Searching

The next step is to execute searching, once strings are ready. All relevant papers are downloaded in Zotero in respective folders year-wise as shown in Figure 5. During this activity the following steps are performed by us.

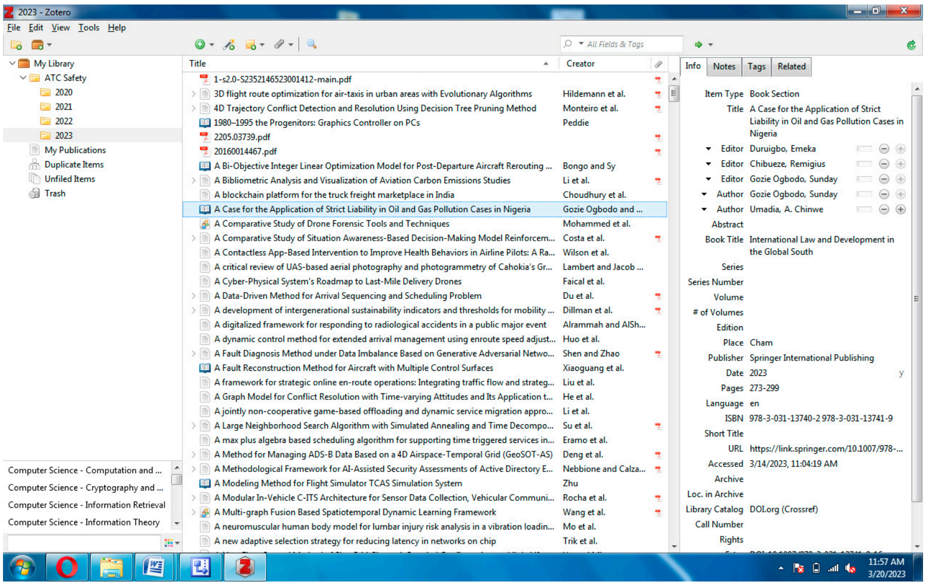

Figure 5. Zotero Folder View.

2.5.1. Inclusion/Exclusion Criteria

The following inclusion/exclusion criterion is defined for this survey.

- Only those articles are downloaded those must have all keywords of a string
- Articles published before 2020 are not considered
- The articles for which only citation is available are not considered.
- Paper less than 4 pages
- Articles not in English
- Dissertation and thesis are not included

2.5.2. Field Selection

The number of articles retrieved by a search clause depends on fields selected in a database. Following options are available for field selection.

- **All fields:** The selected keywords may appear in any field. This will return a high number of results.
- **Title/abstract:** If keywords appear in the title and abstract, the item is likely to be highly relevant. This research relies on well written, descriptive titles and abstracts.
- **Keyword:** Searches for defined keyword in the author supplied keywords.

In this research all field option is selected so that any relevant paper does not get missed. The following Table 5 shows the details of searching which is performed in this research. So far we have downloaded 798 articles in folder 2023, 119 articles in folder 2022 and 119 articles in folder 2021.

Table 5. Searching Details.

Year	Strings	Database	Pages Explored	Available Articles	Related Articles	Not Related Articles	Duplicate Articles	Total
2023	Safety Air Traffic Control	IEEE	3	30	30	0	0	149
		Elsevier	3	30	30	0	0	
		Springer	3	30	29 1 Book	0	0	
		ACM	3	30	30	0	0	
		mdpi	3	30	30	0	0	
	Conflict Air Traffic Control	IEEE	3	30	28	0	2	93
		Elsevier	3	30	17	0	13	
		Springer	3	30	13	0	17	
		ACM	2	16	12	0	4	
		mdpi	3	30	23	0	7	
	Risk Air Traffic Control	IEEE	3	30	15	0	15	97
		Elsevier	3	30	23	0	7	
		Springer	3	30	19	0	10 1 Book	
		ACM	3	24	12	0	12	
		mdpi	3	30	28	0	2	
	Contention Air Traffic Control	IEEE	2	15	10	0	5	36
		Elsevier	1	10	6	0	4	
		Springer	1	10	10	0	0	
		ACM	1	2	2	0	0	
		mdpi	1	10	8	0	2	
	Safety Aviation Control	IEEE	3	30	19	0	11	83
		Elsevier	3	30	20	0	10	
		Springer	3	30	15	0	14 1 Book	
		ACM	2	13	7	0	6	
		mdpi	3	30	22	0	8	
	Conflict Aviation Control	IEEE	3	30	14	0	16	49
		Elsevier	3	30	11	0	19	
		Springer	3	30	8	0	22	
		ACM	1	2	0	0	2	
		mdpi	3	30	16	0	14	
	Risk	IEEE	3	30	19	0	11	69

	Aviation Control	Elsevier	3	30	17	0	13	
		Springer	3	30	14	0	15 1 Book	
		ACM	2	12	1	0	11	
		mdpi	3	30	18	0	12	
	Contention Aviation Control	IEEE	1	2	2	0	0	39
		Elsevier	2	16	13	0	3	
		Springer	3	25	20	0	5	
		ACM	1	1	1	0	0	
		mdpi	1	3	3	0	0	
	Safety Aircraft Control	IEEE	3	30	12	0	18	62
		Elsevier	3	30	15	0	15	
		Springer	3	30	19	0	10 1 Book	
		ACM	2	19	7	0	12	
		mdpi	3	30	9	0	21	
	Conflict Aircraft Control	IEEE	3	30	12	0	18	44
		Elsevier	3	30	5	0	25	
		Springer	3	30	12	0	18	
		ACM	1	3	0	0	3	
		mdpi	3	30	15	0	15	
	Risk Aircraft Control	IEEE	3	30	13	0	17	40
		Elsevier	3	30	7	0	23	
		Springer	3	30	6	0	24	
		ACM	3	22	6	0	16	
		mdpi	3	30	8	0	22	
	Contention Aircraft Control	IEEE	1	4	1	0	3	21
		Elsevier	2	15	9	0	6	
		Springer	3	30	22	0	7 1 Book	
		ACM	1	2	0		2	
		mdpi	1	6	3		3	
2022	Safety Prediction Air Traffic Control	IEEE	3	30	25	5	0	78
		Elsevier	3	30	7	23	0	
		Springer	3	30	16	14	0	
		ACM	2	15	4	11	0	
		mdpi	3	30	26	4	0	
	Conflict prediction Air Traffic Control	IEEE	3	30	15	5	10	41
		Elsevier	3	30	14	12	4	
		Springer	3	30	6	18	6	
		ACM	1	3	0	3	0	

		mdpi	3	30	6	10	14	
2021	Safety Prediction Air Traffic Control	IEEE	3	30	20	10	0	94
		Elsevier	3	30	23	7	0	
		Springer	3	30	23	7	1	
		ACM	2	15	7	8	0	
		mdpi	3	30	21	9	0	
	Conflict prediction Air Traffic Control	IEEE	3	30	11	9	10	36
		Elsevier	3	30	18	4	8	
		Springer	3	30	5	18	7	
		ACM	1	8	0	6	2	
		mdpi	3	30	2	18	10	

2.6. Title-Based Filtering

It is the first stage of filtering which is called title-based filtering, as shown in Table 5 which is diagrammatically represented in Figure 6. All papers which are not relevant to the topic of the problem are excluded from folders created in Zotero. Since the number of papers relevant to the research questions is very high so it is hard to track them manually, therefore, we have made an excel file as shown in Figure 4. The papers having ***occurrences of 3 keywords*** are selected as they are most relevant to our research whereas all other papers are excluded.

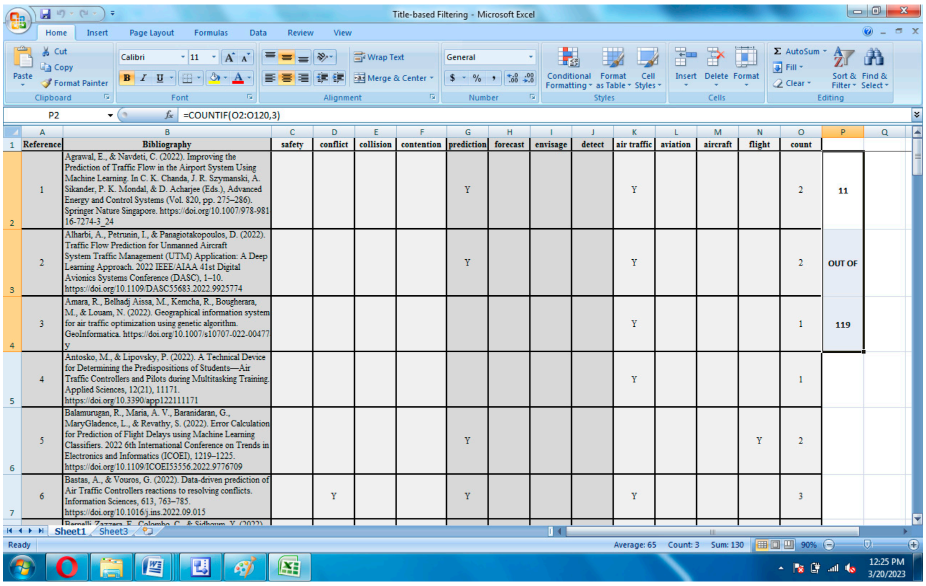

Figure 6. A spreadsheet Prepared for Title-based Filtering.

2.7. Abstract-Based Filtering

In the second level of filtering, abstract-based filtering is conducted. All the papers in which the abstracts are irrelevant to the problem are excluded from all the selected databases as shown in Table 5. Following is the exclusion criteria defined for this filtering.

Paper length less than 6 pages, spacecraft and aircraft, performance-shaping factors , mental workload, reaction, training, flight delay prediction, flight planning, signal processing, traffic flow prediction, trajectory prediction, situation awareness, airspace sectorization, staffing, disaster management, aeronautical communications, unmanned aircraft and drones, feasibility study, tutorial, survey, views and reviews, comparative studies, answering open questions, cognitive analysis, physiological studies , social sciences studies, conflict distribution and resolution , prediction of aircraft go-around, flight scheduling, cultural studies, road and railway network and anomaly detection.

2.8. Objective-Based Filtering

In the third level of filtering, objective-based filtering is conducted as shown in Table 6 which is diagrammatically represented in Table 7 and Figures 7 and 8.

Table 6. Results of Objective-based Filtering.

Ref	coordinate/ trajectory	time-to-fly/ touch down	Separation Minima	safety performance	controller/ pilot role	data attacks	risk prediction	conflict prediction
[1]	Y							
[2]	Y							
[3]		Y						
[4]				Y				
[5]							Y	Y
[6]								Y
[7]			Y					
[8]		Y						
[9]							Y	
[10]								Y
[11]								Y
[12]								Y
[13]								Y
[14]			Y					Y
[15]			Y					
[16]			Y		Y			
[17]	Y							Y
[18]						Y		
[19]			Y					
[20]								Y

[21]						Y		
[22]			Y					Y
[23]			Y					Y
[24]			Y					

Table 7. Results of Filtering on Selected Databases.

Database	Pre-Filtering Count (ZOTERO)				Title-based Filtering Count				Abstract-based Filtering Count			
	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
IEEE	22	25	45	178	5	31	40	18	2	2	5	2
Elsevier	12	32	24	199	4	32	24	9	0	0	2	2
Springer	11	29	21	182	3	29	21	13	0	0	1	1
ACM	2	6	4	79	0	6	4	4	0	0	0	0
mdpi	30	23	64	268	1	23	32	14	1	2	4	0
Total	77	115	158	906	13	121	121	58	3	4	12	5

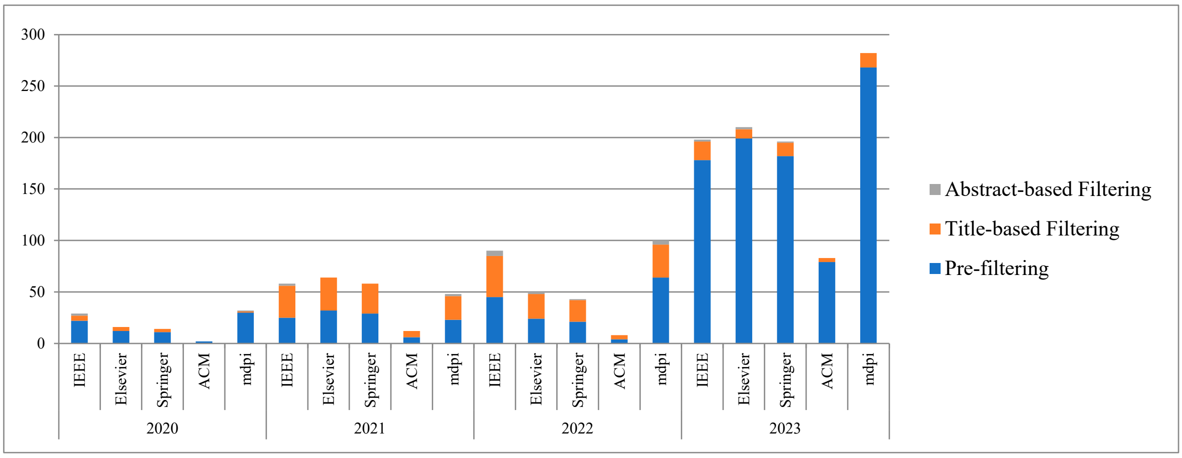

Figure 7. Graph showing Results of Filtering.

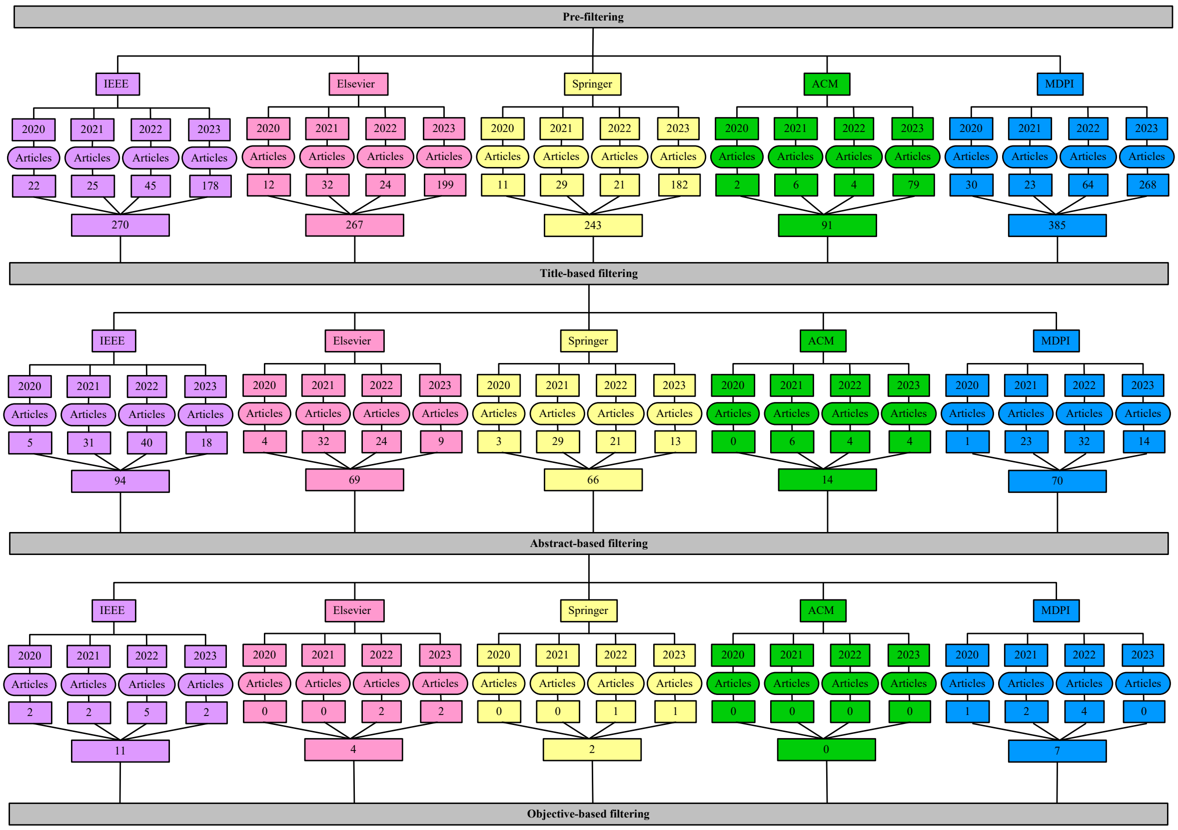

Figure 8. Results of Filtering on Selected Databases.

2.9. Detailed Literature Review

A hybrid model that uses deep learning is proposed in order to predict aircraft coordinate in [1]. The Automatic dependent surveillance-broadcast (ADS-B) real-world **datasets** from OpenSky network is used. In **methodology**, the spatial features from dataset are extracted by using inception modules and to extract temporal the spatial features from dataset LSTM modules are used. The experimental **results** describes that the proposed model is the local optimal model and the positioning reliability is guaranteed. The **limitation** is that for coordinate prediction ADS-B signal strength is used which is difficult to be interfered but it conveys limited information.

The research work in [2] predicts trajectories of the aerial vehicles by a grouping-based conflict detection algorithm which is a based on ML. The preprocessed ADS-B **dataset** is used in this research. In **methodology** short-term, mid-term, and long-term trajectory predictions are made by using the models LSTM, CNN and LS in order to increase timeliness of aircraft conflict detection. The **results** disclose a greater accuracy in short-term as compare to mid-term and long-term trajectory predictions. Further, in all prediction tasks LSTM-based model demonstrated higher performance than CNN-based and the LS-based methods. The **limitations** are that the problem is that performance of the conflict detection algorithm is affected by performance drop down that is observed in case of mid-term and long-term trajectory predictions. The **future work** will focus on solution of aforementioned limitations by targeting design of efficient neural networks and inserting large amount of useful data in training dataset.

Stanley in [3] focuses on the prediction of time-to-fly from the turn onto the aircraft final approach course to the threshold while maintaining separation between landing aircrafts. The flight track **dataset** is used which consists of six months arrivals and departures data to/from a main European airports facilitating 400,000 flights per year. This **methodology** is based on QRF model that can provide uncertainty measure in a prediction result either by means of a prediction interval or by

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making a probability distribution over the dependent variable. The **results** highlight quality of the model which is measured in terms point estimate accuracy, furthermore, some model error measures are examined through probability prediction. The **limitations** are that this approach (i) focus only on how to generate suggestions about time-to-gain/time-to-lose from the predictions based on trade-off between two scenarios which causes a decrease in capacity utilization, (ii) Considers only two factors i.e., the current state of an aircraft and weather and (iii) the application of QRF model on an input of variable length of time-series is yet to be explored. The **future work** is (i) to extend the capabilities of this model to generate suggestions for ATC commands through application of advanced ML techniques and (ii) to increase accuracy and precision of the prediction by considering the feature of track history and by considering correlations between multiple aircrafts in the sequence.

The research in [4] predicts the number of losses of separation between aircraft in European Air Traffic Management systems by using variables such as the number of flight hours or the complexity of the airspace. In **methodology**, a predictive approach based on Bayesian inference is developed and four additional models are constructed which integrate hierarchical approach with a regression model. The common rate of occurrence of separation minima infringements (SMI) and specific rates of occurrence for each air navigation service provider (ANSP) are predicted by using the developed models. The **dataset** used in this research is formulated from the data gathered from a number of European institutions those are involved in monitoring the performance of ATM systems. The **results** show the Poisson model is more efficient for small values of SMIs whereas normal models are more accurate for high values of SMIs. The **limitations** are that (i) the identification of parameters those are important for safe operation of specifically ATM system and generically for whole European system and (ii) the identification and quantification of trends and streamline benchmarks in order to compare current and previous year's performance.

In the research work [5], a risk assessment model and system operation safety warning is developed which is based on deep learning algorithm. Quick Access Recorder (QAR) **dataset** is used which contains the data of various aircraft system's operating status. The **methodology** integrates characteristics of QAR data andwith aircraft system failures, the failure mode and impact analysis (FMEA), cause chain analysis (CCA), LSTM, and other methods. The purpose is to primarily predict risk and its severity in aviation system through identification of risks caused due to system failure and further to predict flight trend parameters. The **results** are obtained by a case study of the Aircraft Refrigeration System (ARS), the validation of safety risk warning model is conducted in order to calculate the risk level that may face and hazard sources of civil aircraft operation is identified in order to improve the safety level of civil aircraft operation. The **limitations** are (i) there is a need to address time-constrained dynamic risk analysis, and (ii) the correlation between failures and its empirical value needs to be analyzed.

In [6] a flight conflict prediction model which uses stochastic differential equation and Monte Carlo method in order to enhance safety in route area and terminal area. In the **methodology**, the safety zone around an aircraft is selected to be ellipsoidal, the stochastic differential equation is applied to predict aircraft position and the probability of flight conflict in terminal area is computed by using Monte Carlo method. Different scenarios are simulated based on different characteristics of the route area and the terminal area then simulation experiments are conducted to detect flight conflicts. The **results** of experiments revealed that the flight conflict probability of proposed method shows high accuracy which guarantees the applicability of proposed model practical field. The **limitations** are that only the factor of wind influence is considered in this study while incorporation of more factors ad their correlation is left as **future work**.

A predictive methodology is presented in [7] which is based on the definition of models called Safety Performance Functions in order to define airspace safety as a measure of SMI between aircrafts in en-route phase. The main **dataset** used in this study comprises of structured data of contextual information about all aircrafts and their trajectories in airspace, including rare instances in which loss of separation occurred obtained from CRIDA Data WareHouse. A conceptual **framework** based on Bayesian Inference is presented which integrates conflict causal factors with SMI precursors acquired from available dataset. The **results** are obtained by using sensitivity analysis in order to identify the variable that has most influence on violation of ATM safety barriers which can result an occurrence of SMI. The **limitations** are (i) only high relevance variables such as instantaneous demand or occupancy of a sector are considered, (ii) variables related to aircraft operation, such as changes in flight level or flight speed and heading, are yet to be explored, and (iii) the factors like controller's workload and controller's response time to deal with conflict also need to be explored.

Yingxiao et. al. in [8] develop a model based on ML in order to predict the touchdown vertical speed numerically during landing of an aircraft. Sample Flight Data belonging to DASHlink is used as a **dataset**. In **methodology**, the touchdown vertical speed is predicted by a trained Bayesian recurrent neural network which is further applied to quantify the factor of uncertainty in model prediction that facilitate decision-making process. The **results** are obtained by checking model predictions on several flights in the test dataset and computation results reveal that proposed approach demonstrates satisfactory performance. The **limitation** are (i) only a particular airport is considered for construction of Bayesian deep learning model whereas different runways are govern by different operational procedures and regulation rules, (ii) a single runway is considered which is not adequate for available data while different runways have different configurations even within the same airport, (iii) data of only one aircraft type is considered whereas performance of aircraft is different for different aircraft types, (iv) the feature of gross weight is not available in dataset while reference speed is not possible to estimate without it, and (v) the model shows poor performance in case of inadequate data whereas a data-driven model deals with various factors such as environmental conditions and pilot operations. As a **future work** there is a need of a hybrid model in order to integrate physics modeling and actual data which is to be investigated.

In [9], a framework is presented that incorporate human factor in predicting risk involved in air-ground speech communication with the objective to improve air traffic safety. In the proposed **framework**, real-time traffic airspace dynamics is fetched which is given as input to automatic speech recognition and the spoken instruction understanding techniques. In this research a prototype application is designed which is deployed in the Chengdu area control center, Changsha aerodrome and approach, China and it predicts safety-critical risks of air-ground communication such as readback confirmation, normative instruction check, trajectory conformance, and potential aircraft conflict detection. The **results** and data statistics are collected from real-world environment which shows that the proposed framework has a potential to enhance air traffic safety as well as it minimizes air traffic controllers workload through automatic understanding of air traffic dynamics. The **limitations** of this research are (i) currently the presented approach exhibit good performance which can be further improved through application of solid dynamic sensing and (ii) to increase practical applicability of proposed approach, front user's feedback can also be incorporated.

Seyedhamed in [10] presents an approach to predict conflict between two aircraft observing flight at the same altitude level by using mid-term probabilistic technique. The **methodology** describes probabilistic relative position of an aircraft as a Gaussian process while considering the factor of fully correlated wind field and the accuracy of conflict prediction is also calculated. Numerical **results** are obtained by using simulator that incorporates a fully correlated wind field model and parameter's sensitivity is calculated. Results reveal the effectiveness of presented algorithm as it computes the safety while maintaining a defined accuracy level. The **limitation**s of this study is that (i) the estimation error increases in case an aircraft exhibit sharp turns because of variation in small heading and (ii) non-Gaussian wind models can also be investigated in order to calculate relative position of an aircraft.

The research in [11] develops a probabilistic simulation methodology for detecting lateral separation violations in en-route safety assessment of multiple aircraft flying within an airspace sector over a particular duration while considering the multiple factors of uncertainty. This study uses FlightAware's public ADS-B **database** which consists of historical trajectory about position of an aircraft flying over Houston air traffic sector containing information such as altitude, latitude, longitude, course angle and true air speed, at a sampling rate of 16 s. The **methodology** makes use of

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two prediction models known as kinematics-based Generalized National Airspace Trajectory-Prediction System (GNATS), and the dynamics-based Base of Aircraft Data (BADA) in order to find trajectory and devise aircraft dynamic model which also include model error as an input. The recorded flight data is used by a Bayesian state estimation and the discrepancy is observed. The **results** demonstrated that proposed approach exhibit low computational burden which shows its practical applicability in real world. The **future work** includes in flight monitoring of aircraft online and to detect probabilities of separation violation for rest of the flight based on its trajectory. Also different conflict resolution techniques can further be evaluated by using proposed approach.

The article in [12] deals with the ability of an air traffic controller in prediction of aircrafts conflict before they violate SMI. The **data** used in this study is obtained from Air Navigation Services Provider (ANSP) and data comprises of knowledge and real operational of aircrafts. In **methodology**, Bayesian Inference technique is applied because of its strong feature to give high prediction in case of low probability events by using existing data and knowledge. For **results** of proposed conflict prediction approach, the sensitivity analysis is conducted through air traffic controllers in order to identify which precursor gives best description about safety events.

The research in [13] presents a digital system for assistance of pilot in prediction of air conflicts and it gives a platform for effective flight safety awareness through utilizing aircraft surveillance data. The **dataset** used in this study is large-scale which comprises of real time air traffic data including aircrafts conflicts data as well. In **methodology**, a widely used successor of recurrent neural networks (RNNs) called long short-term memory (LSTMs) networks are applied, in order to find the air traffic monitoring capabilities in terms of their time-based dynamic behavior and also in classification of error patterns. Numerical The **results** are obtained by utilizing proposed LSTM networks in order to detect various weather events, cyberattacks, emergency situations and human factors. The **limitation** is that it predicts conflicts in sequential flight data.

A conflict prediction tool is presented in [14] which detect SMI between pairs of aircraft. This data-driven approach proposed in this study extracts aircraft trajectory **data** from the OpenSky Network which provides real world ADS-B flight trajectories. In **methodology**, extreme gradient boosting is applied which is a widely used ML model for classification and regression. The **results** are obtained by applying several techniques such as the number of samples, the rate of error of predictions and tendency of ML algorithm.

The article in [15] introduces an ATC conflict prediction tool which is based on ML in order to detect SMI between aircrafts flying within airspace. This data-driven approach extracts ADS-B trajectories **data** from the OpenSky Network, the historical ADS-B trajectories work as 4-Dimensional Trajectory (4DT) predictions to be used as inputs for the database. The **methodology** makes use of two ML algorithms for classification and regression in order to predict potential conflict. The **results** demonstrate that the ML algorithms performs well and predicts conflicts with high-accuracy metrics. The **limitations** of this research are (i) certain variables like operational and environmental variables are not focused, (ii) the Deep Learning approach which is based on neural networks may be applied and (iii) other data sources may be used as an input for 4DT conflict predictions.

The authors in [16] proposed an approach which extracts data from aircraft Safety Reports automatically which is given as input to the Data-Driven Model that predicts whether pilot air traffic controller or both contributes in an incident when loss of separation occurs.

The research in [17] developed conflict detection and resolution framework for for conflict prediction in 4DT. This research uses **data** acquired through Trajectory Predictor which comprises information from most of the Brazilian air traffic. In proposed **methodology** the routes are represented as trajectories and then conflicts are predicted based through Decision Tree Pruning Method which manages large amount of input data effectively. The comparison **results** with other counterparts revealed the effectiveness of developed model in aircraft conflict detection. The **future work** recommended for this study are (i) for measurement of performance other types of search algorithms may also be applied, (ii) other database methodologies may also be explored for determining their possible impacts on proposed aircraft conflict prediction model.

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The research in [18] introduces a method for detection of various attacks in ADS-B in perspective of ATC. The **data** used in this study is ADS-B data which are obtained from real world aircraft flights. In **methodology** the flight plan is integrated with ADS-B information in order to construct image stream of flight in airspace and then generative adversarial network–long short-term memory (GAN-LSTM) model is applied to predict future images. Furthermore, the techniques of normalized cross correlation and mark anomalous targets are used to detect abnormal images. The experimental **results** describes that the developed approach shows better detection rate in prediction of various attacks. The **limitation** of this study is that the attacks are detected and anomalous targets are located only in controlled airspace. The **future work** is to give attack mitigation.

The study in [19] presented framework for prediction of separation error which include long leading time and a multi-facto approach characterizing the inter-relationships between task complexity, behavioral activity, cognitive load, and operational performance. The authors applied synchronization on raw **data** collected from multiple sources at different sampling rates depending on up-date period of the Metacraft simulation system which extracts information about air traffic. The **methodology** proposed in this research uses an encoder-decoder LSTM network to make predictions about long-time-ahead separation errors through combining multimodal features which causes decrease in accumulated errors. The **results** reveal that as compared to the model exploiting one single feature for conflict prediction the performance of proposed multi-feature model improves significantly.

The relation between incident causal factor event and resultant event for commercial air transportation system is evaluated in [20]. The **data** used in this study are incident cases which are acquired from Aviation Safety Reporting System (ASRS). In **methodology** the Bayesian network which is based in a hybrid approach of max–min hill-climbing is constructed for prediction of risk in commercial air flights. A resource investment combination is used to obtain **results**, which shows the usefulness of proposed approach for minimizing safety risk in commercial air transportation system also occurrence of high level of risk is reduced. The **limitations** are (i) ASRS is a database specific to a nation which does not cover incidents from other nations and (ii) the aviation incident reports lack root causes and event outcomes information about an incident. The **future work** is suggested that (i) data can be collected from other sources focusing commercial aviation incidents from other regions, classification schemes with specific strategies and (ii) to combine manual approach with ML algorithm for further research in risk mitigation.

In [21] the various types of attacks are studied to which ADS-B system is exposed and the corresponding states about abnormal data are simulated. The historical **data** of aircraft flights is used in this study. A **methodology** is developed for detection of ADS-B data attacks which is based on techniques of Long Short-Term Memory Encoder–Decoder (LSTM-ED) and hypersphere classifier is proposed in **methodology**. Experimental **results** reveal that proposed approach shows effectiveness in attack detection with increased accuracy.

The objective of work in [22] is to detect if an aircraft crash occurred because of a bird strike or not by making use of data mining techniques. **Data** is gathered about all aircraft accidents which is obtained from National Transportation Safety Board (NTSB). The proposed **methodology** introduces a ML-based model which comprises of decision tree, K-Nearest Neighbors (KNN) and Gaussian Naive Bayes which are effective in safety of aviation system and useful in early finding aircrafts mishaps. The **results** are obtained through model prediction which demonstrates high accuracy percentage.

The authors of [23] study the temporal effects on air traffic densities and number of aircrafts taking turns in given section of airspace in order to detect SMI. The **data** used in this study is extracted from simulator experiment. In **methodology** logistic regression models are applied for prediction of loss of separation between aircrafts as an early warning to maintain safety. The **results** obtained in this research reveal that regression model for the temporal effects on air traffic densities demonstrated greater accuracy as compare the number of aircrafts taking turns and integrating time series sections can make predictions about loss of separation with higher accuracy level. **Future work**

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left for this research is to (i) investigate the proposed algorithm under different dynamic conditions, such as high off nominate scenarios, (ii) enhance model's performance by adjusting learning algorithms and (iii) focus on more factors of dynamic density, such as the mix of aircraft types etc., and to determine feature selection criteria.

In [24], the application of a neural network is demonstrated in order to detect the loss of separation between aircrafts within a given configuration during approach phase of an aircraft. The airspace simulation tool is used to obtain training **database** which is constructed in Matlab/Simulink. In **methodology** a neural network is constructed which is trained by using the Matlab Deep Learning Toolbox. **Results** show that by using neural network predictions are made with high accuracy and it may serve as a foundation towards an effective decision support tool for air traffic controllers and automatic airborne navigation systems. The **future work** for this research is to investigate the application of proposed approach on other phases of aircraft flight.

The results of detailed literature review are as shown in Table 8 in which following abbreviations are used; ANN: Artificial Neural Network, RNN: Recurrent Neural Network, CNN: Convolutional Neural Network, LSTM: long short term memory, QRF: Quantile Random Forest, RF: Random Forest, BI: Bayesian Inference, DT: Decision Tree, GB: Gradient Boosting, C: Classification, R: regression, MC: Monte Carlo, BM: Brownian Motion, LR: Logistic Regression, LS; Least Square, GP: Gaussian Process, P: Pruning KB: Knaive Bayes and KNN: k-Nearest Neighbors. In our systematic literature review on machine learning-based aircraft conflict prediction, our research integrates foundational insights from [36-49].

Table 8. Results of Detailed Literature Review.

Ref	ANN	RNN	CNN	LSTM	QRF	RF	BI	DT	GB	C	R	MC	BM	LR	LS	GP	P	KB	KNN
[1]		Y		Y															
[2]			Y	Y											Y				
[3]					Y														
[4]							Y												
[5]				Y															
[6]												Y	Y			Y			
[7]							Y												
[8]		Y					Y												
[9]		Y	Y																
[10]																Y			
[11]							Y												
[12]							Y												
[13]				Y															
[14]									Y										
[15]										Y	Y								
[16]						Y													
[17]								Y									Y		
[18]				Y															
[19]				Y															
[20]							Y												
[21]				Y															

[22]								Y										Y	Y
[23]														Y					
[24]	Y																		

2.10. Critical Review

This activity is applied for critical review of all the articles selected for detailed literature review. The methodology used in each article is analyzed rigorously in order to find strengths and weakness as shown in Table 9.

Table 9. Results of Critical Review.

Ref.	Year	Scheme	Strengths	Limitations
[1]	2022	Inception	safe aircraft coordinate prediction scheme	ADS-B signal carries limited information
		LSTM	widens the perception field	CNN do not encode position and orientation
		CNN	time window based continuous time points	CNN needs a lot of training data to be effective
			CNN is accurate at image recognition and classification	CNNs tend to be much slower
			CNN offers Weight sharing	long training time for multi layer CNN
			CNN minimize computation via regular neural network	CNN recognize image as clusters of pixels
			CNNs uses same knowledge across all image locations	LSTM small context window size(input's set)
			LSTM handles long-term dependencies effectively	LSTM do not deal big temporal dependencies
			LSTM is less susceptible to vanishing gradient problem	
			LSTM handles complex sequential data efficiently	
			LSTM NN make prediction more accurate	
[2]	2022	LSTM	geometric and grouping-based conflicts detection	slow for mid and long-term trajectory prediction
		CNN	effective short-term trajectory predictions	ADS-B signal carries limited information
		LS	trajectory prediction accuracy's impacts are discussed	less reliable neural network
			CNN is accurate at image recognition and classification	CNN do not encode position and orientation
			CNN offers Weight sharing	CNN needs a lot of training data to be effective
			CNN minimize computation via regular neural network	CNNs tend to be much slower

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			CNNs uses same knowledge across all image locations	long training time for multi layer CNN
			LSTM handles long-term dependencies effectively	CNN recognize image as clusters of pixels
			LSTM is less susceptible to vanishing gradient problem	LSTM small context window size(input's set)
			LSTM models complex sequential data efficiently	LSTM do not deal big temporal dependencies
			LSTM NN make prediction more accurate	
[3]	2021	QRF	a tool for arrival time-to-fly prediction	slow for trade-off between two scenarios
			specific needs of the use case based prediction	considers aircraft present state and weather
			QRF gives non-parametric estimates of median and quantile predicted value	QRF not evaluated for variable length of time-series input
			QRF focus model uncertainty	
[4]	2021	BI (R)	safety prediction for European airspace	only for European Airspace
			compatible with reduced data and expert's opinions	considers only four parameters
			captures hierarchical dependencies between parameters	BI does not inform about prior selection
			BI has high statistical capacity in low probability events	BI makes posterior distributions largely influenced by priors
			BI combines prior information with data	BI gives high computational cost for models with large number of parameters
			BI convenient for hierarchical models and missing data	
			BI provides exact inferences for conditional on data	
[5]	2022	LSTM	combines fault diagnosis and risk theory	lacks time-constrained dynamic risk analysis
			integrates real-time data and post-flight failure data	do not address correlation between failures
			verify the accuracy of the prediction	LSTM small context window size(input's set)
			LSTM handles long-term dependencies effectively	LSTM do not deal big temporal dependencies
			LSTM is less susceptible to vanishing gradient problem	
			LSTM models complex sequential data efficiently	
			LSTM NN make prediction more accurate	
[6]	2022	MC	simulation based real cases are considered	only considers influence of wind

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		GP	MC provides multiple probability and outcomes from large pool of random data samples	Considers only two aircraft
		BM	MC offers clearer picture than a deterministic forecast	MC results are highly dependent on the input values and distribution
			SDE detects actual states in a model from data	MC take excessive computational powers
			SDE prediction remains close to data even when model parameters are incorrect	SDE may not have solutions that can be expressed in terms of elementary functions
				SDE requires substantial mathematical machinery to understand at any depth
[7]	2022	BI	keeps the number of adverse outputs low	only two high relevance variables
			varying input conditions	aircraft operation variables not considered
			BI's high statistical capacity in low probability events	BI does not inform about prior selection
			BI combines prior information with data	BI makes posterior distributions largely influenced by priors
			BI convenient for hierarchical models and missing data	BI gives high computational cost for models with large number of parameters
			BI provides exact inferences for conditional on data	
[8]	2022	BI	model dimension is decreased by increasing relevance and reducing redundancy	constructed for a particular airport
		RNN	a regression model to address class imbalance problem	runway configurations often vary
			gives information about severity of hard landing	data is used from only one aircraft type
			RNN is dynamic and computationally powerful	does not estimate reference speed
			RNN is capable of approximating arbitrary nonlinear dynamic systems with arbitrary precision	poor performance when data is not adequate
			RNN remembers each information through time	RNN has vanishing and exploding gradient
			LSTM NN make prediction more accurate	RNN training is difficult
			probabilistic NN training by Bayesian approach supports risk-informed decision making	RNN can not compute long sequences for tanh and relu activation functions
			BI has high statistical capacity in low probability events	BI does not inform about prior selection
			BI combines prior information with data	BI makes posterior distributions largely influenced by priors
			BI convenient for hierarchical models and missing data	BI gives high computational cost for models with large number of parameters

			BI provides exact inferences for conditional on data	
[9]	2022	RNN	clarify key air traffic operations for safety monitoring	RNN has vanishing and exploding gradient
		CNN	RNN is dynamic and computationally powerful	RNN training is difficult
			RNN approximates arbitrary nonlinear dynamic systems having arbitrary precision	RNN can not compute long sequences for tanh and relu activation functions
			RNN remembers each information through time	CNN do not encode position and orientation
			CNN is accurate at image recognition and classification	CNN needs a lot of training data to be effective
			CNN offers Weight sharing	CNNs tend to be much slower
			CNN minimize computation via regular neural network	long training time for multi layer CNN
			CNNs uses same knowledge across all image locations	CNN recognize image as clusters of pixels
[10]	2022	GP	less computation time.	estimation error increases during sharp turns
			accurate conflict probability as numerical approaches	lacks 3D multi-aircraft encounter
			can be easily applied to 3D scenarios	considers wind models
			GP directly captures the model uncertainty	GP are not sparse and uses complete information of features for prediction
			GP prior about model's shape is provided through selection of different kernel functions	GP efficiency degrades in high dimensional spaces when number of features increases
[11]	2022	BI	handles random variables and process uncertainties	considers only one airspace sector
			reduced computational efforts	BI does not inform about prior selection
			BI has high statistical capacity in low probability events	BI makes posterior distributions largely influenced by priors
			BI combines prior information with data	BI gives high computational cost for models with large number of parameters
			BI convenient for hierarchical models and missing data	
			BI provides exact inferences for conditional on data	
[12]	2022	BI	identification of variables related to controllers performance	BI does not inform about prior selection
			BI has high statistical capacity in low probability events	BI makes posterior distributions largely influenced by priors

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			BI combines prior information with data	BI gives high computational cost for models with large number of parameters
			BI convenient for hierarchical models and missing data	
			BI provides exact inferences for conditional on data	
[13]	2022	LSTM	a digital conflict detection system is developed	predicts conflicts in sequential flight data
			large-scale and real time air traffic models are built	LSTM small context window size(input's set)
			predicts four factors	LSTM do not deal big temporal dependencies
			LSTM handles long-term dependencies effectively	
			LSTM is less susceptible to vanishing gradient problem	
			LSTM models complex sequential data efficiently	
			LSTM NN make prediction more accurate	
[14]	2022	GB	time dependence analysis	GB overemphasize outliers and cause overfitting
			learning assurance analyses performed	GB is computationally expensive
			GB often provides predictive accuracy	GB is less interpretative in nature
			GB has lots of flexibility	GB influence model behavior as it results in many parameters
			GB has no data preprocessing and handle missing data	
[15]	2022	C	Four-Dimension Trajectory based conflict predictions	operation and environment variables not used
		R	C is effective in high dimensional spaces	other sources for 4DT predictions as input
			C is memory efficient	C slow real time prediction
			R uses more than two independent variables	C is difficult to implement
			R determines the unbiased relationship between two variables by controlling effects of other variables	C is based on complex algorithm
				R cannot work properly with poor quality data
				R susceptible to collinear problems
[16]	2023	RF	RF has easy-to-understand hyperparameters	RF increased accuracy requires more trees
			RFclassifier doesn't overfit with enough trees	More RF trees slow down model
				RF an't describe relationships within data
[17]	2023	DT	a large amount of data is handled efficiently	DT are unstable

		P	reduce the computational cost economically	DT predictions neither smooth nor continuous
			DT has simple interpretation and visualization	biased DTs are created if some classes dominate
			DT performs better even if its assumptions breach	P sometimes affects the accuracy negatively
			DT works well with numerical and categorical data also multi-output problems	P performance and accuracy depends on data's nature
			DT is less costly	
			P reduces the size of decision trees	
			P is advantageous in removing the redundant rules	
[18]	2023	LSTM	process airspace flight image frames	can locate anomalous targets
			integrates flight plan with ADS-B data	LSTM small context window size(input's set)
			detection of ADS-B anomalous attack in ATC system	LSTM do not deal big temporal dependencies
			LSTM handles long-term dependencies effectively	
			LSTM is less susceptible to vanishing gradient problem	
			LSTM models complex sequential data efficiently	
			LSTM NN make prediction more accurate	
[19]	2023	LSTM	A multi-factorial model and multi-modal system	small sample size
			An encoder-decoder LSTM network	task complexity design
			LSTM handles long-term dependencies effectively	studies conducted in simulated environment
			LSTM is less susceptible to vanishing gradient problem	LSTM small context window size(input's set)
			LSTM models complex sequential data efficiently	LSTM do not deal big temporal dependencies
			LSTM NN make prediction more accurate	
[20]	2023	BI	data-driven classification approach is provided with a hierarchical structure	regional incident data is used
			resource investment optimization with efficiency	BI does not inform about prior selection
			BI has high statistical capacity in low probability events	BI makes posterior distributions largely influenced by priors
			BI combines prior information with data	BI gives high computational cost for models with large number of parameters

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			BI convenient for hierarchical models and missing data	
			BI provides exact inferences for conditional on data	
[21]	2023	LSTM	LSTM handles long-term dependencies effectively	LSTM small context window size(input's set)
			LSTM is less susceptible to vanishing gradient problem	LSTM do not deal big temporal dependencies
			LSTM is efficient at modeling complex sequential data	
			LSTM NN make prediction more accurate	
[22]	2020	DT	DT has simple interpretation and visualization	over-complex DT do not generalize data well
		KB	DT performs better even if its assumptions breach	DT are unstable
		KNN	DT works well with numerical and categorical data also multi-output problems	DT predictions neither smooth nor continuous
			DT is less costly	biased DTs are created if some classes dominate
			KB is simple to Implement.	KB Conditional Independence Assumption do not always hold
			KB is very fast	KB has Zero probability problem
			KB gives accurate results if conditional Independence assumption holds	KNN does not perform better on large dataset
			KNN no Training Period and new data adds seamlessly	KNN does not perform better on high dimension space
			KNN is very easy to implement	KNN need feature scaling
				KNN sensitive to noisy, missing data and outlier
[23]	2020	LR	use historic traffic time series data in different periods	need to consider more factors
			LR is easier to set up and train	low performance
			LR good differ data outcome are linearly separable	LR fails to predict a continuous outcome
				LR may not be accurate for small sample size
				LR assumes linearity between predicted and predictor variables
[24]	2020	ANN	NN is predictive model and automatic learning feature	NN generates a certain output is questionable
			NN handle large, complex, missing and sequential data	NN is complicated and long development time

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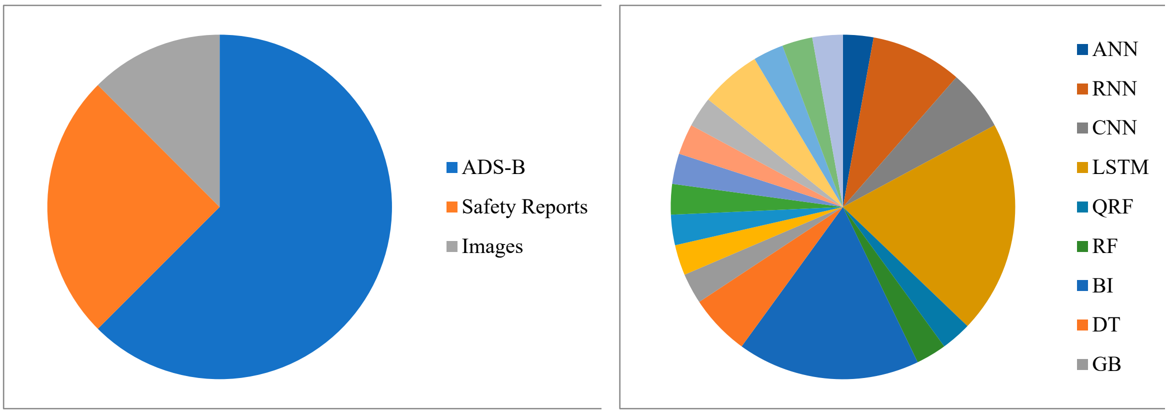
			NN exhibits improved performance	NN usually require much more data
			NN handling structured and unstructured data and also non-linear relationships	NN are more computationally expensive
			NN offers scalability and generalization	

3. Challenges

The challenges identified from above analysis are categorized into following subsections. In this sense, using data from different sources and configurations represents another open challenge as shown in Figure 9(a).



(**a**) (**b**)

Figure 9. (**a**) A Pie Chart showing distribution of Dataset Usage; (**b**) Pie Chart showing distribution of Models Usage.

3.1. Dataset

Following are main challenges regarding dataset used in conflict prediction.

1. The dataset used in all is imbalance because the conflicting scenarios occur very rare.
2. The dataset is real time but restricted to specific location and time frame which are from developed and high income countries.
3. There are less features in available dataset.
4. In case of aircraft accident mostly all features are not available in dataset.
5. Large amount of data is available in dataset.
6. There are datasets of diverse nature such as images, safety reports, past accidents etc.
7. Some dataset are structure while others are unstructured and hard to process directly.
8. Some dataset like ADS-B are not secure and data gets tempered easily by hackers.
9. Biaseness involved when missing values are data is filled by humans.

3.2. Model Used

1. Only short-term and medium-term trajectory prediction
2. Mostly Binary classes are used, little work on multiclass predictions
3. Some work focused factors like wind, weather, human factor during prediction
4. Few number of parameters are used
5. Dependencies/correlation between parameters are less focused
6. most conflict between two aircraft, one study deals four aircraft
7. uncertainties and risk factor involved in prediction is discussed in few studies
8. mostly studies performed time dependant analysis
9. reduction of cost and less computational needs is still a challenge
10. supervised learning is widely used while unsupervised learning least used

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11. classification techniques are mostly applied while Regression is less applied as shown in Figure 9(b)

3.3. Evaluation Technique

1. confusion matrix and is mostly used as shown in Figure 10.

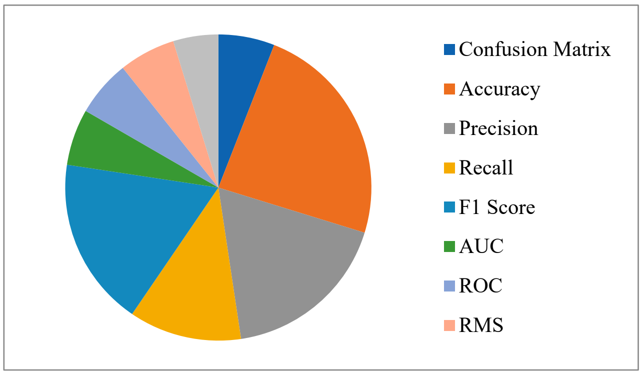


Figure 10. A Pie Chart showing distribution of Evaluation Techniques Usage.

4. Optimal Solution

The solutions proposed for above mentioned challenges are as follows.

4.1. Dataset

Following are main challenges regarding dataset used in conflict prediction.

1. Using global resources and information
2. New Software and Hardware Technologies for Data Collection
3. Real-time Sharing and Transmission of Data
4. Using Data from Different Sources and Configurations
5. new data collection strategy
6. Building New datasets
7. Secure Data Collection
8. New sampling methods

4.2. Model Used

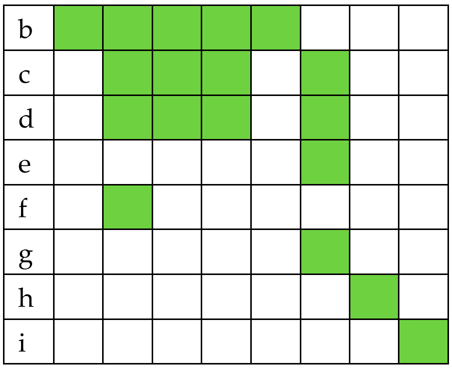
Following are optimal solution for each challenge regarding model used in conflict prediction.

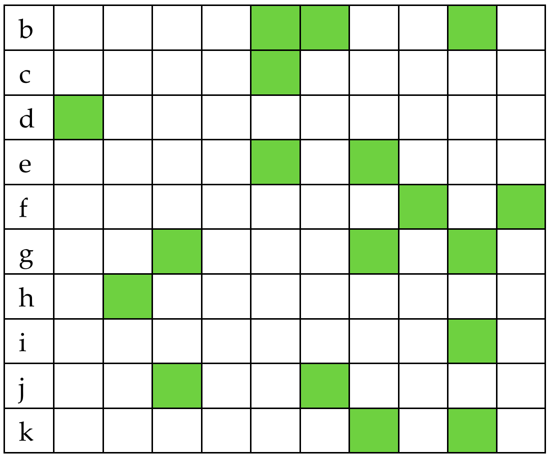
1. More parameters for prediction
2. Temporal Dependence
3. Ensemble learning
4. Robust Prediction
5. Correlation between Parameters
6. Deep Learning
7. Probabilistic vs. Deterministic Prediction
8. Scalable and Integrated approach
9. New Prediction Methods
10. Collaborative decision-making

Table 9. Matrix mapping challenges with suggested solution for Dataset on left and Models on right (Challenges row wise, solution column wise).

	a	b	c	d	e	f	g	h
a								

	a	b	c	d	e	f	g	h	i	j
a										





5. Conclusion

This research serves as a foundation for future research and towards integration of ML based safety prediction techniques into modern ATC system. In this study we present a SLR about the applications of ML techniques in safety prediction of ATC system. Initially, the existing aircraft conflict prediction models are classified into three broad categories; logical, geometric and probabilistic. A formal process of SLR is then conducted which is initiated with preprocessing and effective searching. A series of filtering called title, abstract and objective-based are then applied to extract the most relevant articles. Detailed and critical reviews of selected articles are performed to identify challenges which are segregated into dataset, model and evaluation techniques, furthermore, the optimal solutions for each are proposed. Finally the matrices to map the identified challenged with their proposed solutions are constructed.

The aviation industry has been significantly reluctant in practicing new technologies, as there have been many researches demonstrating outstanding results around for at least a decade. Although the basic objective of an ATC system is to provide maximum level of safety but there are few factors such as making changes to existing equipment and procedures, higher costs and staff training also makes the advent of new technologies and research in this domain questionable. However the integration on ML in ATC system has a greater potential to improve overall safety in terms predicting aircraft incidents, conflicts and accidents before they actually happen and turn into a disaster. Currently, the Federal Aviation Administration (FAA) in the United States of America is investigating the implementation of AI based next-generation (NextGen) technologies to enhance the efficiency of ATC system while increasing the level of safety. However, safer ATC system more intelligent systems that allows lower separation distances between aircraft in controlled airspace are yet to be realized.

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