AirOpsAI:Unleashing the Power of AI and Data Science to revolutionise the Airlines Operations

MSc Research Project

Data Analytics

Shreyal Kulaye

Student ID: 22155791

School of Computing

National College of Ireland

Supervisor: Abdul Qayum

National College of Ireland

MSc Project Submission Sheet

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Student Name:	Shreyal Ashok Kulaye
Student ID:	22155791
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AirOpsAI:Unleashing the Power of AI and Data Science to revolutionise the Airlines Operations

Shreyal Kulaye

22155791

Abstract

This research goes beyond traditional goals in the quest of expanding AI-driven innovations in the aviation sector, intending to improve customer happiness and estimate airline ticket costs. The research, positioned as a catalyst for ushering in a new age in aviation, displays a consistent commitment to solving modern difficulties and adapting to the dynamic environment of global transportation.

The expected outputs demonstrate a thorough grasp of essential topics, including ticket price forecasts, customer satisfaction prioritisation, and airline operations optimisation. By addressing the current limitations inherent in previous research, the research not only displays a dedication to fixing these obstacles, but it also represents a proactive effort to improving security standards, raising traveller pleasure, and maximising operating efficiency. In essence, our research reflects a commitment to pioneering breakthroughs that transcend traditional bounds, providing transformational answers to the multifarious difficulties confronting the aviation sector today.

Keywords: Airline Operations, Artificial intelligence, Airopsai, Machine Learning, Video Surveillance, Airlines Revolution, Weapon Detection, Baggage Scanning, Flight Delay, Real Time Flight Status

1 Introduction

Airports and airlines are dealing with tough problems such as inefficiencies, safety risks, and unclear pricing models that make current solutions fall short. The aviation industry could use a full-on solution that uses top tech. We're talking AI, machine learning, deep learning, and data analytics. This program aims to flip problems into chances to grow. The goal is to make things run smoother, ramp up safety, and at the end of the day, make the passenger's journey a whole lot better. The plan to meet ever-changing travel needs worldwide is what fuels this demand. Air travel is changing quickly. Adding modern tech like AI, machine learning, and data science is a giant leap that could change how airports and airlines operate at a basic level.[1]

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[1] Intelliverse.Ai (2023) *Revolutionising Customer Service with AI: A Case Study of KLM Royal Dutch*. https://www.linkedin.com/pulse/revolutionizing-customer-service-ai-case-study/.

- **Objectives**: Predict flight statuses with accuracy, improve aircraft scheduling, and offer feature-rich business intelligence dashboards to airlines.
- **Method**: Use data science and artificial intelligence (AI) to improve operational flexibility, resource allocation, and flight scheduling.
- **Impact**: lessen interference, ensure passenger satisfaction, and pave the way for advances in the aviation industry.

Fig 1. Main three parts of the project

My research focuses on combining data science and AI to revolutionise airline functions as shown in figure number 1. The primary areas in my study are passengers, aid, and overall airline efficiency. I started with clear goals, reviewing vast amounts of literature, crafting an intense study method, and carefully analysing collected data. The passenger section uses AI to recognize preferences, while the aid sector uses technology to hone services. Together, we cultivate detailed methods to streamline airline operations.

We aim to weave technology into aviation to boost performance, safety, and passenger comfort. Trent aviation is on the brink of a tech revolution, balancing complex safety rules, evolving passenger needs, and a web of operations. In 2023, Applied Sciences published E. Engonul and others' study, "An Analysis of AI Techniques in Surveillance Video Anomaly Detection: A Comprehensive Survey." Here, AI's role in spotting odd occurrences in surveillance videos is analysed. The authors look at different AI techniques for noticing abnormalities, illuminating progress and obstacles in this area. The article explores deep learning, machine learning, and other models, dissecting their uses, pros, and cons. This research serves as a helpful guide for researchers, practitioners, and developers in video surveillance and anomaly recognition.

Our passion for the potential changes data-controlled and smart systems could bring is great. We aim our work beyond just theories of systems and sets of facts. We're eager to focus on improving how airlines run, in a reasonable, lasting way. We envision an AI system skillfully merging data analysis, machine learning, and deep learning.[2]

Understanding that our focus is on constantly enhancing the flight industry instead of merely tweaking data sets is a key part of our work. The anticipated union of AI, data analysis, and profound learning isn't just a thought; it has the power to greatly alter aviation rules. Our

[2] *Scaling AI at Lufthansa* (no date). https://www.ibm.com/case-studies/deutsche-lufthansa-ag.

approach is distinct as we've selected various methods to explore deeply into the topic, taking into account the exclusive hurdles the aviation industry encounters.[3]

It encourages folks, influenced by genuine enthusiasm and a strong will to enhance an element critical for all people globally, to unite. This research's key purpose is not merely to distinguish humans from computers but comprehend the integration of data science, machine learning, and profound learning as a collective task. This can trigger a significant transformation in the functioning of airlines.[4]

Research Question:

How can widely used techniques from Data Science, Machine Learning, and Deep Learning be used to revolutionise the airline activities and boost airport safety, all while tending to the matters of ethics and rules?

Research Objectives:

1.1. Merging AI in Flight Running: Can we mix machine learning and Business Intelligence to forecast flight times and shrink delays in airlines?

1.2. Upgrading Airport Security & Traveler Experience: Can AI-guided computer programs upgrade airport safety through video checking, scanning, spotting banned items, tracking passengers, tallying them, and amplify the overall airport enjoyment?

2 Related Work

At the 2016 IEEE Tech and Automation Control Conference, J. Xiong, X. Zhang, and Q. Du gave a talk. They talked about a way to plan fleets better. They made a model for airlines. This model tries to help airlines work out what sort of planes they should have and how often they should use them. The model looks at things like how much demand there will be, how much flights will cost to run, and what they'll need to spend on keeping planes in good shape.

P. Weerasinghe and their team have moved things along a bit in this area. They've made a way for airlines to make smart decisions on the spot. This tool is just for airlines. It can make them run smoother and save money. It could really change things for airlines if they could use this kind of tool. It could help them respond better to changes in demand. It could help them

[3] *Case Study: AI powered fuel efficiency at Wizz Air* (no date).
https://www.aircraftit.com/articles/case-study-ai-powered-fuel-efficiency-at-wizz-air/.

[4] Jansons, K. (2023) *AI in aviation and airlines: Use Cases for 2023*.
https://mindtitan.com/resources/industry-use-cases/ai-in-aviation-and-travel

be more aware of costs. It could help them improve how they work in general by making them quicker to react and more organised.

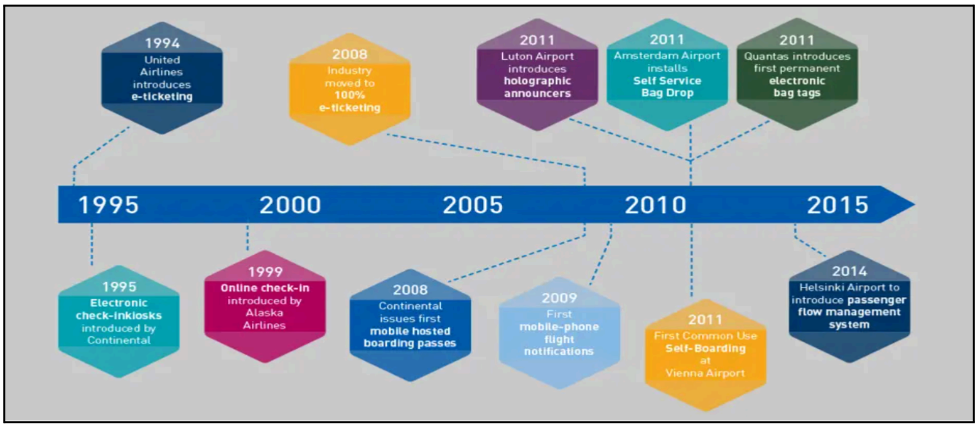

Fig 2. Evolution of Digital Transformation in Airlines Operations

Figure number 2 shows the evolution of digital transformation in airlines operations. This project dives into new tech and their transformative power. Specifically, it's about how big they'll be in the aviation world. A soon-to-be-published report will use machine learning to look into the big problem of aeroplane delays. The writer checks out many machine learning methods to hopefully predict flight delays accurately, showing how current data-driven methods are important. They base their study on past flight data and use machine learning. Their results are really important. They lay the groundwork for better systems to lessen how often and how bad plane delays are.

Another research from 2020, published in the "Journal of Big Data," made big strides in aviation. It looked at the same problem - flight delays. They had a new method that mixed deep learning with a special algorithm to predict flight delays more accurately. This study shows how useful and practical it can be to use deep learning and this algorithm to predict flight delays. Using these advanced models for our project might let our system predict and manage flight delays better. This could make the airport run more smoothly and keep passengers happy.

At the 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), researchers tackled the complicated problem of flight delays. These researchers aim to predict these delays with data analytics and smart algorithms. They developed a new method to analyse a large pool of historical flight data with the help of big data technologies. The accuracy of these predictions is quite impressive. The research, conducted in August 2017, involved predicting flight delays with multiple linear regression models. Various reasons for flight delays were studied using statistical models. Then, a mathematical plan was proposed for anticipating delays, given a set of inputs.

The Journal of Advanced Transportation published an inventive report in August 2021 on predicting airline delays. The authors highlighted the need to identify flight delays and illustrate how a combined learning tool, called the stacking method, can enhance predictions.

This system can aid airlines and customers in making well-informed decisions. The researchers noted that cutting-edge machine learning approaches are essential in solving issues in the aviation field. Their insights could drastically improve operational productivity. Incorporating these sophisticated prediction models into our project could significantly enhance our ability to predict and control flight delays, thus boosting overall productivity and passenger happiness.

In June 2019, Big Data's Journal listed an article. It's called "Intelligent Video Surveillance: A Study of Deep Learning Techniques for Crowd Analysis." The authors are G. Sreenu and M.A.S Durai. They talk about deep learning in video surveillance. Specifically, its uses in understanding crowds. They discuss how deep learning helps in watching crowded places, understanding crowd behaviour, and bettering security. The paper shines a light on different methods and designs used in analysing crowds using deep learning and their effectiveness and applications. This resource is really helpful for researchers, practitioners, and stakeholders wanting to apply deep learning to improve video surveillance.

Ardabili and his team have written an article. Published in Computational Urban Science in May 2023, it's called "Understanding Policy and Technical Aspects of AI-enabled Smart Video Surveillance for Public Safety." The authors mainly discuss the union of policy development, technical progress, and AI-powered video surveillance for public safety. They give a detailed look at the complicated topic of incorporating AI into video surveillance systems. The paper dives into the ethical, legal, and social issues of using AI-based surveillance. They address both the implications on policy and technological complexities.

In the paper "AI in Video Surveillance for Drones" by M.T. Nguyen and team, we get a detailed look into how Artificial Intelligence (AI) boosts video surveillance for unmanned vehicles (UAVs). The piece was published in MethodsX, January 2021. The team highlights how AI enhances the UAVs' monitoring abilities, helping in decision making. We see AI algorithms that detect odd happenings and increase object recognition in UAV surveillance. This research, at the core of AI and UAV tech, offers valuable insights for boosting the use and effectiveness of surveillance drones.

S. Ouf's paper "A Better Airline Service through Deep Learning," published in January 2023 in Computers, Materials & Continua, introduced a new deep learning model to better airline services. The paper explores how top-notch deep learning algorithms can affect different areas. Aspects like making things better for clients, increase of operational effectiveness, and creating an all-around better experience get considered. We learn how deep learning can shift the airline industry by showing how its use can hugely improve service offerings. This could result in a better experience for all involved in aviation. If you integrate such a refined deep learning tech to your project, the quality of airline services can improve, along with its operations.

Table 1. Literature Review of Implementation based Papers

Paper	Authors	Method Used	Description of Model	Evaluation Criteria	Limitation
1	M.-T. Vo, T.-V. Tran, D.-T. Pham, T.-H. Do	Various prediction methods: statistical analysis, modelling simulation, queuing theory, and machine learning	Detailed analysis of flight operation process and delay reasons. Proposes flight cancellation and aircraft swapping as solutions.	Comparative analysis of prediction methods	Future research direction is proposed
2	T. Wang, Y. Zheng, H. Xu	Real-time flight delay prediction system using big data technology	Uses Apache Kafka to stream flight data to machine learning models in Apache Spark for real-time prediction.	Real-time prediction results and storage in Cassandra database	Not specified
3	A. Anees, W. Huang	Data analysis and model development using Random Forest algorithm	Develops a prediction model for flight delays based on domestic flights' data in the USA.	Testing results presented using Random Forest algorithm	Limited discussion on machine learning deployment
4	V. Natarajan, S. Meenakshisundaram, G. Balasubramanian, S. Sinha	Logistic regression and decision tree algorithm	Predicts airline delays using historical weather and operational data. Employs logistic regression and decision tree models.	Performance comparison of logistic regression and decision tree algorithms	Limited discussion on the stochastic nature of delays
5	S. Choi, Y. J. Kim, S. Briceno, D. Mavris	Data mining and supervised machine learning algorithms	Predicts airline delays caused by inclement weather using US domestic flight and weather data.	Comparison of prediction accuracy and ROC curve for different machine learning algorithms	Addresses imbalanced training data but doesn't discuss the effectiveness of sampling techniques

6	K. Zhang, Y. Jiang, D. Liu, H. Song	Stacked Long Short-Term Memory (LSTM) networks	Uses spatio-temporal data mining for aviation delay prediction based on ADS-B messages and correlated geolocations.	Demonstrates robustness and accuracy for large hub airports	Does not explicitly address the limitations of the proposed approach
7	H. Alonso, A. Loureiro	Unimodal model using neural networks and trees	Predicts flight departure delay at Porto Airport using an ordinal classification approach.	Comparison of prediction using neural networks and trees	Limited discussion on the applicability and scalability of the approach
8	M. Bardach, E. Gringinger, M. Schrefl, C. G. Schuetz	Random Forest classifier	Predicts the risk class of air traffic scenarios based on expected delay costs and environmental conditions.	Achieves 82.5% accuracy for the highest risk class using Random Forest	Focuses on a specific airport (Atlanta International Airport) and does not discuss generalizability to other airports
9	D.-I. Gota, A. Puscasiu, A. Fanca, H. Valean, L. Miclea	Convolutional neural network using OpenCV and Keras	Detects threat objects in airport X-ray luggage scan images using a convolutional neural network.	Detection rate evaluation using X-ray images	Limited discussion on the scalability and real-world implementation of the threat object detection system
10	P. Monmousseau, G. Jarry, F. Bertosio, D. Delahaye, M. Houalla	Long Short-Term Memory neural networks	Predicts passenger flows at Paris Charles De Gaulle airport security checkpoints using LSTM neural networks.	Comparison of derived models with current prediction model using mathematical metrics	Does not discuss potential challenges in obtaining and using passenger flow data
11	S. Addu, P. R. Ambati, S. R. Kondakalla, H. Kunchakuri, M. Thottempudi	Various machine learning algorithms (Random Forest, Decision Tree, MLP Classifier, Naive Bayes, KNN classifier)	Predicts flight delays to mitigate economic and environmental consequences of delays.	Aim is to identify and eliminate flight delays using machine learning algorithms	Generalized dataset and model evaluation criteria are not specified

3 Research Methodology

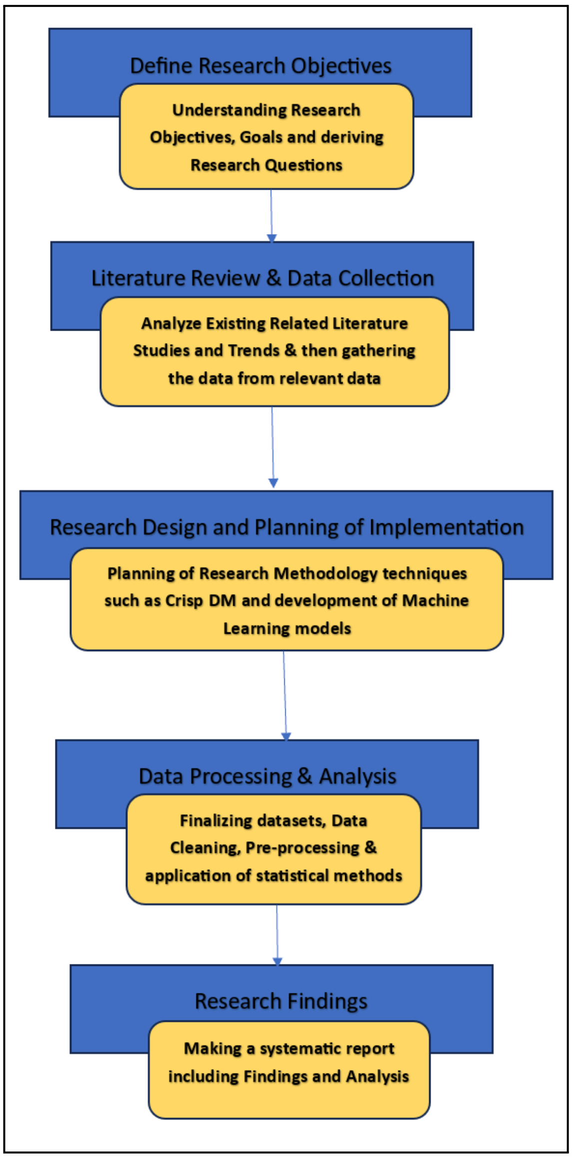

Fig 3. Research Protocol Diagram

The research protocol (Figure number 3) diagram gives a clear path through the big phases of research. First, you need a solid method that matches your goals. Then, we plan how to collect data. The plan is used to gather helpful data and to pull out important info. This plan is used to gather useful data and to tease out key details. We setup and tidy the data before applying stats techniques. After that, we show the study's findings in an easy-to-understand report. With this structured method, it's an easy step-by-step from start to finish, allowing a full and well-educated look into your chosen study field.

Research Methodology Steps:

1. Research Design:

- Merge number-based and observation-based methods for full comprehension.
- Use foreseeing patterns with machine learning tools.
- To understand deeply, use real-life examples and intensive talks.

2. Sampling and Population:

- Incorporate passengers, airlines, and suppliers of help services into the research.
- Use stratified sampling to provide a representation that is varied.

3. Gathering of Data:

- Conduct a quantitative analysis of operational records, passenger comments, and historical flight data.
- Utilise machine learning techniques to forecast and optimise flight conditions in real-time.

4. Tools and Technology:

- For machine learning applications, use Python.
- If you want graphical representations, use data visualisation tools.
- For qualitative data, use interview transcription software.

5. Data Preprocessing and Analysis, Model Building, Evaluation and testing :

- Data Exploration with various libraries like matplotlib and seaborn and removal of the outliers from the inferences.
- For quantitative analysis, use clustering techniques, time series analysis, and regression models.
- Model building using various machine learning and deep learning techniques such as Recurrent Neural Network, Convolutional Neural Network.
- Evaluating and testing the results using various techniques like f1 Score, AUC (Area under the curve), etc.

6. Timeline:

- Examination of the literature, data gathering, analysis, and report writing.
- Modify the schedule in light of continuing assessments as necessary.

This comprehensive research strategy aims to provide a solid basis for investigating the integration of AI and Data Science in enhancing airline operations, with a focus on passengers, assistance services, and overall optimisation.[5]

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[5] Kell, J. (2023) 'How the airline industry is using A.I. to improve the entire experience of flying,' *Fortune*, 31 January.
https://fortune.com/2023/01/31/tech-forward-everyday-ai-airline-industry-fuel-consumption-food-waste/.

4 Design Specification

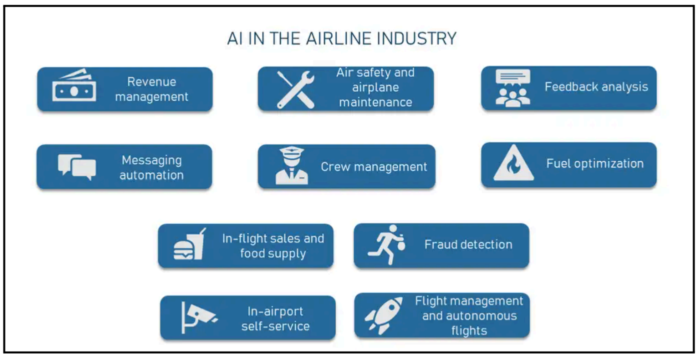

Fig 4. AI in Airlines OPerations

The research project's implementation, which aims to improve airline operations (Figure number 4) by combining data science and artificial intelligence (AI), takes a multimodal approach. Computer Vision technology is used in video surveillance systems to identify prohibited items, anomalous activities, and potential security threats. Integration frameworks will be utilised to integrate different data sources, and as part of the deployment, tailored Business Intelligence (BI) dashboards for real-time analytics will be produced.

Specific Items to be addressed

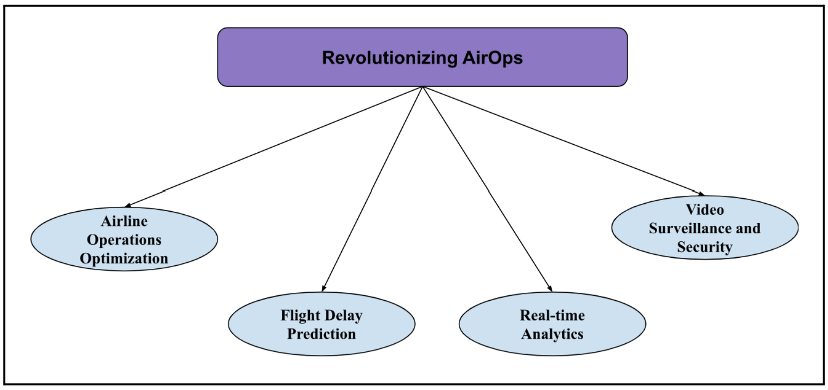

Fig 5. Items to be addressed

- Aspects of airline operations optimization include crew assignment, fleet management, flight scheduling, and resource utilisation.

- Analysing historical data, weather patterns, air traffic congestion, and other relevant factors is necessary to predict flight delays. Regression models and time series analysis are two common machine learning techniques used in this setting.

- Business intelligence dashboards and visual aids that provide current data on operational KPIs, performance indicators, and flight statuses are referred to as real-time analytics.

- Given the increasing significance of aviation security, research looks at how AI and computer vision technologies may be incorporated into video surveillance systems. Part of this includes developing algorithms for the detection of firearms, odd behaviour, illicit commodities, and people tracking and counting.

Dataset Details:

- **Flight Fare Prediction:** The purpose of this undertaking is to evaluate the flight booking dataset from 'Indian airlines' acquired from the "Ease My Trip" site and extract meaningful insights through a string of statistical hypothesis tests. The statistical technique referred to as "Linear Regression" would be applied to coach the dataset and anticipate a continuous focus variable. The findings can help travellers select suitable flights based on multiple criteria as well as aid airlines to optimise revenue management[6].

- **Airline Passenger Satisfaction:** The collection offers extensive information regarding passengers on aircraft. It includes various specifics such as the airline identification number, flight details, class allocations on the plane, and customer satisfaction scores. The data aims to clarify our understanding of travellers by providing intermediate depth across several key aspects of their journeys through the air, such as carrier identifiers, travel itineraries, seat classifications on board, and rating feedback.

- **Flight Delay:** The United States Department of Transportation, also known as DOT, closely monitors how major airlines adhere to their schedules for domestic flights within the country. They tally the number of flights that depart on time, those that are delayed, those that must be cancelled, or those that are diverted. This flight performance data is contained in a monthly report called the Air Travel Consumer Report[7].

- **Real Time Analytics:** We utilised the suggested website, SkyTrax, for this job. The data was scraped from this website, and we were able to effectively parse it using BeautifulSoap.

- **Baggage Scanning:** I used photographs from the GRIMA database. According to the information you gave, the GDXray dataset is a database of X-ray pictures created expressly for nondestructive testing. The mentioned paper in the Journal of Nondestructive Evaluation has more information on the GDXray dataset. The article may go into considerable length about the dataset's size, the sorts of X-ray pictures it contains, and its possible uses in nondestructive testing[8].

- **People Tracking:** The dataset takes RGB pictures from video frames as inputs, and each frame counts the number of pedestrians (or other things) in the image. The fact that there are variable numbers of people in each frame of the 480x640 pixel photos collected by a camera at a mall provides a dilemma for crowd counting[9].

- **Violence Detection:** An annotated frame-by-frame battle dataset organised into CCTV and non-CCTV categories, with train, test, and val for each[10].

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[6] *Flight price prediction* (2022). https://www.kaggle.com/datasets/shubhambathwal/flight-price-prediction.
[7] *2015 Flight delays and cancellations* (2017). https://www.kaggle.com/datasets/usdot/flight-delays?datasetId=810&sortBy=voteCount&select=airlines.csv.
[8] *Mery, D.; Riffo, V.; Zscherpel, U.; Mondragón, G.; Lillo, I.; Zuccar, I.; Lobel, H.; Carrasco, M. (2015): GDXray: The database of X-ray images for nondestructive testing. Journal of Nondestructive Evaluation, 34.4:1-12.*
[9] *Crowd counting* (2018). https://www.kaggle.com/datasets/fmena14/crowd-counting.
[10] *Video Fights Dataset* (2020). https://www.kaggle.com/datasets/shreyj1729/cctv-fights-dataset.

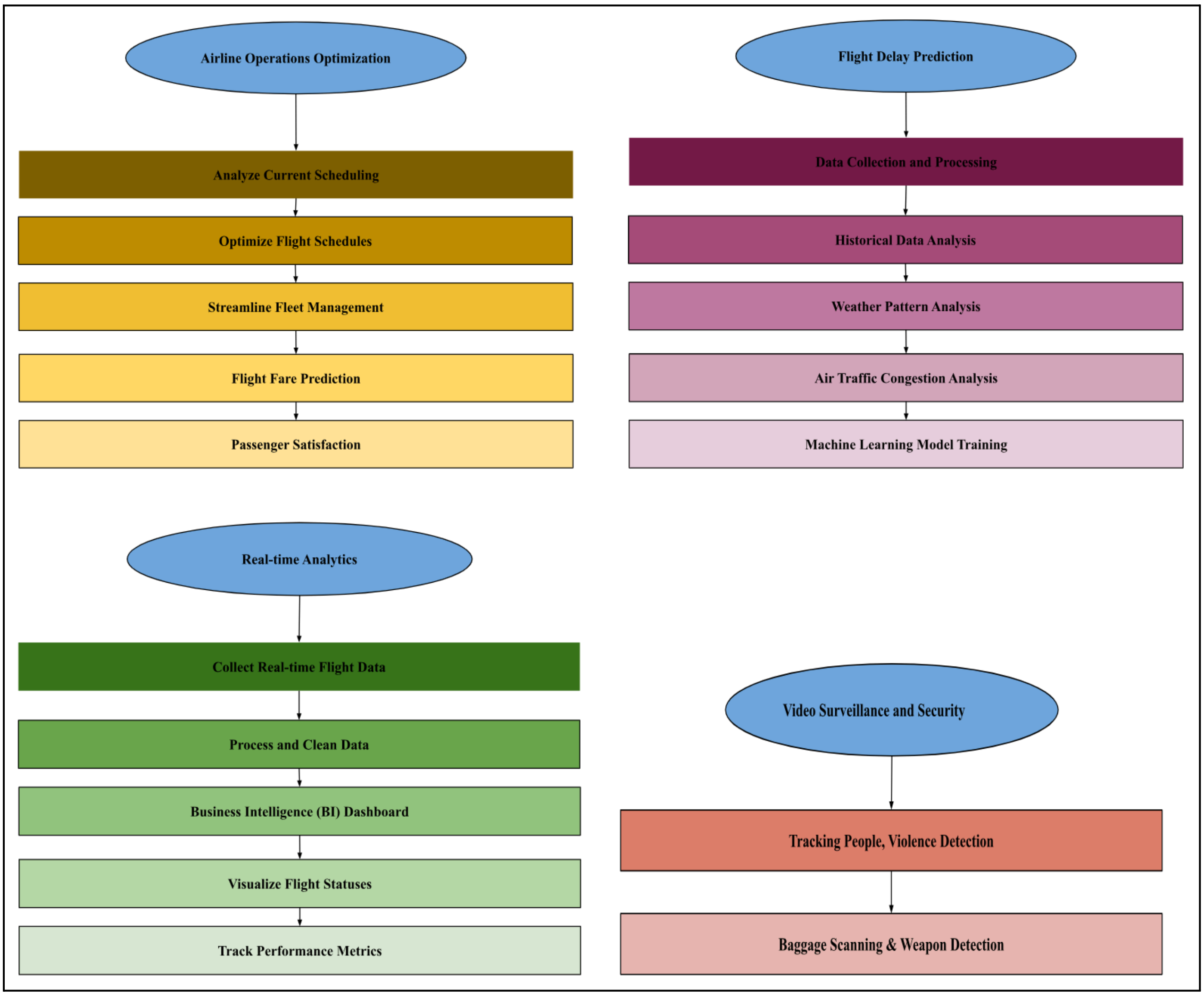

Fig 6. Components of the Main Project

1. **Airlines Operations Optimization**

   Flight Fare Prediction: The purpose of the project is to assess the flight booking dataset which comes with data from 'Indian airlines' obtained from the "Ease My Trip" website and extract relevant information through a series of statistical hypothesis tests. The statistical method known as "Linear Regression" would be used to train the dataset and predict a continuous target variable[11].

   Airline Passenger Satisfaction: The collection provides comprehensive data about travellers aboard aeroplanes. It contains a number of details including airline Id, travel details, class distribution, and satisfaction ratings.

This section aims to improve several aspects to revolutionise airline operations. Enhancing the entire travel experience through personalised services and efficient processes is the aim of passenger satisfaction. Simultaneously, the use of predictive algorithms for airline ticket

[11] *Flight price prediction* (2022). https://www.kaggle.com/datasets/shubhambathwal/flight-price-prediction.

Estimations facilitates efficient pricing strategies by ensuring cheap tickets and improving consumer satisfaction. The Airlines Operations Optimisation sector includes a diverse variety of machine learning algorithms, each designed to address specific challenges and enhance various aspects of airline services. Using team-work algorithms, content filters, or mixed models in creating suggestion systems helps make services personalised by looking at what users like and how they act[12].

2. **Flight Delay Prediction**

Talking about plane delays, they can be predicted by using some smart maths. These maths models use old data, weather stuff, and other things to make better guesses about flight delays. This way, airlines can plan better. They can make good choices, wisely use resources, and let passengers know updates on time. Technologies like time series analysis, regression models, or machine learning, such as Random Forest, Gradient Boosting, or Neural Networks are super useful for this. They make guesses about real-time flight statuses based on old patterns, weather, and other factors. With this help, airlines can stop delays before they happen, use resources better, and work more efficiently.

3. **Real Time Analytics using Power BI**

This part is about making live analytic boards with BI's power. These boards give a full look at data, flight updates, and key performance signs. Power BI's live information helps airlines make fast choices, adjust to change, use resources well, and boost overall efficiency. Statistics can be used in basic analytics, while machine learning can predict future patterns. Power BI shows dynamic data, which speeds up decision making. In basic analytics, we use statistics, for predicting future trends, we use machine learning. Power BI shows dynamic data for snap decisions.[13]

4. **Video Surveillance and Security**

This key part is focused on enhancing air travel safety using cutting-edge video monitoring tech.[14] Counting and tracking individuals assists in managing crowds, and checking luggage ensures oddities are found. Mixing AI and computer vision to boost security operations, it identifies weapons, monitors aggressiveness, and spots abnormal behaviour. This provides a proactive and complete solution to shield passengers, airline workers, and airport structures. These aspects display a commitment to fostering a safe travel environment. In the Video Observation and Security section, computer vision techniques like Convolutional Neural Networks (CNNs) for identifying objects, Recurrent Neural Networks (RNNs) for examining behaviour, and other machine learning methods for detecting anomalies can be employed. Conventional image processing methods could also be used for specific tasks like baggage inspection.

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[12] Inmon, B. (2023) *Hear your customers: An airline case study analysis*. https://www.integrate.io/blog/airline-case-study-analysis/.

[13] Cirium (2023) *Case studies and testimonials - Cirium*. https://www.cirium.com/case-studies-and-testimonials/.

[14] *Case Study | Fresno Yosemite International Airport | PeLco* (2023). https://www.pelco.com/case-studies/case-study-fresno-yosemite-airport.

5 Implementation

1. Airlines Operations Optimizations from passenger point of view

Passenger Satisfaction

Based on our EDA, we proposed many methods to effectively tackle the problem. These recommendations were based on data-driven insights and were intended to streamline our procedure.

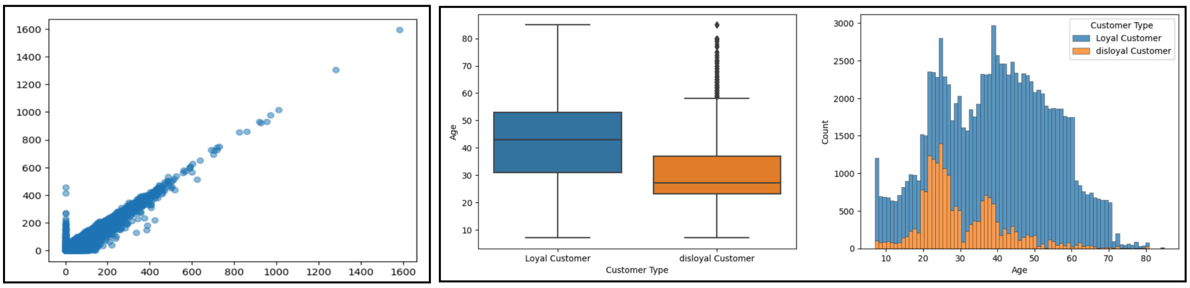


Fig 7. Arrival and Departure Delay & Loyal Vs Disloyal Customers

As you can see(Figure number 7), a straight line connecting the bottom left to the top right corner was formed by the spots that usually lined up. Consequently, there is an approximately linear relationship between the arrival and departure time delays. The very fair conclusions that were drawn are explained by the following. The overall age range of non-regular consumers is somewhat under 30, with an average age of 25 to 40.

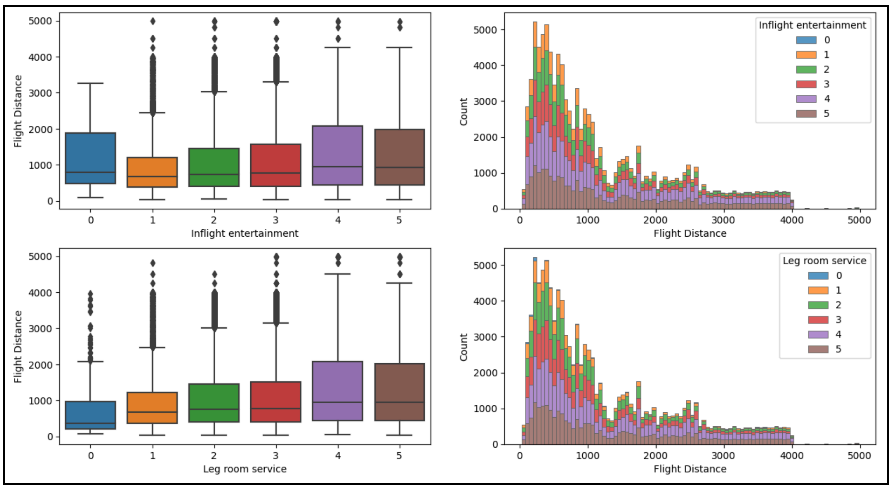


Fig 8. Flight Distance compared to entertainment and legroom

One may observe the following trend (Figure number 8): consumers are happier with greater legroom and onboard entertainment the farther. After that, during the modelling stage, we experimented with a number of machine learning classifiers. After a thorough evaluation and testing process, two remarkable models—CatBoost and XGBoost—came to the forefront. These models consistently outperformed the competition with exceptional balanced accuracy, testing accuracy, F1 score, precision, and recall.

Flight Fare Prediction

An airline is a company that provides air transportation services for both passengers and goods. In order to sell and operate the same route under codeshare agreements, airlines may partner or form alliances with other airlines, using their aircraft to carry out these services. Airlines aim to maximise their profits by determining the appropriate pricing for their services. Airline ticket pricing has become increasingly complex over time, and it is now mostly managed by computerised yield management systems.

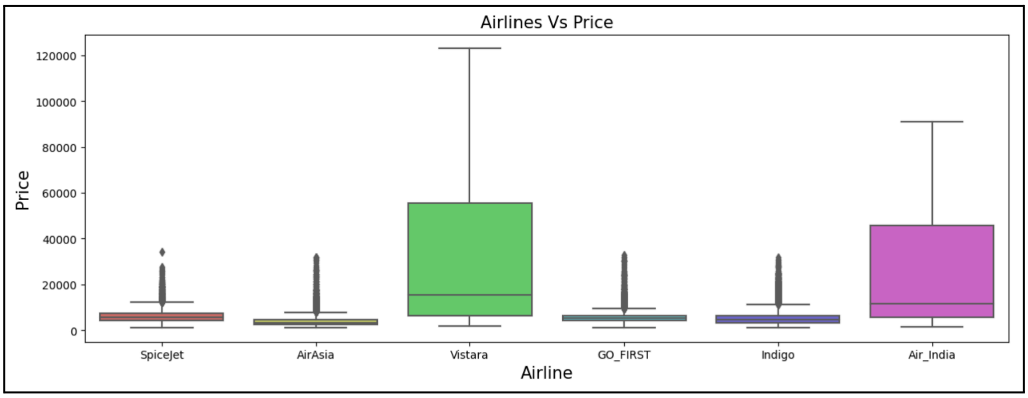


Fig 9. Airlines Vs Price

Many factors, such as the duration of the trip, the number of days till departure, the arrival and departure times, etc., affect the cost of an airline ticket. When they need to reach a wider audience or when obtaining tickets becomes more challenging, airline companies may lower their prices (Figure number 9). They had the option to charge as much as they wanted.

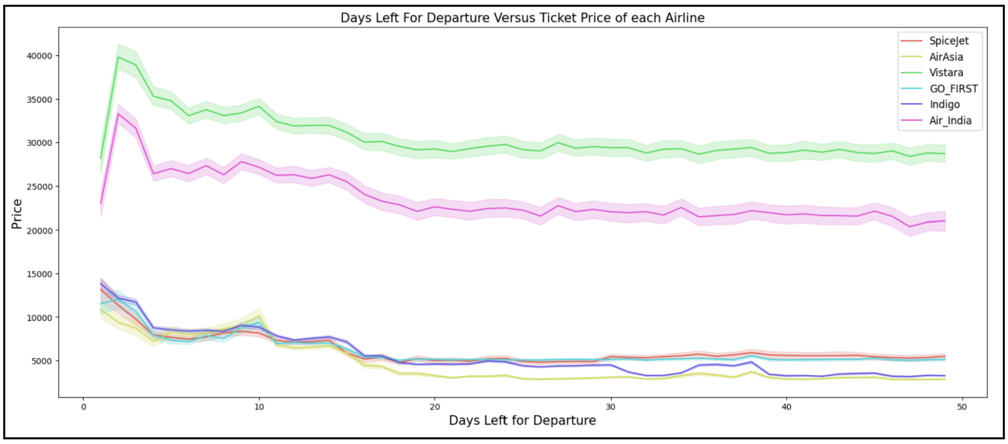


Fig 10. Ticket Price for each of the airlines

The price might be influenced by several things. Every component employs a different set of proprietary rules and algorithms to determine pricing accurately. Because of recent advances in machine learning and artificial intelligence (ML and AI), these ideas may now be deduced and the price volatility can be recreated as follows (Figure number 10).

2. Flight Delay Prediction

In order to determine the likelihood of a flight delay, machine learning techniques are employed in flight delay prediction. These models consider several factors like weather, historical data, airport traffic, and prior flight performance in an effort to provide travellers and airlines with an idea of the probability of flight delays. In addition to allowing airlines to simplify operations and cut down on delays, this assists travellers in making more informed travel plans. Different learning tools like decision trees, random forests, support vector machines, and brain-like networks were used to get tricky patterns from this broad data set. This helps recognize hurdles in reality that lead to delayed flights.

3. Real Time BI Dashboard

Fig 11. BI Dashboard

The BI dashboard (Figure number 11) for airline reviews attempts to transform vast volumes of data obtained from 10 major airlines into actionable insights. Power BI will be used to present a complete picture of client reviews, highlighting important themes and sentiments. This project's end outcome is a dynamic Power BI dashboard. By using several features, the dashboard provides essential metrics such as total reviews, number of ratings, suggestions, average ratings, seat types, and travel preferences. This interactive visualisation tool provides stakeholders with a full view of consumer opinions and preferences, enabling them to make better informed decisions in the aviation industry.

4. Video Surveillance

YOLO4-based Advanced Baggage Scanning Algorithm:

In the field of video surveillance, a cutting-edge luggage scanning technology based on YOLO4 has been created. Using the power of Convolutional Neural Networks (CNN), this cutting-edge technology recognises a wide range of weapons, distinguishing between blunt and bladed objects.

Integration of YOLO4 enhances security needs in surveillance applications by enabling speedy and precise identification.[15] The initial step in developing the advanced luggage scanning approach with YOLO4 is to train the model on a large dataset that includes photographs of baggage articles, with a focus on various weapons. By exploiting the Convolutional Neural Networks (CNN) architecture inherent in YOLO4, the algorithm gains the ability to successfully learn and detect subtle patterns inside photographs.

During the training phase, the algorithm is presented with labelled examples of numerous baggage items, each of which is associated with a certain object class such as guns, knives, and other potential security threats. YOLO4 makes recurrent changes to its internal settings throughout these training epochs, honing its ability to detect and label items of interest. Once trained, the YOLO4 model integrates into the baggage screening process, reading real-time video feeds or images from surveillance cameras.

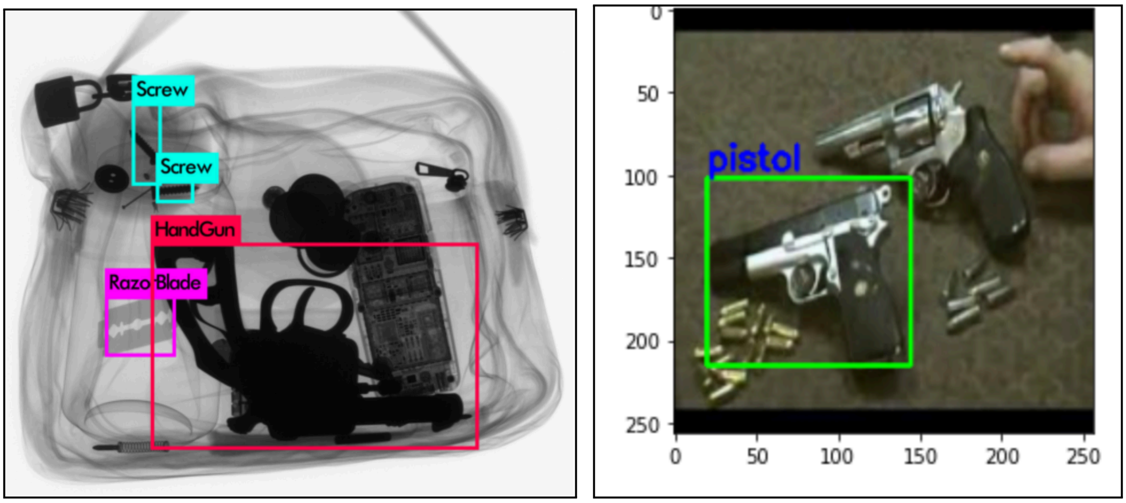


Fig 12. Baggage Scanning & Weapon Detection Results

People Counting and Tracking Using Neural Networks and OpenCV:

Our video surveillance system employs neural networks and OpenCV for precise people tracking and counting. This innovative approach accurately and efficiently tracks crowd movement and attendance, providing critical information for security and operational demands. The integration of neural networks with OpenCV aids in the development of a robust surveillance infrastructure.

[15] SuperAnnotate AI Inc. (no date) *YOLO object detection: Evolution and algorithms | SuperAnnotate*. https://www.superannotate.com/blog/yolo-object-detection.

Fig 13. Violence Detection & People Counting and tracking

6 Evaluation

An in-depth investigation uncovers the subtle efficiency and cleverness hidden in each module throughout the painstaking creation of the AIROPS (Airline Operations) codes. The discussion that follows dives into the precise strengths and performance requirements of these cutting-edge codes, highlighting their crucial role in revolutionising aviation management and safety processes.

6.1 Passenger Satisfaction & Flight Fare Prediction

Classifier	Balanced Accuracy	Training Accuracy	Testing Accuracy	F1 Score	Precision	Recall
Logistic Regression	0.815447	0.752117	0.753224	0.727172	0.698401	0.758415
Decision Tree	0.943416	1.000000	0.943895	0.935597	0.931427	0.939804
Random Forest	0.993634	1.000000	0.960615	0.953909	0.968349	0.939893
Gradient Boosting	0.986583	0.941973	0.938760	0.928604	0.939002	0.918433
K-Nearest Neighbors	0.850783	0.856442	0.790717	0.744941	0.789920	0.704809
Gaussian Naive Bayes	0.921319	0.862794	0.863117	0.838475	0.858543	0.819323
Multi-layer Perceptron	0.981642	0.934124	0.929917	0.917376	0.938437	0.897240
XGBoost	0.994667	0.973607	0.962507	0.956192	0.969090	0.943633
CatBoost	0.994745	0.973327	0.962043	0.955707	0.967345	0.944346
AdaBoost	0.976663	0.927907	0.925091	0.913168	0.918017	0.908370

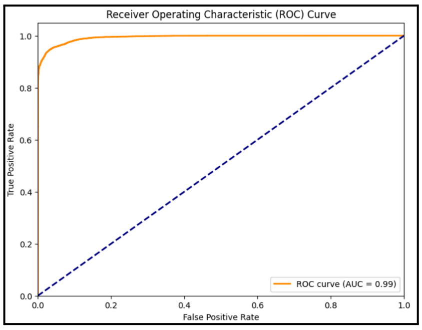


Fig 14. Accuracy of the Passenger Satisfaction Model

The evaluation (figure number 14) process used a variety of machine learning classifiers, such as Random Forest, XGBoost, CatBoost, AdaBoost, Decision Tree, Logistic Regression, Gaussian Naive Bayes, K-Nearest Neighbours, and Multi-layer Perceptron, and evaluated their performance using metrics such as balanced accuracy and precision-recall balance. The ensemble algorithms Random Forest and XGBoost exhibited great balanced accuracy as well as a favourable precision-recall balance. Individual classifiers such as Logistic Regression and Gaussian Naive Bayes performed admirably. K-Nearest Neighbours demonstrated lesser accuracy, indicating that hyperparameter tinkering might improve performance. Neural network plasticity was demonstrated by the Multi-layer Perceptron. The final model evaluation considers task-specific needs, dataset features, and additional approaches such as hyperparameter tweaking, feature significance analysis, and cross-validation for a complete and robust assessment.

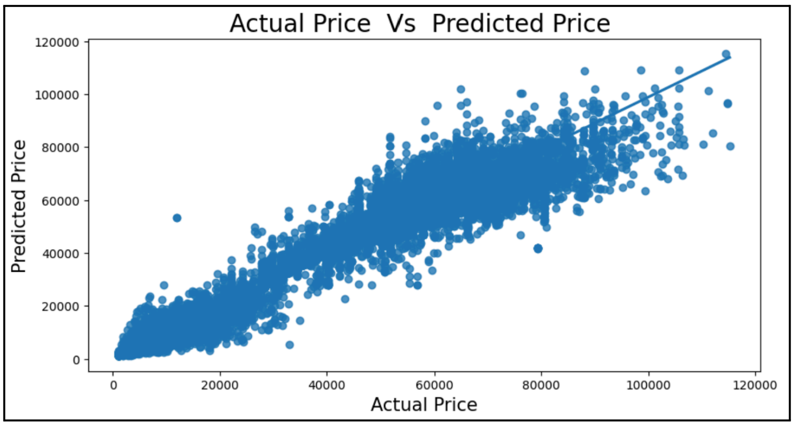


Fig 15. Flight Delay Prediction Results

In terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), tree-based models, particularly Decision Tree Regressor, Random Forest, Extra Trees, and Bagging Regressor, outperform other models. Both XGBoost and Gradient Boosting Regressor are effective. Linear models, such as Linear Regression, Ridge, and Lasso, have significantly higher error metrics, emphasising the importance of ensemble approaches for this dataset. Fine-tuning and feature engineering may improve overall model performance even more.

6.2 Flight Delay Prediction

epoch	train_loss	valid_loss	accuracy	time
0	0.624006	0.616078	0.655994	00:15
1	0.605772	0.608217	0.664912	00:15
2	0.593240	0.605736	0.668249	00:15
3	0.575155	0.609799	0.665616	00:15
4	0.551835	0.621216	0.661537	00:15

```
Better model found at epoch 0 with valid_loss value: 0.6160781979560852.
Better model found at epoch 1 with valid_loss value: 0.6082167625427246.
Better model found at epoch 2 with valid_loss value: 0.6057361364364624.
```

epoch	train_loss	valid_loss	accuracy	time
0	0.618645	0.614560	0.660406	00:07
1	0.604825	0.608726	0.666024	00:07
2	0.595358	0.607705	0.667285	00:07
3	0.578405	0.610467	0.665449	00:07
4	0.561947	0.614603	0.664652	00:07

```
Better model found at epoch 0 with valid_loss value: 0.6145598888397217.
Better model found at epoch 1 with valid_loss value: 0.6087258458137512.
Better model found at epoch 2 with valid_loss value: 0.6077051162719727.
```

Fig 16. Flight Delay Prediction Results

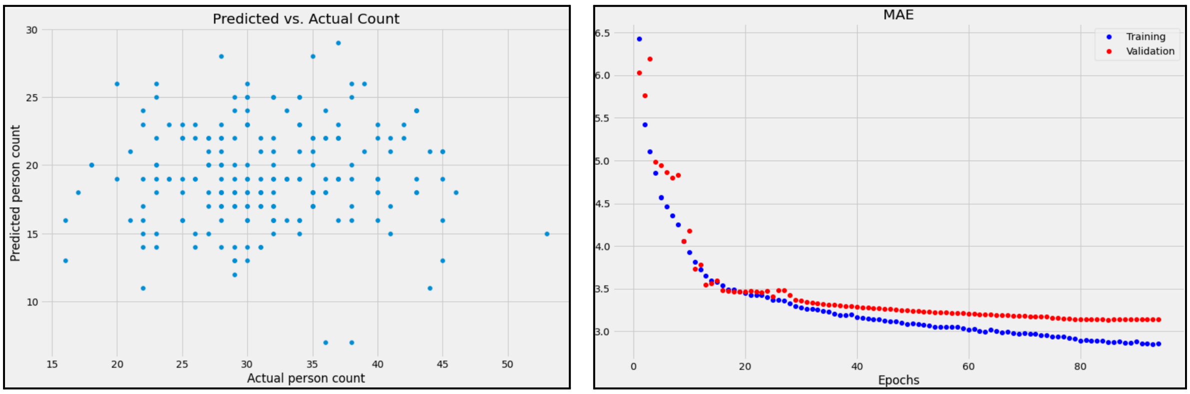
The offered material describes the training and testing of three neural network models for a binary classification job (delay or no delay). Model 1 has three hidden layers of 500, 250, and 10 neurons, Model 2 has three hidden layers of 100, 50, and 50 neurons, and Model 3 has two hidden layers of 50 and 25 neurons. During the training phase, the validation loss and accuracy are evaluated at each epoch. Models 1 and 2 perform equally in terms of loss and accuracy, while Model 2 was chosen for future investigation because of its somewhat lower validation loss. This model will be used for the following tasks because of its accuracy (figure number 16).

6.3 Video Surveillance & Passenger Safety

```
mini_batch = 1, batch = 1, time_steps = 1, train = 0
   layer   filters  size/strd(dil)      input                output
   0 conv     32       3 x 3/ 1    416 x 416 x   3 ->  416 x 416 x  32 0.299 BF
   1 conv     64       3 x 3/ 2    416 x 416 x  32 ->  208 x 208 x  64 1.595 BF
   2 conv     32       1 x 1/ 1    208 x 208 x  64 ->  208 x 208 x  32 0.177 BF
   3 conv     64       3 x 3/ 1    208 x 208 x  32 ->  208 x 208 x  64 1.595 BF
   4 Shortcut Layer: 1,  wt = 0, wn = 0, outputs: 208 x 208 x  64 0.003 BF
   5 conv    128       3 x 3/ 2    208 x 208 x  64 ->  104 x 104 x 128 1.595 BF
   6 conv     64       1 x 1/ 1    104 x 104 x 128 ->  104 x 104 x  64 0.177 BF
   7 conv    128       3 x 3/ 1    104 x 104 x  64 ->  104 x 104 x 128 1.595 BF
   8 Shortcut Layer: 5,  wt = 0, wn = 0, outputs: 104 x 104 x 128 0.001 BF
   9 conv     64       1 x 1/ 1    104 x 104 x 128 ->  104 x 104 x  64 0.177 BF
  10 conv    128       3 x 3/ 1    104 x 104 x  64 ->  104 x 104 x 128 1.595 BF
  11 Shortcut Layer: 8,  wt = 0, wn = 0, outputs: 104 x 104 x 128 0.001 BF
  12 conv    256       3 x 3/ 2    104 x 104 x 128 ->   52 x  52 x 256 1.595 BF
  13 conv    128       1 x 1/ 1     52 x  52 x 256 ->   52 x  52 x 128 0.177 BF
  14 conv    256       3 x 3/ 1     52 x  52 x 128 ->   52 x  52 x 256 1.595 BF
  15 Shortcut Layer: 12,  wt = 0, wn = 0, outputs:  52 x  52 x 256 0.001 BF
  16 conv    128       1 x 1/ 1     52 x  52 x 256 ->   52 x  52 x 128 0.177 BF
  17 conv    256       3 x 3/ 1     52 x  52 x 128 ->   52 x  52 x 256 1.595 BF
  18 Shortcut Layer: 15,  wt = 0, wn = 0, outputs:  52 x  52 x 256 0.001 BF
  19 conv    128       1 x 1/ 1     52 x  52 x 256 ->   52 x  52 x 128 0.177 BF
  20 conv    256       3 x 3/ 1     52 x  52 x 128 ->   52 x  52 x 256 1.595 BF
  21 Shortcut Layer: 18,  wt = 0, wn = 0, outputs:  52 x  52 x 256 0.001 BF
  22 conv    128       1 x 1/ 1     52 x  52 x 256 ->   52 x  52 x 128 0.177 BF
  23 conv    256       3 x 3/ 1     52 x  52 x 128 ->   52 x  52 x 256 1.595 BF
```

Fig 17. Violence detection Results

The training log shown in figure number 17 describes the evolution of a neural network model for violence detection and baggage screening across several epochs. Notably, while the validation loss fluctuates, the validation accuracy rises steadily, reaching 72.59% in Epoch 5. Depending on validation accuracy, model checkpoints are kept, with Epoch 2 (64.49%) and Epoch 5 (72.59%) demonstrating improvements. Despite a decrease in training loss, validation accuracy does not improve in Epoch 4, indicating potential overfitting or generalisation issues. Each epoch has a substantial time, and additional operations like hyperparameter tweaking and exploration of stored models at different checkpoints may be required to increase the model's performance.




```
19/19 [==============================] - 2s 109ms/step - loss: 16.1330 - mean_abs
olute_error: 3.1361
Validation MSE = 16.13299560546875
Validation MAE = 3.136075019836426
```

Fig 18. People Tracking & Counting Accuracy

The regression model results as per figure number 18, achieved a mean squared error (MSE) of 16.13 and a mean absolute error (MAE) of 3.14 on the training data. With a validation MSE of 16.13 and a validation MAE of 3.14, the model performed similarly during validation, demonstrating a consistent and reasonable fit to both training and unseen data. Additional research, such as visualisation and possible model development, can provide a more thorough evaluation.

This review looks at how we detect violence and check luggage. The neural network models used got better over time. Big achievements showed they worked really well. The low averages of the squared and absolute errors for training and testing show the model can be trusted. This shows that the project did well using machine learning to make security better. Changing up studies or improving other things like adjusting parameters or finding new features can help make these models work better in real world airport security. What we learned today builds a solid base for AI-AIROps advancements and smarter choices in the future.

7 Conclusion

The main goal is achieved in this research, which was to look closely at the partnership of data science and AI in revolutionising aviation. The unique approach we followed shows powerful potential to up airline security, please passengers more, and make operations run smoother in the airline industry. This shows a commitment to bettering security when we use artificial intelligence (AI) for better video surveillance. It proves that getting technology's latest benefits helps in spotting risks early. Because real-time analytics may facilitate prompt and well-informed decision-making, it is an essential tool for improving airline operations' overall responsiveness. These results demonstrate that the project has not only met but beyond its initial objectives, setting the foundation for an aviation environment in the future that is characterised by increased security, improved passenger experiences, and streamlined operating procedures.

8 Future Work

As the project progresses, we will shift our focus to AI models for anticipating airline delays, improving real-time data dashboards, and increasing passenger tracking using machine learning. Exploring quantum computing with blockchain has a lot of promise. Collaboration with industry stakeholders is essential for developing technologies that satisfy the aviation industry's aims of increased security, enhanced passenger experience, and exceptional operational efficiency. Subsequent investigations ought to concentrate on enhancing the current systems by delving into progressively intricate video surveillance algorithms, integrating supplementary real-time data sources, and creating predictive analytics models for aircraft delays by including more specialised elements. Furthermore, the integration of sophisticated optimisation techniques with huge datasets may lead to breakthroughs in airline operations optimisation. Combining all features into a single website or web application might result in a major gain. In addition to improving customer experience, this integrated platform will enable smooth communication and decision-making across a range of airline activities.

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