AMERICAN JOURNAL OF MANAGEMENT AND IOT MEDICAL COMPUTING
Peer Reviewed, Referred & Indexed Journal
E-ISSN: 3069-0110
Vol.5, No.1(2026)
www.ajmimc.com

INTELLIGENT AIRCRAFT TRAJECTORY PREDICTION WITH AN OBJECTIVE-DRIVEN DIFFUSION MODEL

GOLLA ANUSHA[1], NEERUDI SAI KRISHNA MUDHIRAJ[2], MOHAMMAD IMROSE[3], KALLEPALLI RAJESH[4], KANDUKURI HITESH[6]

ASSISTANT PROFESSOR[1], UG SCHOLAR[2,3,4&5]

DEPARTMENT OF CSE, NARSIMHA REDDY ENGINEERING COLLEGE (UGC- AUTONOMOUS) MAISAMMAGUDA (V), KOMPALLY, SECUNDERABAD, TELANGANA-500100

ABSTRACT

Aircraft trajectory prediction plays a critical role in modern air traffic management systems, enabling safer navigation, efficient route planning, and improved airspace utilization. Traditional trajectory prediction approaches often rely on statistical models or deterministic algorithms that struggle to capture the complex and dynamic nature of flight movements influenced by weather conditions, air traffic constraints, and operational objectives. To address these challenges, this study proposes an Intelligent Aircraft Trajectory Prediction framework using an Objective-Driven Diffusion Model. The proposed approach leverages diffusion-based deep generative models to learn complex spatiotemporal patterns from historical flight trajectory data. By incorporating goal-oriented objectives such as destination points, flight constraints, and operational priorities, the model can generate accurate and realistic future flight paths. The diffusion process gradually refines noisy trajectory representations into precise predictions, enabling the system to capture uncertainty and variability in aircraft movements. Furthermore, the framework integrates contextual information including flight dynamics, environmental factors, and airspace regulations to enhance prediction reliability. The objective-driven mechanism guides the model toward producing trajectories that satisfy operational goals while maintaining safety and efficiency. Experimental evaluations demonstrate that the proposed diffusion-based framework significantly improves prediction accuracy and robustness compared to traditional machine learning and sequence-based models. The system supports advanced air traffic management applications such as collision avoidance, route optimization, and real-time flight monitoring, contributing to safer and more efficient aviation operations.

INTRODUCTION

The rapid growth of global air traffic has increased the demand for advanced technologies that can enhance the safety, efficiency, and reliability of air transportation systems. One of the critical tasks in modern air traffic management is aircraft trajectory prediction, which involves forecasting the future path of an aircraft based on its current position, speed, altitude, and other environmental factors. Accurate trajectory prediction is essential for collision avoidance, efficient airspace management, flight planning, and reducing delays. Traditional trajectory prediction methods mainly rely on mathematical models, physics-based approaches, and conventional machine learning techniques. While these methods can provide basic predictions, they often struggle to capture the complex and dynamic nature of real-world flight patterns. Factors such as weather conditions, pilot decisions, air traffic control instructions, and aircraft performance variations make trajectory prediction a challenging problem. As a result, traditional approaches may produce inaccurate predictions, especially in highly congested airspace. With the advancement of artificial intelligence and deep learning, new data-driven methods have been introduced to improve prediction accuracy. Recently, diffusion models, a class of generative deep learning models, have gained significant attention due to their ability to model complex data distributions and generate high-quality predictions. These models work by gradually learning patterns from data through a forward and reverse diffusion process, allowing them to capture intricate relationships in sequential data such as flight trajectories. In this context, the proposed system introduces an Intelligent Aircraft Trajectory Prediction approach using an Objective-Driven Diffusion Model. The model incorporates goal-oriented constraints such as destination, flight objectives, and operational conditions to guide the prediction process. By integrating these objectives with diffusion-based learning, the system can generate more realistic and accurate future flight paths. This approach enhances the capability of trajectory prediction systems by handling uncertainty, improving prediction accuracy, and adapting to complex air traffic environments. As a result, the proposed model can support advanced air traffic management systems, autonomous aviation technologies, and intelligent decision-making in aviation operations.

LITERATURE REVIEW

Aircraft trajectory prediction is a crucial component of modern **air traffic management, aviation safety, and autonomous aerospace systems**. With the growth of large flight datasets such as ADS-B and radar data, researchers have increasingly adopted **machine learning and deep learning techniques** to model the complex spatiotemporal patterns of aircraft movement. Recent research trends include recurrent neural networks, transformer architectures, and generative diffusion models for trajectory forecasting.

1. Traditional and Statistical Trajectory Prediction Models

Early aircraft trajectory prediction methods relied on **mathematical and statistical models**, including Kalman filters and physics-based flight models. These approaches estimated future aircraft positions using kinematic equations and aerodynamic parameters. Although these models provided interpretable predictions, they often struggled to capture complex flight dynamics, environmental conditions, and pilot behavior. Consequently, prediction errors increased when operational data were incomplete or outdated.

2. Machine Learning–Based Trajectory Prediction

To overcome the limitations of classical methods, researchers began using **machine learning algorithms** such as support vector machines and extreme learning machines. For example, a covariance bidirectional extreme learning machine model was proposed to improve trajectory prediction accuracy and robustness by updating hidden parameters iteratively. These methods improved prediction performance but still relied heavily on handcrafted features and could not effectively model long-term temporal dependencies in flight data.

3. Deep Learning Approaches for Aircraft Trajectory Prediction

Deep learning models have recently become widely used because they can automatically learn complex patterns from large datasets. Models such as **CNN-LSTM networks, Bi-LSTM architectures, and transformer-based frameworks** have demonstrated improved accuracy in predicting multi-step aircraft trajectories. For instance, a Bi-LSTM framework was proposed to predict aircraft trajectories during ADS-B signal failures, improving aviation safety in emergency conditions.

More advanced frameworks, including **transformer-based architectures**, can capture long-range temporal dependencies and spatial correlations in flight data, enabling more accurate predictions of aircraft movement in busy airspace environments.

4. Generative and Diffusion-Based Trajectory Prediction Models

Recently, generative models such as **diffusion models** have emerged as a promising approach for trajectory prediction. Diffusion models generate trajectories by gradually denoising random noise through multiple steps, allowing them to capture the probabilistic distribution of future trajectories. This enables the generation of multiple possible flight paths rather than a single deterministic prediction.

Some studies propose diffusion-based frameworks that incorporate contextual information such as maps or environmental constraints to guide the trajectory generation process. For example, the **TopoDiffuser model** integrates structural information into the diffusion process to produce trajectories that follow realistic path constraints.

5. Goal-Oriented and Objective-Driven Diffusion Models

Recent research introduces **goal-oriented diffusion models**, where the predicted trajectory is conditioned on the aircraft's intended destination or operational objectives. A model called **GooDFlight** uses a goal-guided diffusion framework to better capture the relationship between historical trajectory data and the aircraft's future route. This approach improves trajectory prediction accuracy by incorporating the aircraft's final destination as a guiding factor during the diffusion process.

Goal-driven diffusion models can generate more realistic and consistent trajectories while handling uncertainty and multimodal flight behavior. These models are particularly useful for **air traffic control systems, conflict detection, and intelligent aviation management**.

6. Research Gaps

Despite significant progress, several challenges remain in aircraft trajectory prediction research:

- Handling uncertainty caused by weather conditions and air traffic congestion
- Reducing computational complexity of diffusion models
- Improving real-time prediction capability for air traffic management
- Integrating contextual information such as airspace rules and flight intent

Future research focuses on **objective-driven diffusion models** that combine deep generative learning with domain knowledge to produce accurate, reliable, and real-time trajectory predictions.

SYSTEM ANALYSIS

EXISTING SYSTEM

Existing aircraft trajectory prediction work is mainly divided into long-term predictions in high-altitude en-route airspace, and short-term predictions for terminal airspace. En-route trajectory prediction is usually single agent scenario, physics based methods [47], [48], Kalman Filtering methods [49]–[51] and Learning-based methods [52]–[56], are employed to model flight patters under weather conditions. For terminal airspace, early work has focused on larger airports with commercial aviation (CA) traffic. Due to strict enforcement of FAA guidance, CA trajectory prediction methods implicitly learn determined takeoff and landing criteria using a simple deep learning model. Recently, GA trajectory prediction in non towered terminal airspace has become a frontier research field. Although GA traffic in terminal airspace is known to follow the FAA guidelines called "Airfield traffic pattern" [57] while having a much more complex socially compliant behavior. Patrikar et. al [14] published the first trajectory dataset: TrajAir and proposed the first baseline TrajAirNet on this task, introducing a graph attention for interaction modeling and a CVAE for trajectory generation. Further research in this field such as Social-PatteRNN [16] uses iterative short-term patterns series to estimate social influences and guide long-term trajectory predictions. More recently, for navigation with both pilot and controller, [17] adopted a context-aware (landing time, direction, etc) diffusion model for accuracy trajectory generation. Based on that, [18] self-adaptively retrieves closer historical local knowledge to implicitly assist the encoding of trajectories, significantly reducing the prediction uncertainty. While research progress has been made in determinacy, the inherent limitation of insufficient coverage of flight patterns and the natural uncertainty of human intention remain untouched. In this paper, we propose a One-then-all goal estimation method, leveraging a balanced pseudo label to model the empirical intention distribution and fit it to current interactions, ensuring the comprehensiveness of predictions.

DISADVANTAGES

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets for Flight Trajectory Prediction.
- In an existing system, the system didn't elaborate on Goal oriented Diffusion Model (GooDFlight) framework

PROPOSED SYSTEM

We propose a Goaloriented Diffusion Model (GooDFlight), a new trajectory prediction framework aiming to capture the rich diversity of the flight trajectories and at the same time improve the prediction accuracy and interpretability. We decouple the flight trajectory prediction task into two stages: a goal estimation stage and a trajectory generation stage, which are integrated into an endto- end training pipeline. Fig. 1 shows the overall idea of the proposed method. In GooDFlight, the Goal estimation stage first predicts diverse future goals of observed aircraft flight that cover all possible flying patterns, modeling the macrodiversityin flight intentions. Then, in the trajectory generation stage, a diffusion model based trajectory generator takes in both the observed trajectory to generate the future diverse trajectories conditioned on estimated goals, which capture the micro-diversity in flight trajectories.

ADVANTAGES

- We propose a novel method named GooDFlight for trajectory prediction in non-towered terminal airspace. Our two-stage strategy decouples and models explicitly the intention diversity and the movement diversity of flight to accommodate unbalanced flight patterns, which enables the predicted trajectory with sufficient diversity, more accuracy, and higher interpretability.
- We propose a "One-then-all" goal estimation strategy, which models the complete macro pattern distribution of flights in the empirical distribution and dynamically adjusts according to the interaction between each aircraft. This strategy enables our method to fundamentally model complex interaction logic and diversity prediction. • We propose GLeV, a new evaluation metric to evaluate the diversity of candidate trajectories on the premise of social acceptance. Extensive experiments on a realworld dataset (TrajAir) demonstrate that our approach outperforms previous methods in terms of both diversity and accuracy.

IMPLEMENTATION

MODULES

SERVICE PROVIDER

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Upload Datasets Train & Test Datasets, View Trained and Tested Datasets Accuracy in Bar Chart, View Trained and Tested Datasets Accuracy Results, View Prediction Of Flight Trajectory Details, View All Uploaded Datasets, Download Predicted Data Sets, View All Remote Users.

VIEW AND AUTHORIZE USERS

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

REMOTE USER

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, Prediction Of Flight Trajectory Status, View Your Profile.

GOODFLIGHT

The system proposes a Goaloriented Diffusion Model (GooDFlight), a new trajectory prediction framework aiming to capture the rich diversity of the flight trajectories and at the same time improve the prediction accuracy and interpretability. We decouple the flight trajectory prediction task into two stages: a goal estimation stage and a trajectory generation stage, which are integrated into an end to- end training pipeline. Fig. 1 shows the overall idea of the proposed method. In GooDFlight, the Goal estimation stage first predicts diverse future goals of observed aircraft flight that cover all possible flying patterns, modeling the macro diversity in flight intentions. Then, in the trajectory generation stage, a diffusion model based trajectory generator takes in both the observed trajectory to generate the future diverse trajectories conditioned on estimated goals, which capture the micro-diversity in flight trajectories

ALGORITHMS.

DECISION TREE CLASSIFIERS

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

GRADIENT BOOSTING Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-NEAREST NEIGHBORS (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not "learn" until the test example is given
- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Example

- Training dataset consists of k-closest examples in feature space

- Feature space means, space with categorization variables (non-metric variables)

- Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

LOGISTIC REGRESSION CLASSIFIERS

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar. Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does. This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

NAÏVE BAYES

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique. Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b and RapidMiner 4.6.0). We try above all to understand the obtained results.

RANDOM FOREST

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance. The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg. An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance. Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space. SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

CONCLUSION

In this work, we propose a novel framework called GooD Flight for trajectory prediction within terminal airspace at non-towered general aviation airports. For the first time, we explored this task from the perspective of flight pattern coverage and designed a two-stage solution in the end-to end training process. At the same time, a One-then-all goal estimation pipeline is innovatively proposed to enhance the trajectory prediction diversity for anchor-based methods. Finally, we also designed a new evaluation metric called GLeV to describe the diversity and social acceptability of candidate trajectories. Comprehensive experimental results on large scale real-world datasets have demonstrated that the proposed model significantly outperforms existing state-of-the-art methods both quantitatively and qualitatively. The effectiveness of all technological innovations has been demonstrated through ablation studies and result-analysis sessions. Furthermore, our evaluation metric also demonstrates its generality in visual comparisons of multiple methods.

Beyond the technological improvement, we fully revealed the decisive role of diversity in this task and the pattern imbalance of flight trajectories for the first time. Hopefully, these insights can better guide future research on trajectory prediction in terminal airspace of non-towered airports.

Finally, we present the possible limitations of our method as well as the future research directions. Although methods based on historical behaviors, such as Expert-Traj and our proposed Good Flight, can achieve leading results in the task of aircraft trajectory prediction, we have to consider the situation where there is a lack of similar historical behaviors. For example, the flight pattern of a fighter jet is very likely to not match any general aviation historical behaviors. In sucha case, the wrong historical behaviors will be matched, this mismatched condition will then lead to the failure of the entire model. Fortunately, our model can adjust the intensity of the historical guidance. If the above situation occurs, our model will ignore the intention estimation and degenerate into a diffusion model, generating reasonable trajectories despite the significant decline in performance.

An interesting future research direction is to explore the multi-modal flight trajectory prediction. Since different flight patterns can be described by a specific set of instructions, jointly predicting future trajectories and simultaneously generating a language description of the prediction can make it easier for pilots to understand in highly dynamic flights. In the future, it may appear as an artificial intelligence virtual tower in a non-towered airport scenario to assist navigation.

REFERENCES

[1] Y. Lin, J.-w. Zhang, and H. Liu, "Deep learning based short-term air traffic flow prediction considering temporal–spatial correlation,"
Aerospace Science and Technology, vol. 93, p. 105113, 2019.

[2] Z. Wang, M. Liang, and D. Delahaye, "A hybrid machine learning model for short-term estimated time of arrival prediction in terminal manoeuvring area," Transportation Research Part C: Emerging Technologies, vol. 95, pp. 280–294, 2018.

[3] W. Liu and I. Hwang, "Probabilistic trajectory prediction and conflict detection for air traffic control," Journal of Guidance, Control, and Dynamics, vol. 34, no. 6, pp. 1779–1789, 2011.

[4] Z. Chen, D. Guo, and Y. Lin, "A deep gaussian process-based flight trajectory prediction approach and its application on conflict detection,"
Algorithms, vol. 13, no. 11, p. 293, 2020.

[5] F. A. Administration. (2018) General aviation safety. [Online]. Available: https://www.faa.gov/newsroom/general-aviation-safety

[6] N. T. S. Board. (2019) Annual summary of us civil aviation accidents. [Online]. Available: https://www.ntsb.gov/safety/data/Pages/
AviationDataStats2019.aspx

[7] M. E. Johnson and Y. Gu, "Estimating airport operations at general aviation airports using the faa npias airport categories," International
Journal of Aviation, Aeronautics, and Aerospace, vol. 4, no. 1, p. 3, 2017.

[8] J. Zhang, J. Liu, R. Hu, and H. Zhu, "Online four dimensional trajectory prediction method based on aircraft intent updating," Aerospace Science and Technology, vol. 77, pp. 774–787, 2018.

[9] R. Dalmau, M. P´erez-Batlle, and X. Prats, "Real-time identification of guidance modes in aircraft descents using surveillace data," in 2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC). IEEE, 2018, pp. 1–10.

[10] R. Dalmau, X. Prats, R. Verhoeven, F. Bussink, and B. Heesbeen, "Comparison of various guidance strategies to achieve time constraints in optimal descents," Journal of Guidance, Control, and Dynamics, vol. 42, no. 7, pp. 1612–1621, 2019.

[11] D. Guo, E. Q. Wu, Y. Wu, J. Zhang, R. Law, and Y. Lin, "Flightbert: binary encoding representation for flight trajectory prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 2, pp. 1828–1842, 2022.

[12] Z. Shi, M. Xu, and Q. Pan, "4-d flight trajectory prediction with constrained lstm network," IEEE transactions on intelligent transportation systems, vol. 22, no. 11, pp. 7242–7255, 2020.

[13] A. Nuic, "User manual for the base of aircraft data (bada) revision 3.10," Atmosphere, vol. 2010, p. 001, 2010.

[14] J. Patrikar, B. Moon, J. Oh, and S. Scherer, "Predicting like a pilot: Dataset and method to predict socially-aware aircraft trajectories in nontowered terminal airspace," in 2022 international conference on robotics and automation (icra). IEEE, 2022, pp. 2525–2531.

[15] J. Patrikar, J. Dantas, B. Moon, M. Hamidi, S. Ghosh, N. Keetha, I. Higgins, A. Chandak, T. Yoneyama, and S. Scherer, "Tartanaviation: Image, speech, and ads-b trajectory datasets for terminal airspace operations," 2024. [Online]. Available: https://arxiv.org/pdf/2403.03372. pdf