Journal of Inventive Engineering and Technology (JIET)
ISSN: 2705-3865
Volume-6, Issue-3, pp-9-21
www.jiengtech.com
Research Paper Open Access

Modeling Airplane Surveillance System to enhance security using Machine based Algorithm

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ABSTRACT: *Effective air traffic management is crucial for ensuring safety, reducing delays, and optimizing operational efficiency in aviation. This study presents the development of an Airplane Trajectory Prediction (ATP) model for Air Traffic Management System (ATMS) using a Support Vector Machine (SVM) algorithm. The aim of the study is to provide real-time trajectory monitoring and anomaly detection while classifying flight behaviours into three categories: normal flight, in-flight delay, and high-speed. A secondary dataset of aircraft trajectories was pre-processed using methods including mean imputation and Z-normalization as part of the approach. Flight behaviours were analysed using a multi-class SVM classifier, and hyperparameter adjustment was done to get the best prediction accuracy. The result showed how well the model performed in correctly predicting and categorizing flight paths. The ATP model provided substantial advantages for operational and safety decision-making by successfully detecting possible abnormalities and diverging from intended routes with 89% success rate. To further increase prediction accuracy and scalability, future studies might investigate the use of more advanced deep learning models and bigger datasets.*

KEYWORDS: *Airplane Trajectory Prediction (ATP); Air Traffic Management System (ATMS); Support Vector Machine (SVM); Machine Learning; Z-Normalization; Aircraft Trajectories*

Date of Submission: 07-10-2024 Date of acceptance: 09-12-2024

I. INTRODUCTION

In the ever-evolving realm of aviation, where safety, efficiency, and precision reign supreme, emerges the Flight Surveillance and Tracking System (FSTS) as a formidable guardian of the skies (Domenic et al., 2012). As aircrafts embark on their journeys, this technological marvel assumes the role of a communication, offering a comprehensive solution to monitor, track, and masterfully manage their every maneuver during flight operations (Plass et al., 2015). Powered by cutting-edge technology and seamlessly orchestrated data exchange, the FSTS not only bolsters safety and situational awareness but propels operational efficiency, ushering in a new epoch of aviation excellence (Anwar et al., 2019).

Imagine a world where each aircraft's trajectory, location, and operational status are not merely comprehended but instantaneously accessible in real-time. This forms the bedrock upon which the flight surveillance and tracking system is meticulously constructed (Edward et al., 2007). Through an intricate web of sensors, communication channels, and data analytics, this system crafts a vivid canvas of the skies. The beneficiaries of this intricate tapestry are air traffic controllers, aviation experts, and stakeholders who wield this real-time information to make informed decisions that safeguard lives and improve operations of airplane (Guvenc et al., 2018).

According to Kaeye et al. (2018).The objective of the FSTS is to furnish precise and timely information concerning aircraft movements throughout their flights. This goal is achieved by seamlessly integrating a fusion of technologies including radar, satellite navigation, and data communication (Alexander et al., 2015). The resulting panorama extends far beyond solitary points of reference, intertwining effortlessly with ground control centres, air traffic management systems, and even the aircraft themselves. This harmonious flow of information meticulously moulds the trajectory of each flight.

In the rapidly evolving realm of aviation, the Flight Surveillance and Tracking System (FSTS) stands as a testament to technological progress, promising a quantum leap in both safety and efficiency (Prevot, 2005). Yet, this innovative advancement does not traverse the skies unburdened by challenges. Some of the observed challenges are data privacy and security, cyber threats exposure, standardization and complexity, operational proficiency and reliance to the communication infrastructure. The intricate integration of cutting-edge technology and the intricacies of real-time data exchange bring forth a new dimension of complexity that demands careful consideration (Nicolas, 2019). These challenges, when not diligently addressed, cast shadows upon the realm of flight security, reminding us that even the most groundbreaking innovations bear intricacies that warrant meticulous attention.

The ADSS is a surveillance approach which airplane automatically provides data links via on-board navigation and position fixing system It uses onboard data of the flights relayed with a transponder device for analysis to monitor and track the planes. Transponder is a telecommunication device installed on the airplanes onboard system for information relay to the ground for monitoring (Plass et al., 2015).In the tapestry of modernization sweeping through the aviation industry, ADS-B emerges as a cornerstone, harmonizing precision, real-time insight, and comprehensive data dissemination. This technology is more than a mere tool; it's a paradigm shift, meticulously engineered to transcend limitations and enhance the fundamental fabric of aviation operations(Plass et al., 2015; Dinc et al., 2017).

This study presents a secure aviation control by streamlining Automatic Dependent Surveillance-Broadcast (ADS-B) perception system. Three assaults were the major topics considered: velocity drift attacks, ghost aircraft injection, and route modification. This study seeks to give a novel approach that can successfully identify injected messages even in the face of novel assaults (zero-day attacks). The key benefit was using a current dataset to produce training and testing materials that were more adaptable and dependable. These materials were then pre-processed before being used with several machine learning algorithms to potentially provide the most accurate and time-efficient model. (Al-Haija & Al-Tamimi 2024).

According to Wireless Avionics Intra-Communications (WAI, 2015), the bedrock of ADS-B's prowess is its seamless integration with the Global Positioning System (GPS). This celestial navigation backbone furnishes ADS-B with the accuracy and reliability required for precision surveillance. The resulting stream of data pulsates with integrity, providing air traffic controllers, pilots, and stakeholders with a comprehensive, real-time overview of aircraft in the skies. Machine learning algorithms play a significant role in improving airplane communication and tracking surveillance systems. These algorithms leverage the power of data analysis and pattern recognition to enhance the efficiency, accuracy, and security of communication and tracking processes (Fleischman et al., 2006; Kekong et al., 2019).

The fusion of data science and aviation expertise within the scope of FTMS and ML holds the key to overcoming these challenges, through the intricate comprehension of the aviation operation via informed flight data modelling and ML algorithm, thus presenting a reliability and yet autonomous system which optimize the overall performance of flight surveillance and security in the aviation industry. To this end, this study proposed to develop an autonomous system which can track and monitor flight patterns intelligently using ML algorithm and deployed at the aviation industries for real time flight surveillance operations.

II. RESEARCH METHODOLOGY

The methodology for the study begins with collection of data, data analysis and deduction methods. A new Airplane Trajectory Prediction (ATP) model was proposed and developed using machine learning algorithm. The ATP model was integrated into the ATMS and programmed using MATLAB. The performance was tested using simulation and results validated with deduction method, after comparative analysis.

A. Data Collection

This is the secondary data collection, as the primary data collection earlier was used for characterization purposes. The secondary data collection considered the Ibom Air, flight report from Enugu to Lagos, in the year 2023, from the AkanuIbiam International Airport, Enugu, Nigeria. The data collection considered key flight plan parameters such as altitude, latitude, longitude, time, speed, course, signal strength, losses, and latency. The collected data consider three classes of common flight behaviours which are normal flight, in-flight delay and high-speed behaviour. The data visualization for each class was reported in the Table 1-3 using explorative data analysis which visualized the first few columns of the dataset.

Table 1: Data visualization for normal flight behaviour

Time (mm:ss)	Latitude	Longitude	Altitude (ft)	Speed (mph)	Course	Signal Strength (dBm)	Losses (%)	Latency (ms)
2023-01-13 16:00	6.7777° N	7.6553° E	36000	600	120°	80	1	15
2023-01-13 16:15	6.8835° N	7.6994° E	38000	620	130°	78	1.2	14
2023-01-13 16:30	6.9986° N	7.7443° E	34000	580	110°	85	1.8	17
2023-01-13 16:45	6.4313° N	7.5352° E	31000	530	95°	93	1.5	19
2023-01-13 17:00	6.2700° N	7.5066° E	37000	610	125°	82	1.3	16

Table 2: Data visualization for In-flight delay

Time (mm:ss)	Latitude	Longitude	Altitude (ft)	Speed (mph)	Course	Signal Strength (dBm)	Losses (%)	Latency (ms)
2023-02-13 16:00	6.7777° N	7.6553° E	36000	200	70°	78	1.7	11
2023-02-13 16:15	6.8835° N	7.6994° E	38000	120	70°	79	1.4	11
2023-02-13 16:30	6.9986° N	7.7443° E	34000	280	60°	83	1.2	13
2023-02-13 16:45	6.4313° N	7.5352° E	31000	230	57°	93	1.6	16
2023-02-13 17:00	6.2700° N	7.5066° E	37000	210	105°	82	1.1	13

Table 3: Data visualization for High speed

Time (mm:ss)	Latitude	Longitude	Altitude (ft)	Speed (mph)	Course	Signal Strength (dBm)	Losses (%)	Latency (ms)
2023-01-13 16:00	6.7777° N	7.6553° E	36000	800	120°	120	2.1	23
2023-01-13 16:15	6.8835° N	7.6994° E	38000	850	130°	118	3.2	27
2023-01-13 16:30	6.9986° N	7.7443° E	34000	970	110°	115	3.8	24
2023-01-13 16:45	6.4313° N	7.5352° E	31000	860	95°	109	3.5	25
2023-01-13 17:00	6.2700° N	7.5066° E	37000	820	125°	102	3.3	27

B. Data processing

The data collected was processed using imputation methods such as missing data replacement and normalization method. The methods used for the missing data replacement is the mean imputation technique, which the average of the column values is computed and used to determine the missing value. For the normalization process, the Z-normalization process was applied, considering the standard deviation and mean of the data to generated new form of data within values between 0 and 1.

C. Frequency Doubling Transformation approach

Feature transformation is a crucial step in preparing the data for machine learning models. The technique used is the frequency doubling transformation approach. This transformation method involves manipulating the frequency content of the features through the duplication of the frequency components within the data. This process enhances the discriminatory power of the features, making them more suitable for the machine learning model.

D. Support Vector Machine (SVM) concept

A Support Vector Machine (SVM) is a powerful machine learning algorithm which can solve both classification and regression problem. Because of its diverse capacity, good classification and regression performance, especially when there is limited training data, it was applied in this research for the generation of the ATM. The SVM operates by determining the optimal hyper-plane (classifier) which classified the input data points into support vectors classes, to solve a problem. Support Vector Machines (SVMs) utilize several crucial hyperparameters to shape the model's learning process. These hyper-parameters influence the SVM's performance. The kernel defines the type of decision boundary, while the regularization parameter (C) controls the trade-off between smoothness and accurate classification. Gamma determines the influence of individual training samples, while degree and coefficients are relevant for polynomial and sigmoid kernels. Decision function shape defines the strategy for multi-class classification, and the shrinking hyper-parameter speeds up training for large datasets. Adjusting these hyper-parameters, often through cross-validation and grid search, is crucial to finding the optimal configuration for a given dataset, ensuring the SVM achieves optimal performance on unseen data. The operation of the SVM following the following steps in Fig.1:

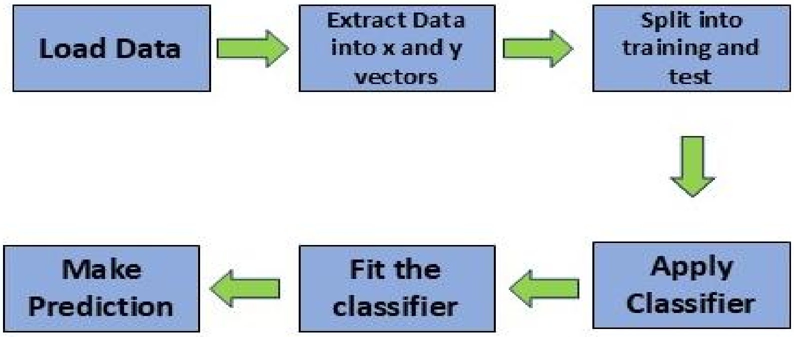

Fig.1: Block Diagram of SVM operations

The SVM operated by extracting the data imported into X and Y support vectors. These data are divided into training and test sets, then the classifier is applied to determine the optimal hyper-plane i.e the decision boundary and then make prediction. The support vector algorithm is presented as:

E. Support Vector Algorithm

1. Start
2. Load dataset
3. Split dataset into training and test set
4. Initialize hyper-parameters
5. Extract data features into support vectors
6. Adjust hyper-parameters to determine optimal decision boundary
7. Determine hyper-plane
8. Apply for classification
9. Return prediction output
10. End

F. Training of the SVM with the Flight Data Processed

To train the SVM, the data processed classes were separately imported into the model, while the hyper-parameters such as kernel, regularization parameter (C), width and bias function are optimally adjusted until the optimal hyper-plane is generated which is the classifier for each class. Before the training process, the data are divided into test, train and validation sets. The test set which are the true values are used to test the trained model which are the predicted values, while the disparities between them is the error, which informed that optimization process of the hyper-parameters. During the training, parameters such as accuracy, positive predictive value, true positive rate, true negative rate, area under curve are all applied to evaluate the model. The results were reported in the chapter four, while the ATM model generation process flow was presented in the Fig.2.

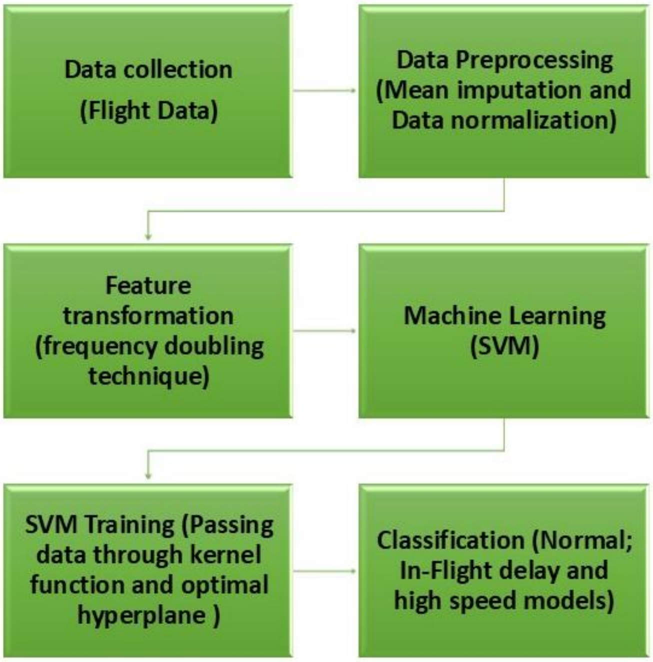

Fig. 2: Process diagram of the ATM

The data of flight information which has three classes of Normal; In-flight delay and high speed were imported separately for processing, using imputation and Z- normalization process. The data process was performed to ensure data completeness and minimize the risk of over-fitting problem during training of machine learning models. The class was each was transformed using frequency doubling technique, then imported into SVM for training and generation of the hyper-plane classifier of Normal; In-flight delay and high-speed classifiers respectively which was applied for the prediction of flight behaviour. The Fig.3 presented the flow chart for the SVM training.

To train the SVM, as a multi-classifier, the three data classes were separately imported to the after processing and transformation to the SVM model and train. During the training, the SVM hyper parameters such a kernel, weight, regularization are adjusted while monitoring the error between the hyper-plane generated and the support vectors. When the error is minimized the training stops, then the classifier which is the optimal hyper-plane is generated. In this case three different classifiers were generated, each for the data class and were used to model the SVM based multi-classifier.

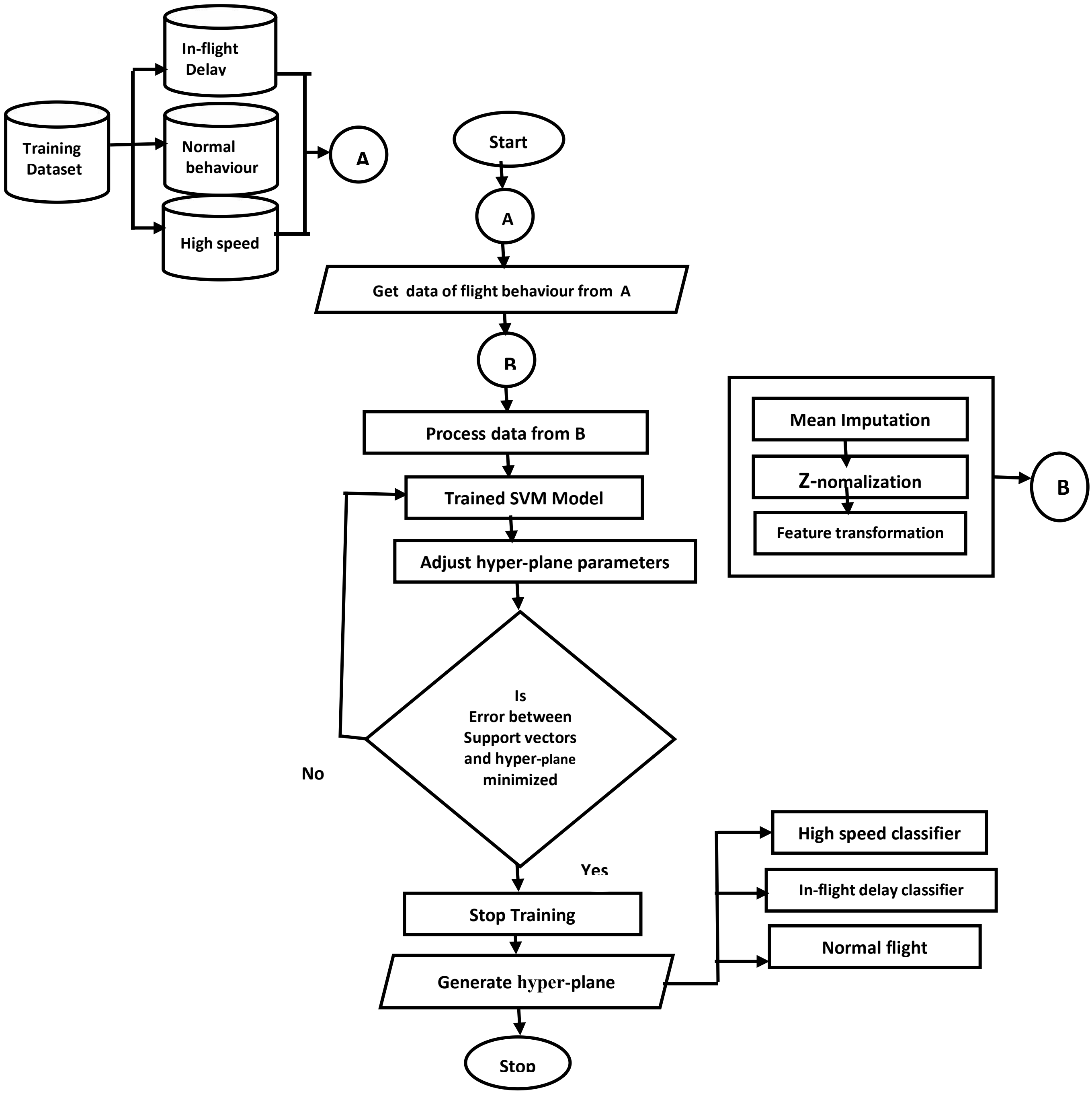

Fig. 3: Flowchart of the SVM training to generate multiple classifiers

G. The SVM Based Multi-classifiers

Traditionally SVM is applied for binary classification, as it operated considering only two classes of positive and negative support vector. Hence the multi-classifier generated from the respective flight data training with SVM were integrated for binary classification. To achieve this, the normal flight classifier was used as the positive support vector (X), while the in-flight delay classifier and high-speed flight classifiers were integrated into the negative support vectors (Y). the Fig. 4 presented the graphical model of the multi-class SVM classifier generated.

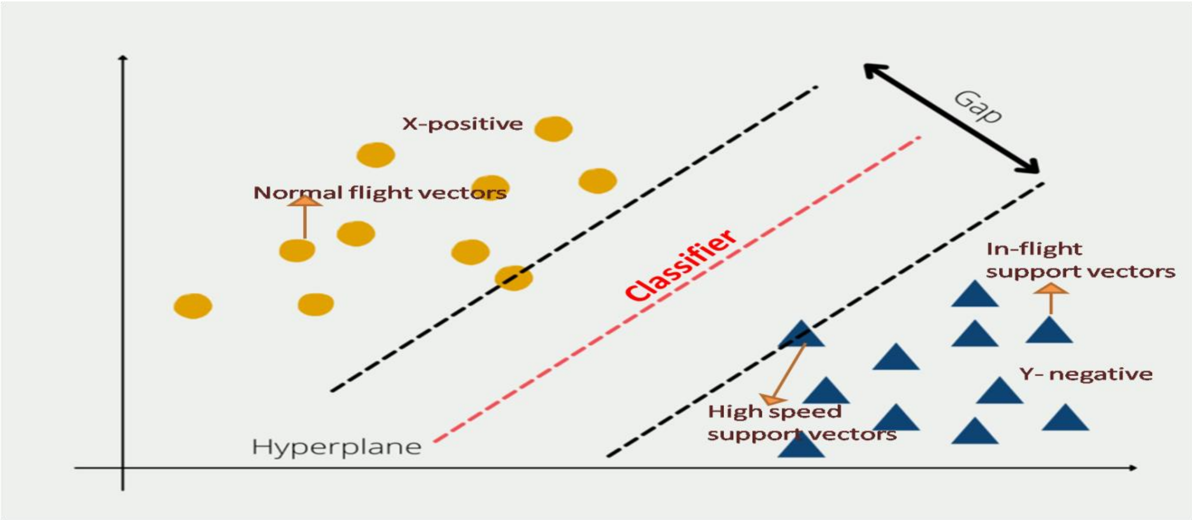

Fig. 4: Multi-class SVM classifiers generated as a binary classifier

The Fig. 4 presented the SVM classifier which showed how the three classifiers were used to formulate the binary classification model used by the SVM for the classification of flight behaviour. The normal flight classifier forms the positive support vectors while the in-flight delay and high-speed classifier formulated the negative class of the support vector. These two classes are used by the hyper-plane to decide the flight behaviour as the ATM.

H. The SVM Based Airplane Tracking Model

The SVM based ATM generated with the three classifiers was utilized for the tracking of airplanes. When test data from onboard flight information is collected, it is processed and the features transformed into support vectors compatible formats for classification using the decision boundary of the SVM hyper-plane. During the classification process, the is the features are classified to the positive class by the decision boundary, it is normal flight behaviour, else if classified in the negative class, it is in-flight delay or the flight on very high speed. However, when none of the features fall within either of the three classes, then flight is detected to have diverted from its trajectory plan. The airplane tracking algorithm is presented as:

I. Airplane Tracking Algorithm

1. Start
2. Load data
3. Load trained SVM model
4. Extract features
5. %% to determine the class of the features
6. Apply decision boundary with hyper-plane
7. If
8. High speed is predicted
9. Return output as "high speed"
10. Else if
11. In-flight delay predicted
12. Return output as "In-flight delay"
13. Else if
14. Normal flight is predicted
15. Return output as "Normal flight behaviour"
16. Else
17. Predict expected flight position
18. Then
19. Return output as "flight out of trajectory
20. End If
21. Return to step 2
22. End

The Airplane Tracking Algorithm showcased how the trained SVM was used to predict diverse behaviour of the flights online. When the data from the flight was loaded into the model, the features are extracted, then the classifier made of three hyper-planes was used to determine the flight behaviour. In addition, when data stop coming into the model for prediction, the system was able to predict the expected position of the flight. The Fig. 5 presented the flow chart of the algorithm.

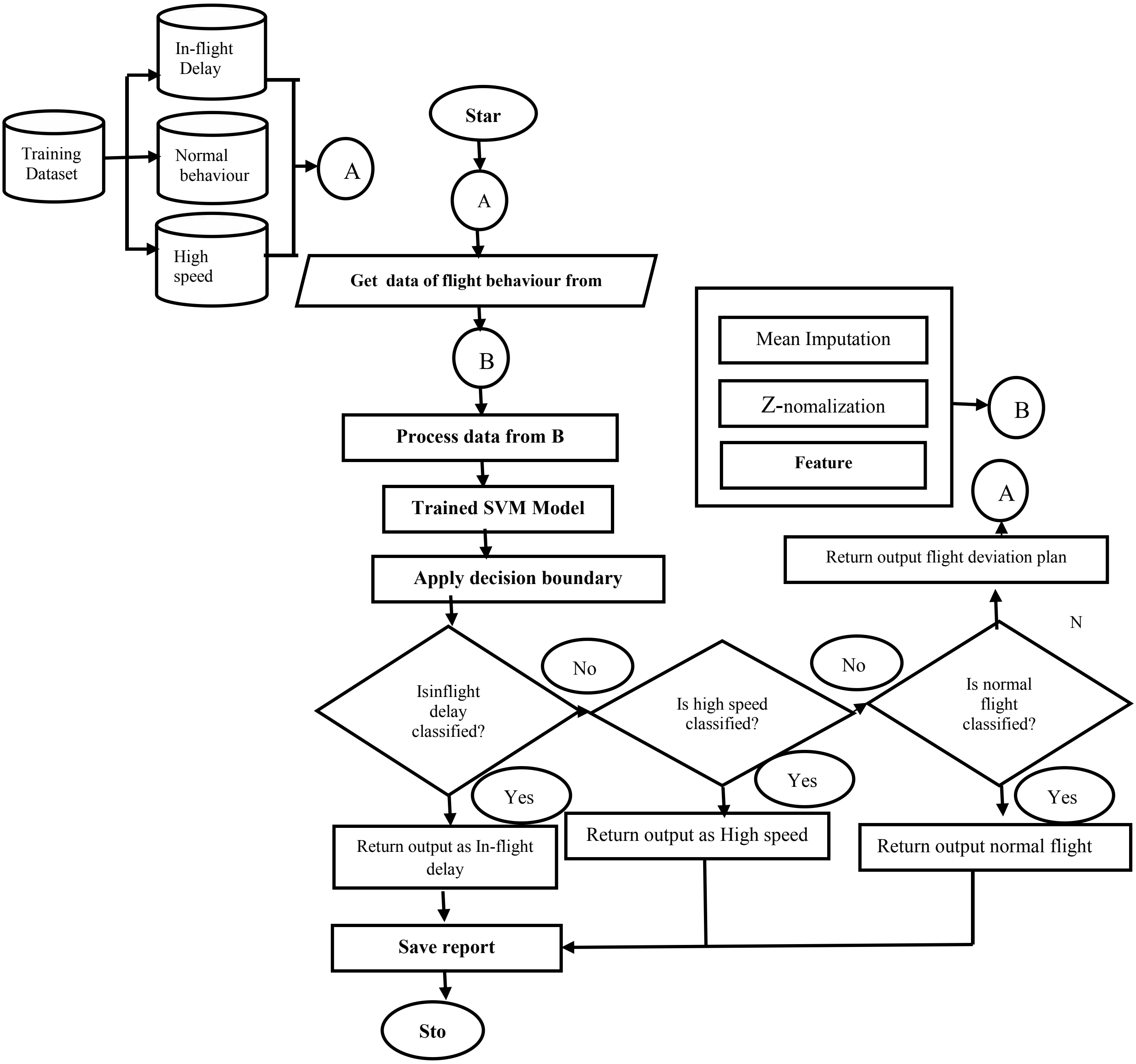

Fig. 5: Flow chart of the ATM

The Fig. 5 showed the flow chart of the ATM, starting with the data input which is testing and training dataset of the flight behaviour. The data was processed using mean imputation method or data completeness, then Z-normalization was applied to normalize the data features into a compatible format and transform the features using frequency doubling technique. The transformed data was feed to the trained SVM which applied the hyper-plane for decision boundary to predict the flight behaviour.

J. SYSTEM IMPLEMENTATION

MATLAB, is a high-level programming environment primarily designed for numerical computing, data analysis, and visualization. In MATLAB, programming is facilitated through an interactive and user-friendly interface that enables the manipulation of arrays, matrices, and data structures with ease. The language is renowned for its extensive built-in functions and toolboxes, covering diverse areas such as signal processing, image processing, machine learning, and more. This makes MATLAB a powerful tool for scientific research, engineering applications, and algorithm development. With its intuitive syntax and a rich set of features, MATLAB promotes efficient prototyping and testing of algorithms, making it a popular choice in academia, industry, and research environments. Additionally, MATLAB provides an Integrated Development Environment (IDE) with a script editor, debugger, and visualization tools, contributing to a seamless and interactive programming experience.

III. RESULTS AND DISCUSSION

In the realization of this goal, SVM algorithm has been trained as a predictive model to estimate the position of flights in real-time. During the training process, parameters such as regression mean absolute error and regression-square were all applied to measure the performance of the SVM hyper-plane which is the tool used for the decision process. The Fig. 6 presented the results of the MAE.

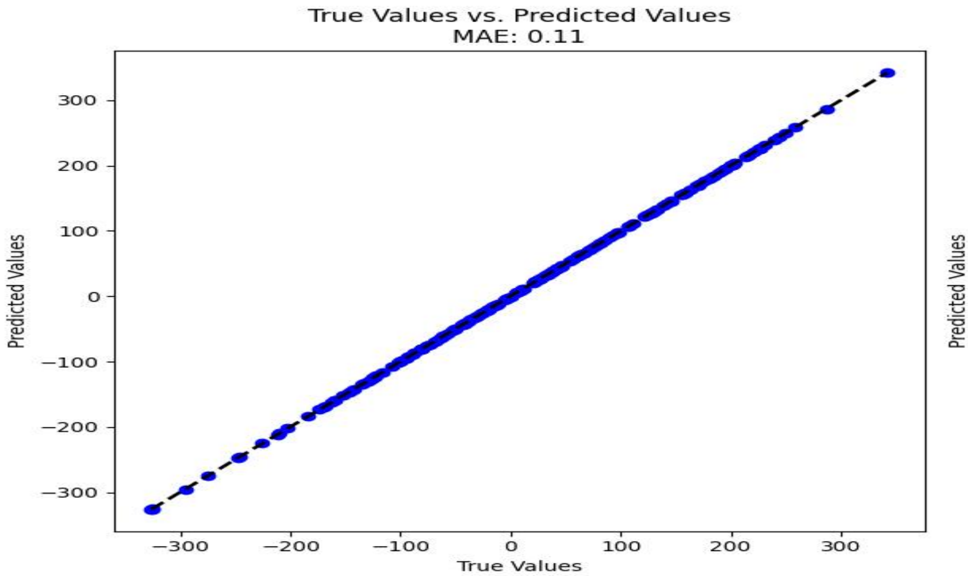

Fig. 6: Result of the MAE

The Fig.6 showcased the MAE performance which measured the relationship mean error which during the prediction of true values with actual flight values. The aim is to report the error values equal or approximately zero, which implied perfect fitting of the model. From the result it was observed that the average MAE recorded 0.11, which is good at it implies significantly low error in the fitting process. In the Fig.7, the R^2 graph was reported.

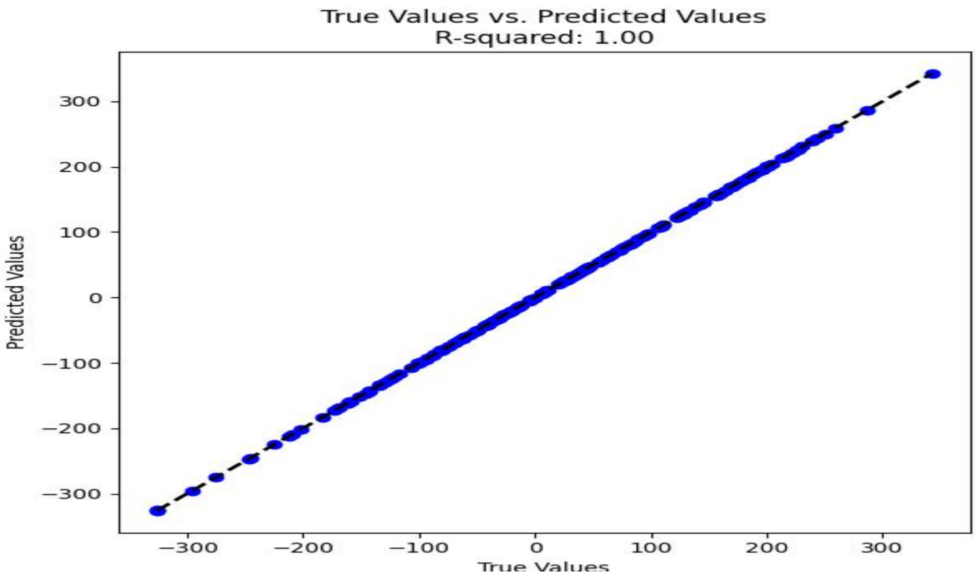

Fig. 7: Result of the R-squared

The Fig. 7 showcased the R-squared result of the SVM model used in checking the model probability of correct model fitness. This graph tells how much of the variation in the dependent variable is explained by the independent variables included in the model. It's a measure of how well the regression model fits the observed data. The aim is to achieve targeted R-squared value of 1 or approximately 1. From the result it was observed that the R-squared recorded a value of 1, which implied that the trained model was able to correctly predict the actual position of flight. Other results such as the accuracy reported 0.89, which indicated an 89% classification success, and also a false detection rate of 11%. Overall, the results showed that the trained SVM model for the prediction of flight trajectory was able to correctly predict flight behaviour with an accuracy of 89%. Based on this positive success rate, the model was integrated into the control system of the ground working station for the tracking and monitoring of flight behaviour.

A. Result of system integration

The section presented the result of the system integration. This process involved the deployment of the SVM-based airplane tracking system at the control network of the ground station for the autonomous monitoring and tracking of airplanes. Here the deployed system was applied to track the Ibom air travelling from Enugu to Lagos. The result of is presented in the Table 4:

Table 4: Result of Ibom Air tracking with SVM

Time (HH:MM)	Latitude (N)	Longitude (E)	Altitude (ft)	Speed(mph)	Course (°)
2023-01-13 16:00	6.4499	7.0981	31150	534	124.6
2023-01-13 17:15	6.4877	7.1399	30972	551.8	123.71
2023-01-13 18:30	6.5254	7.1818	30794	516.2	122.82
2023-01-13 19:45	6.5631	7.2236	30616	471.7	121.93
2023-01-13 20:00	6.6007	7.2654	30438	542.9	121.04
2023-01-13 21:15	6.6383	7.3072	30260	480.6	120.15
2023-01-13 22:30	6.6759	7.3490	30082	445	119.26
2023-01-13 23:45	6.7135	7.3908	29904	507.3	118.37
2023-01-13 24:00	6.7510	7.4325	29726	498.4	117.48
2023-01-13 25:15	6.7885	7.4743	29548	471.7	116.59
2023-01-13 26:30	6.8259	7.5160	29370	534	115.7
2023-01-13 27:45	6.8633	7.5577	29192	551.8	114.81
2023-01-13 28:00	6.9007	7.5994	29014	516.2	113.92
2023-01-13 29:15	6.9380	7.6411	28836	471.7	113.03
2023-01-13 30:30	6.9753	7.6827	28658	542.9	112.14
2023-01-13 31:45	7.0125	7.7243	28480	480.6	111.25

2023-01-13 32:00	7.0566	7.7454	28480	445	111.25
2023-01-13 33:15	7.0164	7.7434	28480	507.3	111.25
2023-01-13 34:30	7.0455	7.7487	28480	498.4	111.25
2023-01-13 35:45	7.0654	7.7534	28480	471.7	111.25
2023-01-13 36:00	7.0656	7.7467	28480	534	111.25
2023-01-13 37:15	7.0566	7.7335	28480	551.8	111.25
2023-01-13 38:30	7.0656	7.7673	28480	516.2	111.25
2023-01-13 39:45	7.0634	7.7658	28480	471.7	111.25
2023-01-13 40:00	7.0687	7.7455	28480	542.9	111.25
2023-01-13 41:15	7.7567	7.4186	29370	480.6	106.8
2023-01-13 42:30	7.8665	7.4925	28925	542.9	102.35
2023-01-13 43:00	7.0564	7.7264	28480	445	111.25
2023-01-13 44:15	7.0545	7.7243	28480	507.3	111.25
2023-01-13 45:30	7.0981	7.7546	28480	498.4	111.25
2023-01-13 46:45	7.2599	7.7257	28480	471.7	111.25
2023-01-13 47:00	7.4518	7.7865	28480	534	111.25
2023-01-13 48:15	7.6736	7.7657	28480	551.8	111.25
2023-01-13 49:30	7.9254	7.7257	28480	516.2	111.25
2023-01-13 50:45	7.0981	7.7246	28480	471.7	111.25
2023-01-13 51:00	7.0454	7.7249	28480	542.9	111.25
2023-01-13 52:15	7.7772	7.4143	29370	480.6	106.8
2023-01-13 53:30	7.8665	7.4925	28925	542.9	102.35
2023-01-13 54:00	7.0133	7.7453	28480	445	111.25
2023-01-13 55:15	7.0453	7.7254	28480	507.3	111.25
2023-01-13 56:30	7.0102	7.7224	28480	498.4	111.25
2023-01-13 57:45	7.0355	7.7234	28480	471.7	111.25
2023-01-13 58:00	7.0252	7.7243	28480	534	111.25
2023-01-13 59:15	7.0435	7.7286	28480	551.8	111.25
2023-01-13 60:30	7.0156	7.7254	28480	516.2	111.25
2023-01-13 61:45	7.0133	7.7876	28480	471.7	111.25

Table 4 presented the performance of the SVM based airplane tracking system on route Enugu to Lagos for Ibom air. From the result, it was observed that the new model, was able to estimate the behaviour of the flight from the route at every 15seconds interval. The result also showed that at every instant, data was estimated which report the supposed flight position. The implication of this result is that the projected flight plane reported here can be used to track the position of the flight at all times. Even if the flight was not able to sends feedback to the ground station operators, the operators can easily depend on the estimated flight plan to make analysis and determine the condition of the flight.

B. System Validation using Ibom air

The validation of the system was performed using deduction method. The method compared the performance of the actual data of Air peace and Ibom air with the new SVM based flight estimation system travelling from Enugu to Lagos and considering speed, altitude and course.

Table 5: Validation result with Ibom air considering speed and altitude

Time (HH:MM)	Actual Altitude (ft)	Actual Speed (mph)	Actual Altitude (ft)	Speed (mph) with SVM	Course (°) with SVM	Actual Course (°)
16:00	35,000	600	31150	534	124.6	140
17:15	34,800	620	30972	551.8	123.71	139
18:30	34,600	580	30794	516.2	122.82	138
19:45	34,400	530	30616	471.7	121.93	137
20:00	34,200	610	30438	542.9	121.04	136
21:15	34,000	540	30260	480.6	120.15	135
22:30	33,800	500	30082	445	119.26	134
23:45	33,600	570	29904	507.3	118.37	133
24:00	33,400	560	29726	498.4	117.48	132
25:15	33,200	530	29548	471.7	116.59	131

26:30	33,000	600	29370	534	115.7	130
27:45	32,800	620	29192	551.8	114.81	129
28:00	32,600	580	29014	516.2	113.92	128
29:15	N/A	N/A	28836	471.7	113.03	N/A
30:30	32,200	610	28658	542.9	112.14	126
31:45	32,000	540	28480	480.6	111.25	125
32:00	32,000	500	28480	445	111.25	125
33:15	32,000	570	28480	507.3	111.25	125
34:30	32,000	560	28480	498.4	111.25	125
35:45	32,000	530	28480	471.7	111.25	125
36:00	32,000	600	28480	534	111.25	125
37:15	32,000	620	28480	551.8	111.25	125
38:30	32,000	580	28480	516.2	111.25	125
39:45	N/A	N/A	28480	471.7	111.25	N/A
40:00	32,000	610	28480	542.9	111.25	125
41:15	33,000	540	29370	480.6	106.8	120
42:30	32,500	610	28925	542.9	102.35	115
43:00	32,000	500	28480	445	111.25	125
44:15	32,000	570	28480	507.3	111.25	125
45:30	32,000	560	28480	498.4	111.25	125
46:45	32,000	530	28480	471.7	111.25	125
47:00	32,000	600	28480	534	111.25	125
48:15	N/A	N/A	28480	551.8	111.25	N/A
49:30	N/A	N/A	28480	516.2	111.25	N/A
50:45	N/A	N/A	28480	471.7	111.25	N/A
51:00	N/A	N/A	28480	542.9	111.25	N/A
52:15	33,000	540	29370	480.6	106.8	120
53:30	32,500	610	28925	542.9	102.35	115
54:00	32,000	500	28480	445	111.25	125
55:15	32,000	570	28480	507.3	111.25	125
56:30	N/A	N/A	28480	498.4	111.25	N/A
57:45	32,000	530	28480	471.7	111.25	125
58:00	32,000	600	28480	534	111.25	125
59:15	32,000	620	28480	551.8	111.25	125
60:30	32,000	580	28480	516.2	111.25	125
61:45	32,000	530	28480	471.7	111.25	125

The Table 5 presented the comparative analysis of the data analysis of the new system developed with SVM based flight estimation model which was deployed for the tracking of Ibom air from Enugu to Lagos. The result showed how the new system was able to monitoring the flight using real time data collected from the flight and also estimated data by the SVM based model which estimated the position of the flight. From the result, it was observed that while the main flight due to bad weather condition was not able to send signal at some point, the trained SVM model was able to estimate the position of the flight. In addition, the result showed that when the online flight sends data of its real-time altitude, the data was very close to the estimated altitude, with 89% correct prediction success rate.From the result in the graph, it was observed that while the normal flight sends its speed information to the ground station, the SVM based model was able to also estimate the flight speed at a close proximity. The result demonstrated the effectiveness of the SVM based model in estimating the flight behavior. Finally, it was observed that while at some points, the fight course was not recorded in the real time from the online flight; the SVM based model was still able to estimate the course of the flight with close proximity. Overall, the implications of the SVM-based model's success in estimating altitude, course, and speed extend to various aspects of autonomous flight tracking and safety, contributing to the advancement and adoption of autonomous aviation technologies in the existing ADSS.

IV. CONCLUSION

This work used the Support Vector Machine (SVM) technique to effectively create and deploy an Airplane Trajectory Prediction (ATP) model integrated into an Air Traffic Management System (ATMS). The approach included feature transformation, secondary data collecting, data preparation, and the use of SVM-based multi-classification to categorize flying behaviours into three groups: regular flight, in-flight delay, and high-speed. Furthermore, a new method called Frequency Doubling Transformation was used, which improved classification accuracy and feature discrimination. The ATMS's use of the SVM-based ATP model offered a reliable framework for monitoring and forecasting aircraft movements in real time. This framework successfully reduced the dangers of overfitting and ensured accurate predictions by utilizing hyper-parameter optimization and sophisticated data pre-treatment techniques like Z-normalization and mean imputation. The effectiveness of the ATP model in recognizing flying behaviours and spotting departures from intended paths was shown by simulation results. Air traffic safety, efficiency, and operational decision-making can all be greatly improved by the system's capacity to anticipate possible in-flight abnormalities, such as delays and high-speed manoeuvres. The project concluded by developing a scalable and flexible model for tracking and predicting airplane behaviour in real time. The results demonstrate how machine learning can improve air traffic control. The achievement level is 89% correct classification of flight behaviour. To further increase the ATP model's accuracy and scalability, future studies can investigate the integration of more sophisticated machine learning models, such deep learning, and real-time testing with bigger datasets.

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