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Aircraft Identification Using Machine Learning

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***Abstract*— Positive aircraft identification plays a crucial role in ensuring the security of the airspace, the safety of the populace, state resources and military establishments. Aircraft identification aids in air traffic management by positively identifying each aircraft entering monitored airspace. Automatic target recognition has allowed the utilization of machine learning algorithms for the classification of aircraft types. Machine learning as a sub-field of artificial intelligence is disrupting many fields by facilitating computers to learn the rom data they are exposed to on their own. This study dives into machine learning algorithms to try and pick one that can be best used for classifying aircraft as friend or foe. In this study, the researchers focused on supervised machine learning for the classification task. Various classification algorithms were implemented in this study to train models and evaluate their accuracy. The algorithms were trained using a dataset made up of motion features extracted from aircraft flight track data. The study showed that the hat classification of aircraft can be achieved by training the models using the aircraft motion features.**

Keywords – Aircraft identification, machine learning, supervised learning

I. INTRODUCTION

This work developed a machine-learning aircraft identification model. In [1], found that recognising aircraft entering monitored airspace is important in determining their identity. The responsible authority can make quick decisions if the aircraft is spotted sooner. Aviation authorities must record all flight plans. The records will track every aircraft in the monitored airspace. The reported flight plans allow the authority to track and identify an aircraft displayed in the monitor room.

An issue emerges when the authority cannot identify a radar-detected aircraft. This emanates from two possibilities. First, the aircraft transponder responding to ground station interrogations may malfunction. Second, the aircrew wants to turn off the transponder for security concerns. For the second reason, the aircraft must be on unauthorised missions and a security risk. The authority must be able to identify suspicious planes before something bad happens. This study examined aircraft identification using machine learning algorithms [1].

II. BACKGROUND TO THE STUDY

Aircraft identification is mainly achieved through Identification Friend or Foe system (IFF). As shown in Figure 1, the transponder searches for an interrogation signal before providing broadcaster information [2]. IFF systems mostly employ radar frequencies. Military and civilian air traffic control interrogation systems identify friendly aircraft, vehicles, and forces and calculate their bearing and range from the interrogator. Both military and commercial aircraft use the IFF system [3].

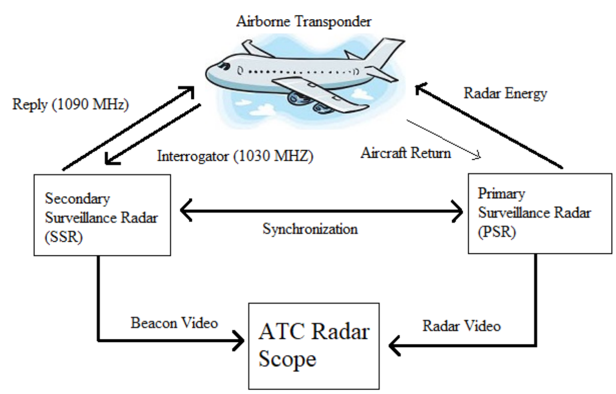

Figure 1: Concepts behind Identification Friend or Foe [4]

Some modern systems are now integrating machine-learning methods to forecast aerial object behaviour. Graphic image processing dominates current research, however, automatic aircraft recognition is still in the exploratory stage [3]. Air traffic control uses radar signals too [1]. Image-based and radar-based approaches identify planes by contour (shape). These approaches have significant drawbacks, including weather and other natural variables limiting image quality [5]. When flying at high speeds, it is hard to snap clear images of most civil aircraft because their shapes are similar. Aircraft form depends on sensor distance and direction. These obstacles make contour-based identification harder to apply in practice. The study used multiple classification methods to train a model to learn from aircraft motion characteristics to solve these obstacles.

IFF system only positively recognises friendly aircraft and forces [2]. In [6], Friendly forces may not properly respond to IFF for a variety of reasons. Equipment malfunction, and parties in the area not involved in the combat, such as civilian airliners, will not be equipped with IFF if an IFF interrogation receives no response or an invalid response, resulting in the object not being positively identified as a foe.

Neural networks and information fusion have been the main topics of machine learning studies for aircraft identification. In these experiments, the effectiveness of supervised and unsupervised neural networks in aircraft detection systems was compared [7]. The Adaptive Resonance Theory (ART) has been selected for the unsupervised neural network and the backpropagation network (BPN) for the supervised one. Other studies have shown the use of two kinds of input i.e. Radar Cross Section (RCS) or radar signature and average speed for aircraft identification.

III. PROBLEM STATEMENT

Events such as that which occurred in America on the 11th of September 2001 terrorist attack and the Simon Mann 2004 incident of aircraft caught trying to smuggle weapons are significant incidents driving the need for positive aircraft identification. Most ground-based surveillance systems rely on aircraft detection and recognition by the use of radar systems and flight plans obtained from aviation authorities to designate aircraft entering monitored air space as a friend or a foe. When the radar system detects an object in the air space, the object or aircraft identification code is used to compare with authorized flights provided. The challenge arises when the aircraft cannot be positively identified using the given identification code against that from the transponder system. In this study, machine learning algorithms were explored and used to successfully recognize aircraft. Machine learning algorithms are not yet fully experimented with when it comes to the identification of aircraft as a friend or a foe, hence the study sought to experiment on various algorithms to come up with the best model.

IV. LITERATURE REVIEW

A. *Overview of aircraft identification*

Manual binoculars identify aircraft by shape and engine sound. [8]. Weather, height, and visibility affect aircraft recognition efficiency. Air traffic control and military applications require aircraft type recognition [3]. Automatic aircraft recognition analyses images to identify targets. Automatic aircraft recognition relies on image extraction of an aircraft's silhouette and contour. Aircraft identification requires effective feature usage. The qualities must be independent of the object's position and orientation and include enough data to differentiate one object from another. However, the aircraft's geometric distortion, which might include shift, scale, and rotation, is often encountered, therefore image patterns must be extracted despite this distortion.

B. *Factors (parameters) affecting aircraft identification*

Many academics and researchers worldwide have studied aircraft remote identification. In-depth research into classification problems has yielded several abstract mathematical models that form the theoretical basis for classifiers [9]. Multivariate statistics generally seek to reduce the number of components needed to conclude the data, according to [10]. Fewer variables make problems easier to understand and solve. Using feature selection, a classification rule's number of variables can be lowered without impacting its performance.

Considering the classification of an aircraft or event. Radar and imaging sensors collect incident data for classification. A feature extractor reduces data by producing features or attributes that indicate distinct kinds of potential occurrences from the measuring system's output. One trait may not be enough to classify events. A feature vector represents a measurement's features as dimensions in feature space [11].

Due to aircraft motion performance differences, historical flight tracks can reveal useful features. In [12], identified nine motion performance factors that potentially influence aircraft recognition, however, some are difficult to compute and require a high-precision acquisition sensor. Thus, this study will examine flight data motion aspects such as maximum speed, cruising speed, acceleration, and climb rate. For conceptual clarity, the equations in the following subsections were adapted from [12].

Aircraft Maximum speed: it was assumed that an aircraft reaches its maximum speed when the engine is at maximum thrust. At the maximum speed, the tail of the aeroplane cannot be heat balanced and this state cannot last long. In the dataset, the researchers approximated the detected instantaneous maximum speed as the maximum speed of the aircraft.

$$V_k max = max_i\, v_{ki} \tag{1}$$

At which k is the number of aircraft in the detection record and i is the ith detection time point.

Cruising speed: it is also known as economic speed, when the aircraft does not engage the afterburner, the aircraft can stay in the air for the longest time in this state. The researchers approximated the average speed of the probe to the cruising speed of the aircraft.

$$\overline{V_k} = \frac{\sum_{i=1}^{n} v_{ki}(t_{k(i+1)} - t_{ki})}{t_{kn} - t_{k1}} \tag{2}$$

Where n is the number of probe records of aircraft k.

Maximum acceleration: this feature indicates the maximum capacity of the aircraft to enhance speed. The magnitude of the acceleration is related to the propeller's power, shape and cooling capacity of aircraft. Therefore, the ability of acceleration is an important parameter that reflects the characteristics of different types of aircraft.

$$a_{kv} max = \max_i \frac{v_{k(i+1)} - v_{ki}}{t_{k(i+1)} - t_{ki}} \tag{3}$$

The maximum rate of climb: The maximum rate of climb reflects the ability of the aircraft to overcome its gravity and resistance and is one of the characteristics that can best reflect the kinematic performance of the attack aircraft. In the flight track information, the maximum value of altitude difference in the detection interval is considered the maximum rate of climb (RoC).

$$\mathrm{RoC} max = \max_i \frac{h_{k(i+1)} - h_{ki}}{t_{k(i+1)} - t_{ki}} \tag{4}$$

Since most aircraft have a fixed route, longitude, latitude, altitude, velocity, heading information, and sensor signal types together with the above four characteristics will be considered as the inputs of the proposed classification model.

C. Aircraft identification techniques

In this section, the researcher looked at different techniques that are used to distinguish aircraft entering protected airspace as friends or foes.

i. Aircraft identification using the identification friend or foe (IFF) system

In [6], identified IFF as an identification tool used in air defence operations to identify approaching aircraft. IFF sends encrypted signals to aircraft via electromagnetic or radio waves. An aircraft is a friend or an enemy depending on how it responds. All aircraft have an IFF transponder that responds to IFF interrogation requests and indicates its purpose. IFF uses two channels to query and receive aircraft responses.

IFF can distinguish between friendly and hostile aircraft. These aircraft-connected systems use electromagnetic and radio frequency (RF) sensors to detect friendly, hostile, and neutral airspace forces [3]. It helps the military identify allies and potential foes. The device challenges and verifies passwords as an advanced digital challenge-and-response password system.

Two-channel IFFs transmit 1030 MHz interrogating signals and receive 1090 MHz signals. Two military and two civilian aircraft methods are available.

ii. Aircraft identification using radar cross-section and speed

The radar cross-section (RCS) measures radar detection. Bigger RCSs make objects easier to find. The detected target's power density is compared to the transmitting source's [7]. RCS components determine each aircraft's radar cross-section.

In [3] it was found that RCS can identify aircraft at several frequencies. Compared to an airliner, a stealth aircraft has flat surfaces, absorbent paint, and features oriented to reflect the signal elsewhere. RCS advances radar stealth technology, especially for ballistic missiles and aircraft. Military aircraft RCS data is usually classified.

Aircraft speed that is presented at the radar sensor can be obtained by using the Doppler principle given by the following equation:

$$f_d = \frac{2v}{\lambda} cos\theta \tag{5}$$

Where f_d is the Doppler principle,
v is aircraft speed,
λ is wavelength

θ is the angle between the direction of incoming signal propagation and with the direction of antenna movement [1].

D. Machine learning techniques for target identification

Machine learning is the study of creating algorithms that produce predictions based on data. Identifying, or learning, a function f: X → Y that translates the input domain X (of data) onto the output domain Y, is the goal of a machine learning task of possible predictions [14]. The functions are selected from different function classes; this all depends on the type of machine learning algorithm that is being used. If a computer program's performance at tasks in a class of tasks (T) as measured by a performance measure (P) increases with experience (E), then it is said to have learned from experience (E) [15]. To show how quantitatively a machine learning algorithm performs, the performance measure *p* is used. When it comes to classification problems the ms, the accuracy of a model is usually chosen as its performance measure, where accuracy is the proportion for which the system correctly produces the output. The main objective of experimenting with machine learning algorithms is to give an overview of the most effective algorithms and their implementations.

i. Computer vision for target identification

Several universities and research institutions have carried out and continue to do in-depth research on moving target-tracking technology [16]. Enormous progress is being achieved in the area of motion target tracking technology. For example, [12] did thorough research on the inter-frame difference algorithm hence he proposed an improved algorithm.

A deep learning application called object tracking follows a collection of initial item detections and creates a unique identifier for each one before monitoring the identified objects as they move between frames in a video. Following a series of initial item detections, an object tracking application generates a unique identifier for each one before tracking the identified objects as they move between frames in a video [16]. Computer vision has gained so much traction when it comes to its applications in artificial intelligence systems. Computer vision has been used in air defence systems for surveillance purposes [17].

ii. Artificial neural networks

Artificial neural networks are computing systems inspired by the biological neural networks that constitute animal brains [18]. According to [19] artificial neuron functions by receiving a signal then processing it and signalling other neurons connected to it. The output of each neuron is calculated by some non-linear function of the sum of its inputs, where the signal at a connection is a real number.

In [13], stated that early researchers tried to simulate the nervous system's processing unit so that its method might be replicated in computing systems, as they noted that neural networks are effective at performing recognition tasks. More specifically, a neural network is a generalization of mathematical models of human cognition based on the assumption that Information processing occurs at many simple elements called neurons. Each connection link has an associated connection weight that multiplies the signals transmitted;;and each neuron applies an activation function to its net input that is typically non-linear to determine its output signals as indicated in Figure 2.

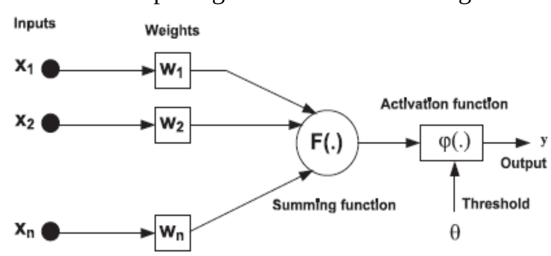

Figure 2: Mathematical model of a neuron [1]

iii. Information fusion

In [19] states that information fusion is a technique in combining physical or non-physical information form from diverse sources to become a single comprehensive information to be used as a basis for prediction or estimation of a phenomenon. The prediction or estimation is then used as the basis for performing decisions or actions. Figure 3 illustrates information fusion.

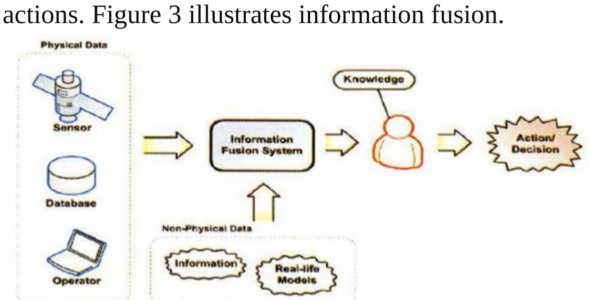

Figure 3: The concept of information fusion [20]

Referring to [1] for acquiring comprehensive information at the decision level, it was observed that we can choose from a variety of techniques, including the Bayes Method, Dempster-Shafer and System, and Boolean operator methods (AND, OR).

iv. Support vector machine

Support vector machine (SVM) is a discriminative classification method that originates from the computational learning theory's structural risk minimization principle. SVM aims to find the best classification function to differentiate between units of classes in training data. By building a hyperplane that maximizes the margin between two datasets and, as a result, creates the greatest distance between datasets, it is possible to determine the most advantageous classification function for a dataset that can be linearly separated [3]. A visualization of this strategy is illustrated in figure 4.

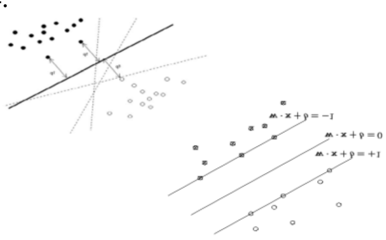

Figure 4: Concept behind support vector machines [21]

The theory behind support vector machines is that the optimum generalization ability is attained by locating the maximum margin and, thus, the most ideal hyper-plane. As a result, both the training data and future data exhibit the best classification performance. Support vector machines are designed to maximize the function presented below about w and b to identify maximum margin hyperplanes:

$$L_P = \frac{1}{2}\|\vec{\mathbf{w}}\| - \sum_{i=1}^{t} \alpha_i \gamma_i (\vec{\mathbf{w}} \cdot \vec{\mathbf{x}_i} + b) + \sum_{i=1}^{t} \alpha_i \tag{6}$$

Where t represents training point quantity, i stands for Lagrangian multipliers and LP exemplifies the Lagrangian. Vector *w* and constant *b* characterize the hyperplane. The data points that sit on the margin of the best-separating hyperplane are known as the support vector points. All other data points are disregarded, and the solution is a linear combination of these support vector points.

iv. Naïve Bayes classifier

According to [9] Naïve Bayes classifier is a machine learning model that applies the Bayes theorem, presented in the equation below, for probabilistic classification. By observing the values (input data) of a given set of features or parameters, represented as B in the equation, the naïve Bayes classifier can calculate the probability of the input data belonging to a certain class, represented as A. Equations in this sub-section were adapted from [22]

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{7}$$

For the classification of input data to take place, the probabilities of it belonging to each of the existing classes must be determined and the one with the highest probability will be the class to which the input data belongs. Therefore, class *a* with the highest probability must be found as expressed in the given equation below, where *bi* is one of the n features or predictors observed.

$$a = argmax_a P(a|b_1, \cdots, b_n) \tag{8}$$

Since a naïve Bayes classifier assumes that all variables are independent, only a small training data is necessary to estimate ate parameters necessary for classification. In the context of fault diagnosis, classes would represent faults or a set of faults that a system could develop and the predictors would represent the symptoms the system is presenting. Although naïve Bayes classifiers are easy and quick to implement, considering the predictors as independent variables can be seen as a disadvantage of the method, since in most real fault diagnosis cases, the symptoms can be dependent on each other (a high vibration can cause an increase in temperature, for example).

E. Studies on Aircraft Identification

In this section, the researcher looked at other related studies done so far about aircraft identification.

i. Deep learning for aircraft classification from VHF (Very High Frequency) radar signatures

The researchers in this study observed that a full-wave simulation of three size classes of aircraft shows that their bi-static radar cross-sections are statistically comparable, albeit perform differently in time while the plane is flying. This difference can be exploited to recognize the size of the aircraft concerning these classes. To deal with various representations of RCS, the researchers in this study suggested either a convolutional neural network (CNN) or a recurrent neural network (RNN).

Machine learning algorithms used in this research were: a 2D- CNN classifier of the sparse BS-RCS, a 1D-CNN classifier of the BS-RCS time series and angles, and an RNN taking as input only the BS-RCS time series. These three approaches deserve specific comments. In their conclusion they observed that their simulations have demonstrated in general, that the BS-RCS values of aircraft of different sizes (large, medium, and small) are similar, rendering their discrimination on the sole basis of BS-RCS values difficult [23].

ii. Target classification using the deep convolutional networks for SAR images

The focus of this research was on the synthetic aperture radar automatic target recognition (SAR-ATR) technique, which is typically made up of the extraction of a set of features that turn the raw input into a representation and a trainable classifier. The accuracy of the classification can be greatly impacted by the feature extractor, which is frequently manually constructed using domain knowledge. Deep convolutional networks have lately achieved state-of-the-art performance in several computer vision and speech recognition tasks by autonomously learning hierarchies of features from huge training sets. Convolution nets were immediately applied to SAR-ATR, but this resulted in significant overfitting because there weren't enough training images. Researchers proposed a new all-convolutional network that uses only sparsely linked layers rather than fully connected ones to lower the number of free parameters. Experimental findings on the Moving and Stationary Target Acquisition and Recognition (MSTAR) benchmark data set show that All Convolution Networks are significantly more accurate than traditional CNN at classifying target configuration and version variants, with an average accuracy of 99% on the classification of ten-class targets [3].

iii. Radar target classification using support vector machine and subspace methods

The researchers found that target classification is an important area for future research in the radar sector. They found that a good target electromagnetic scattering characteristic for real-time target categorization is the range profile. To achieve difficult target categorization, this study suggested a technique that blends SVM and subspace approaches. Range profiles produced by the graphical electromagnetic computing method are used to examine the performances of SVM and three representative subspace algorithms. The SVM classifier outperforms conventional classifiers in terms of robustness to sample variation, according to experimental results. The researchers concluded that their experimental findings demonstrate that SVM is more resilient to variation in feature samples than other classifiers [24].

iv. A machine learning based 77 GHz radar target classification for autonomous vehicles

This study focused on millimetre wave (mmW) radar which is a powerful essential sensor for state-of-the-art and future autonomous vehicles. Besides the traditional intended functionality of mmW radars in target detection and measuring its range and speed, in this work researchers show that by utilizing the knowledge of targets' statistical RCS information, over 90% classification accuracy can be achieved for distant targets (range over 50m). For advanced radars with beam-steering capabilities, the classification accuracy can reach more than 99% in the near range. For the data categorization problem in this study, a machine learning technique based on artificial neural networks (ANN) is utilized [9].

F. Conceptual Framework

Figure 5 depicts the conceptual framework of the study.

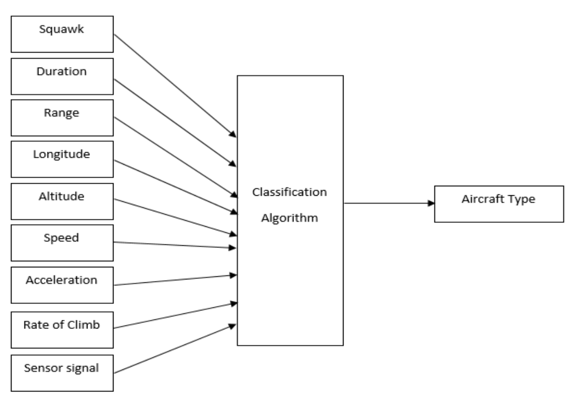

Figure 1: Conceptual framework of the proposed model

i. Longitude

An aircraft's east-west position on the surface of the Earth or another celestial body can be determined using the geographic coordinate longitude. This position is used to assess whether or not the aircraft is flying inside its intended azimuth.

ii. Latitude

Similar to longitude, latitude is a different way to describe how far away from or close to the equator an aircraft is. It is a metric used to judge whether the position of the aircraft is within a predetermined route.

iii. Altitude

A measurement of altitude or height is the distance between an aircraft and a reference datum, typically in the vertical or upward orientation. Authorities require each aircraft to fly at a particular altitude.

iv. Speed

The aircraft's change in speed is measured or recognized by sensors. Our parameter is important to this investigation since abrupt changes will make aircraft behaviour suspicious. The percentage of speed values recorded for the aircraft falling into each of the five-speed quantiles recorded for the sample of 500 aircraft are used in this study to observe it.

v. Heading

The direction that an aircraft's longitudinal axis is pointing is often stated in terms of degrees from North. An aeroplane maintains a set heading, and sudden deviations from that heading make an aircraft suspicious.

iv. Sensor Signal

A sensor translates the physical activity to be monitored into an electrical equivalent for electrical signals to be easily transferred and further processed.

V. METHODOLOGY

Figure 6 depicts the research process adopted.

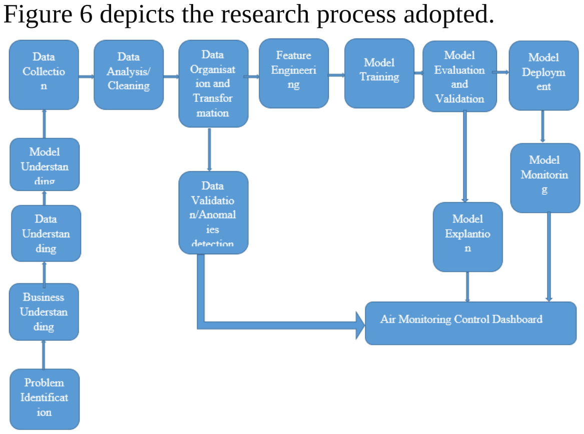

Figure 6: Block Diagram showing the research process

The proposed implementation process is depicted in Figure 7.

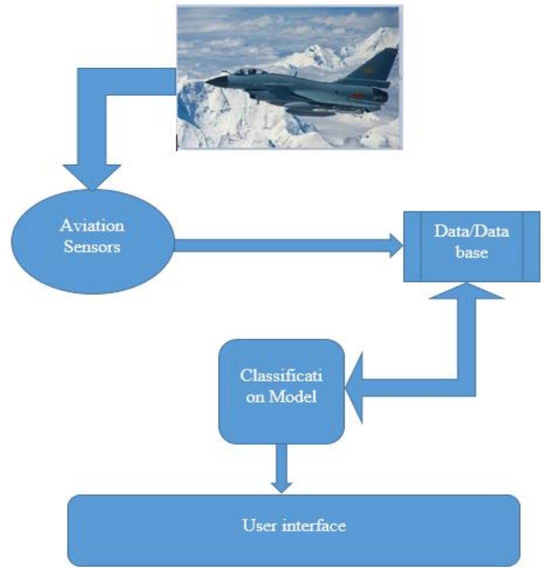

Figure 7: Classification model application procedure

C. Model building

The classification algorithms used are the Gaussian Naïve Bayes, K-Nearest Neighbour (KNN), Decision Tree, Random Forest, Logistic Regression and SVM. The task was a binary classification problem hence the algorithms stated above could be trained using the provided data. The researcher used the append function to define and initiate the algorithms to train all the models at one go, and also the metrics to evaluate their performances were called.

VI. RESULTS

A. Exploring the categorical features

To effectively build the model, it was first necessary to identify the variables or elements that influence aircraft identification. The dataset utilized for this experiment was made up of samples with motion features of the aircraft which were used to classify them as either friendly or unfriendly. The dataset was segregated into categorical and numerical variables as shown in figure 8.

```
There are 2 categorical variables

The categorical variables are :

 ['adshex', 'type']
```

Figure 8: Exploring categorical variables

It was discovered that the dataset was made up of two categorical variables which are ‘adshex’ and ‘type’. These variables indicate that an aircraft can be identified using its call sign (adshex) which is its unique identifier and by type, that is whether Boeing or Airbus.

B. Target feature distribution

The target feature or the output vector is the feature that tells whether the detected aircraft was friendly or not. The following figure depicts the distribution of the target feature classes.

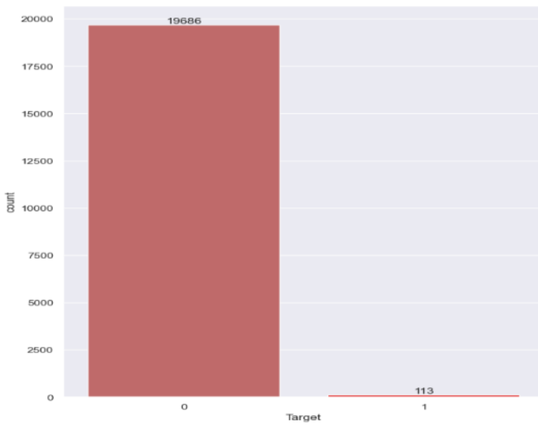

Figure 12: Target class distribution

The research revealed that the target feature was made up of two classes depicted by 0 and 1 where 0 is the majority class representing ‘friendly’ aircraft while 1 is the minority class representing ‘foe’ aircraft. The analysis revealed that the researcher was dealing with a significantly high imbalanced dataset which required resampling to deal with the imbalance. The majority class was made up of 19686 observations while the minority class comprised only 113 observations.

```
sm = SMOTE(random_state = 42)

X_res, y_res = sm.fit_resample(x, y)

X = pd.DataFrame(X_res)
Y = pd.DataFrame(y_res)

print("After SMOTE Over Sampling Of Minor Class Total Samples are :", len(Y))
```

Figure 13: Resampling the dataset

To correct the imbalance, the above resampling technique was carried out. Samples from the minority class were replicated to balance the two classes.

C. Feature selection

In the experiment, the researchers utilized the information gain technique to discover relevant or important features of the training model. The figure below shows features importance that was obtained from the information gain feature selection technique.

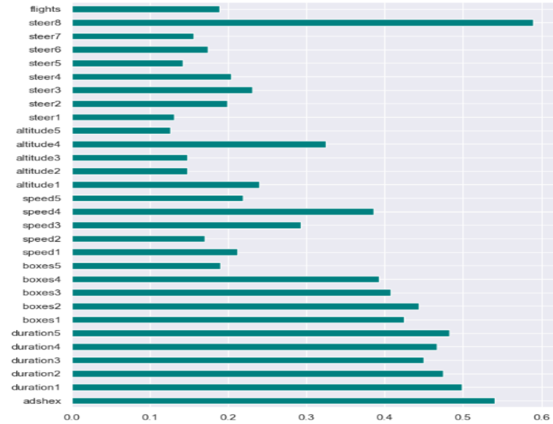

Figure 14: Feature Selection using information gain

The results revealed that steers and speed variables had a significant impact on the training of the model. The other features cannot be ruled out as they also contribute to the learning of the model. The technique proved that it could not render desired results for effectively training the model hence the researchers used another selection technique. The researchers then used the recursive feature selection method to come up with an optimum number of features or columns required for effectively and efficiently training the model. The algorithm showed that 25 features out of 30 could be used for effectively training the models.

```
print("Optimal number of features : %d" % rfecv.n_features_)

Optimal number of features : 25
```

Figure 15: Feature Selection using RFE

D. Results of classification algorithms

In this work, the researchers experimented with various machine-learning classification algorithms to come up with the best model for aircraft identification. The algorithms that were implemented or experimented on are; Naïve Bayes (GNB), K-Nearest Neighbors (KNN), Decision Tree Classifier (DTC), Random Forest Classifier (RF), Logistic Regression (LR), Support Vector Machine (SVM) and Artificial Neural Network (ANN). The results from the trained algorithms are shown in figure 16.

	Model	Accuracy Score Test	Accuracy Score Train	Recall Score Test	Recall Score Train	F1 Score Test	F1 Score Train	Precision Score Test	Precision Score Train
0	RF	0.999390	1.000000	1.000000	1.000000	0.999392	1.000000	0.998784	1.000000
1	SVM	0.999086	0.999323	1.000000	1.000000	0.999088	0.999323	0.998177	0.998647
2	DTC	0.998171	1.000000	0.999594	1.000000	0.998176	1.000000	0.996762	1.000000
3	LR	0.996749	0.996173	1.000000	1.000000	0.996764	0.996188	0.993548	0.992401
4	KNN	0.992685	0.995090	1.000000	1.000000	0.992748	0.995111	0.985600	0.990270
5	GNB	0.923905	0.929798	0.917005	0.923973	0.923470	0.929358	0.930027	0.934805

Figure 16: Summary of model performances

The initial model experiment findings are shown above. Algorithm performance measurements were based on Accuracy Score Test, Accuracy Score Train, Recall Score Train, F1 Score Train, Precision Score Test, and Precision Score Train. F1 Score Test ranked the best model. Scores are decimal numbers from 0 to 1 with 1 being 100%.
Random Forest classifier performed best in this experiment with an F1 Score Test of 99.94% and an Accuracy Score Test of 99.93%. The above models have similar accuracy values of 95% to 99.9%. Other data reveal that the models identified friendly and foe aircraft differently. An imbalanced dataset algorithm's accuracy score was not the ideal metric. Since it combines precision and memory, the F1 score was best.

Instead of the precision score, the accuracy score was used to rank models because it gives a percentage of properly categorised samples when all predicted samples are considered. Negative samples may outnumber positive ones in an imbalanced data collection. Even if all positive samples were misclassified, this would have increased accuracy. The accuracy score was not the greatest performance metric for this study's dataset. Precision score revealed more about the imbalanced circumstance above.

E. Classification using artificial neural network (ANN)

ANN was also implemented on the data to evaluate its performance in the aircraft classification task. The ReLu (Rectified Linear Unit) and Sigmoid functions were used as activation functions during the training of the Artificial Neural Network.

```
val_accuracy = np.mean(history.history['val_accuracy'])
print("\n%s: %.2f%%" % ('val_accuracy is', val_accuracy*100))
```

```
val_accuracy is: 99.94%
```

Figure 17: ANN Accuracy Score

ANN obtained an accuracy score of 99.94% also proving that it could be highly considered for aircraft identification purposes. Due to the modest size of the training dataset, practically all of the necessary features had been learned in the first iteration. Figure 4.19 below shows the training and validation accuracy. Figure 4.20 show the training and validation loss.

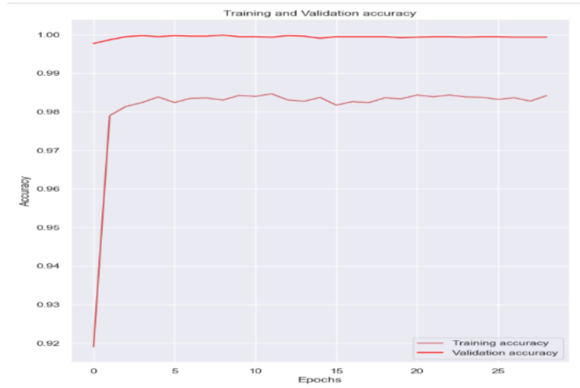

Figure 19: Training and Validation accuracy

The training and validation accuracies are quite comparable with no significant variation between the two proving that no overfitting was detected. The model obtained a training accuracy of close to 100% and had a validation accuracy of more than 98.00%.

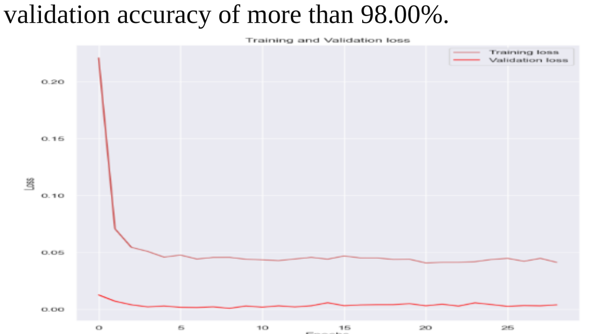

Figure 20: Training and Validation loss

The aforementioned training loss shows that the model fits the training data well, and also the validation loss showed that the model fit the new data well. The training and validation losses are both minimal. Both the validation and training loss stabilize at a certain point.

F. Evaluation and comparison of all the models

After training the classification models with hyper-tuned parameters, the models were evaluated and compared using their accuracy scores. Figure 4.21 below shows results obtained from evaluation metrics.

	Model	Score
4	Support Vector Machines	99.940000
6	Artificial Neural Network	99.937414
3	Random Forest	99.880000
0	Logistic Regression	99.800000
2	Decision Tree	99.660000
5	K - Nearest Neighbors	99.490000
1	Naive Bayes	92.390000

Figure 21: Evaluation of Models using their accuracy scores

The study showed that machine learning relies on hyperparameter adjustment. The SVM model outperformed the ANN in all experiments. The accuracy score determined the best model after Grid search hyper-parameter tuning. The SVM was chosen because of its F1 score, Recall, and Precision. All accuracy values are above 92%. These findings support the findings of [13]. He suggested utilising a machine learning classification model with motion cues from flight track data to automatically and reliably identify aircraft types.

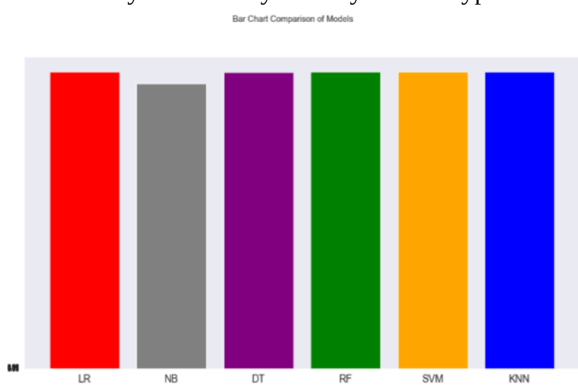

Figure 22: Comparison of Models

The figure above is the comparison of the classification algorithms used in this study showing that their accuracy scores were quite high and quite comparable. The accuracies did not vary much hence the study had to rely on other metrics to choose the best-performing algorithm.

G. Cross-validating the best-performing algorithm

```
from sklearn.model_selection import cross_val_score
svc = svm.SVC()
scores = cross_val_score(svc, X_test, y_test, cv=10, scoring = "accuracy")
print("Scores:", scores)
print("Mean:", scores.mean())

Scores: [0.99796954 0.99898477 0.99898477 0.99695122 0.99796748 0.99695122
 0.99796748 0.99898374 0.99898374 0.99695122]
Mean: 0.9980695183855393
```

Figure 23: Cross-validating Support Vector Machine Model

Since this method was used to examine how the model will generalize to an independent dataset, the model's mean value of 99.81% in Figure 23 demonstrated that prediction could be made with a reasonably high degree of accuracy.

H. Evaluating the best-performing model

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      4915
           1       1.00      1.00      1.00      4928

    accuracy                           1.00      9843
   macro avg       1.00      1.00      1.00      9843
weighted avg       1.00      1.00      1.00      9843

Confusion Matrix:
 [[4906    9]
 [   0 4928]]
ROC AUC 0.9990844354018311
```

Figure 24: Model Evaluation

The SVM model classified aircraft detected with 100% precision, recall, and F1 scores for "friendly" and "foe" aircraft, respectively. The model's confusion matrix showed 9 erroneous predictions and 0 false negatives (Figure 24). The model performs well because it makes a few erroneous predictions. The model classified aircraft as friends or adversary with 99.9% accuracy.

I. Summary of results

The researchers found that full flight characteristics data was needed to train aircraft recognition models. Models were trained using aircraft motion features to classify aircraft as friendly or foe. The dataset utilised to train the models showed an uneven data distribution between friendly and foe classifications. Exploratory data analysis showed that most aspects of the data set were important because losing one meant losing essential data on aircraft motion characteristics at any given time. One of the objectives was to determine the parameters that affected aircraft identification.

In aircraft identification studies, the SVM model outperformed all other machine-learning classifiers. When the F1 score was used to rank models trained without hyper-parameters, the Random Forest classifier outperformed the others. SVM models outperformed other classification algorithms after hyperparameter tuning. The study used multiple performance measures to evaluate algorithms. Table 4.1 shows performance algorithm findings.

Table 1: Model Summary

Model	Accuracy Test Score	Recall Test Score	Precision Test Score	F1 Test Score
SVM	99.94%	100%	99.87%	100%
RF	99.93%	100%	100%	99.93%
DTC	99.81%	99.95%	99.67%	99.81%
LR	99.67%	99.61%	99.35%	99.67%
KNN	99.26%	100%	98.56%	99.51%
GNB	92.39%	91.70%	93.00%	92.93%

The performance metrics above show that SVM could predict "friendly" and "foe" aircraft with comparable parameters. The model's precision, recall, and F1 score suggest that it can predict a batch of 100 planes correctly. This study tested other categorization algorithms.

J. Comparison with past work

Table 2 compares our research to earlier classification systems that used machine learning to identify aircraft. Reviewing five studies. Despite diverse settings, multiple categorization algorithms scored 90%. Hyper-tuned models averaged 95%. This study's SVM and Logistic Regression scores averaged 97%–98%. In some research, the lack of large datasets may have limited machine learning algorithms' accuracy.

Table 2 Comparison with past studies

RESEARCHER	APPROACH	ALGORITHM	ACCURACY
(Huang *et al.*, 2018)	Aircraft type recognition using ELM	ELM SVM	**82.81%** **96.35%**
(Rong, Jia and Zhao, 2014)	Aircraft recognition using modular extreme learning machine.	ELM SVM DT KNN GNV	**92.26%** **81.59%** **81.29%** **82.79%** **73.30%**
(Cai and Sarabandi, 2019)	A Machine Learning Based 77 GHz Radar Target Classification for Autonomous Vehicles	ANN	**90.20%**
(Liu, 2022)	A Deep Neural Network-Based Target Recognition Algorithm for Robot Scenes	DNN	**81.90%**
(Chen *et al.*, 2016)	Target Classification Using the Deep Convolutional Networks for SAR Images	CNN	**99.00%**

Researchers used multiple machine-learning methods to identify aircraft. The table above shows their results. Algorithms will score differently for the same assignment. The researcher's results also differed for different algorithms when trained on the same dataset. Due of their ability to classify things, neural networks always performed well.

VII. CONCLUSION

This study found that less complex categorization approaches can be used to develop aircraft-type recognition models. Researchers can test aircraft identification models with reduced computing complexity. The study positively identifies aircraft entering monitored airspaces, helping air traffic management and civil and military aviation. Scholars are increasingly studying aircraft type recognition, a vital air traffic management technique. Military aircraft identification is crucial to preventing fratricide deaths. Air traffic control requires aircraft identification and landing approval. This paper answered three research questions. By incorporating ideas that arose during topic selection and research, this paper's future work could expand its reach.

This paper originally used computer vision to detect and classify aircraft. It was limited to aircraft identification due to a lack of resources and unified optical satellite data for aircraft classes. This could be a future research area. Second, the SVM method could incorporate more hyper-parameters to maximise training to expand the research. Using CPUs with increased core counts to parallel process the algorithm's complexity and GPU clusters to boost model training can be a solution. Other methods from the literature study that classify aircraft well can be chosen. To compare aircraft identification models, more efficient classification methods could be utilised.

REFERENCE

[1] A. Datumaya, W. Sumari, and I. A. Force, "A Study on Identification Friend , Foe , or Neutral Methods : The Performance of Supervised and Unsupervised NEURAL NETWORKS," no. July 2009, 2019.

[2] T. Q. S. Q. H. Wu, Z. Zhang, C. Jiao, C. Li, "Learn to sense: a meta-learning-based sensing and fusion framework for wireless sensor networks," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 1089–1100, 2019.

[3] B. Zhao, W. Tang, Y. Pan, Y. Han, and W. Wang, "Aircraft Type Recognition in Remote Sensing Images : Bilinear Discriminative Extreme Learning Machine Framework," pp. 1–24, 2021.

[4] "What is IFF (Identification Friend or Foe)? - everything RF." [Online]. Available:

https://www.everythingrf.com/community/what-is-iff

[5] H. Huang, "Aircraft Type Recognition Based on Target Track.," *J. Phys. Conf. Ser.*, vol. 1061, no. 1, 2018.

[6] E. Meyers and N. Prince, "Infantry I . F . F . (Identification Friend or Foe) System By," no. 11, 2016.

[7] R. Wu, A. Polk, M. Xi, and T. Kendall, "Big Data and Deep Learning Models for Automatic Dependent Surveillance Broadcast (ADS-B)," pp. 111–114, 2018.

[8] "Deep learning-based strategies for the detection and tracking of drones using several cameras _ IPSJ Transactions on Computer Vision and Applications _ Full Text."

[9] X. Cai and K. Sarabandi, "A machine learning based 77 GHz radar target classification for autonomous vehicles," *2019 IEEE Int. Symp. Antennas Propag. Usn. Radio Sci. Meet. APSURSI 2019 - Proc.*, pp. 371–372, 2019, doi: 10.1109/APUSNCURSINRSM.2019.8888647.

[10] "Machine Learning Methods for Radar Detection, Classification_Estimation, and Tracking _ Frontiers Research Topic."

[11] H. B. M. Pourshamsi, M. Garcia, M. Lavalle, "A machine-learning approach to PolInSAR and LiDAR data fusion for improved tropical forest canopy height estimation using NASA AfriSAR Campaign data," *EEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 11, no. 10, pp. 3453–3463, 2018.

[12] "Machine Learning-Based Multitarget Tracking of Motion in Sports Video."

[13] H. Huang *et al.*, "Aircraft Type Recognition Based on Target Track," *J. Phys. Conf. Ser.*, vol. 1061, no. 1, 2018, doi: 10.1088/1742-6596/1061/1/012015.

[14] J. L. R. Bekkerman, M. Bilenko, *Scaling Up Machine Learning*. Cambridge: University Press, 2012.

[15] T. Mitchell, *Machine Learning*. McGraw Hill, 1997.

[16] and M. D. L. Li, K. Ota, "Deep learning for smart industry: efficient manufacture inspection system with fog computing," *IEEE Trans. Ind. Informatics*, vol. 14, no. 10, pp. 1821–1846, 2018.

[17] S. C. S. De, L. Bruzzone, A. Bhattacharya, F. Bovolo, "IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing," *A Nov. Tech. based Deep Learn. a Synth. target database Classif. urban areas PolSAR data*, vol. 11, no. 1, pp. 154–170, 2018.

[18] L. Liu, "A Deep Neural Network-Based Target Recognition Algorithm for Robot Scenes," *Scientific Programming*, vol. 2022. 2022. doi: 10.1155/2022/4037625.

[19] M. Bistron, "Artificial Intelligence Applications in Military Systems and Their Influence on Sense of Security of Citizens," 2021.

[20] M. Ahmadi, B. Slocumb, and Y. Ahmadi, "Deinterleaving of Interfering Radars Signals in Identification Friend or Foe Systems Related papers Deinterleaving of Interfering Radars Signals in Identification Friend or Foe Systems".

[21] G. F. Luger, *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*, vol. 5th. 2005. [Online]. Available: http://www.amazon.com/dp/0321545893

[22] A. C. Müller and S. Guido, *Introduction to Machine Learning with Python and Scikit-Learn*. 2015. [Online]. Available: http://kukuruku.co/hub/python/introduction-to-machine-learning-with-python-andscikit-learn

[23] J. Fix *et al.*, "Deep learning for aircraft classification from VHF radar signatures," *IET Radar, Sonar Navig.*, vol. 15, no. 7, pp. 697–707, 2021, doi: 10.1049/rsn2.12067.

[24] J. Liu, N. Fang, Y. J. Xie, and B. F. Wang, "Radar target classification using support vector machine and subspace methods," vol. 9, no. September 2014, pp. 632–640, 2015, doi: 10.1049/iet-rsn.2014.0325.