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SUPERVISED MACHINE LEARNING FOR EFFECTIVE MISSILE LAUNCH BASED ON BEYOND VISUAL RANGE AIR COMBAT SIMULATIONS

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ABSTRACT

This work compares supervised machine learning methods using reliable data from constructive simulations to estimate the most effective moment for launching missiles during air combat. We employed resampling techniques to improve the predictive model, analyzing accuracy, precision, recall, and f1-score. Indeed, we could identify the remarkable performance of the models based on decision trees and the significant sensitivity of other algorithms to resampling techniques. The models with the best f1-score brought values of 0.379 and 0.465 without and with the resampling technique, respectively, which is an increase of 22.69%. Thus, if desirable, resampling techniques can improve the model's recall and f1-score with a slight decline in accuracy and precision. Therefore, through data obtained through constructive simulations, it is possible to develop decision support tools based on machine learning models, which may improve the flight quality in BVR air combat, increasing the effectiveness of offensive missions to hit a particular target. [Code][1]

1 INTRODUCTION

In a Beyond Visual Range (BVR) air combat, since pilots do not have visual contact with their opponents, the targets are detected using sensors, such as radar or Radar Warning Receiver (RWR). Lately, due to technological advances in sensors and weapons, BVR air combat has become one of the fundamental elements to achieving air superiority (Higby 2005). Constructive computer simulations have been widely used to emulate the most diverse BVR air combat situations to assess the effects of new combat tactics, sensors, and armaments, at a reduced cost compared to live exercises (Dantas et al. 2022; Costa 2019). In a constructive simulation, an aircraft is modeled as an autonomous agent, which is a computational entity that makes decisions based on data obtained from the environment in which it operates and interacts

[1] Code: https://github.com/jpadantas/effective-missile-launch

with other agents (Russell and Norvig 2020). One of constructive BVR simulation's main challenges is mimicking the complex behaviors in all combat phases. A pilot can perform decision-making processes, such as adapting to new combat situations and conducting collective tactics with other aircraft (Costa et al. 2022). Some research addressed the application of artificial intelligence, game theory, and heuristics in modeling decision-making for autonomous agents in different phases of simulated BVR air combat.

Concerning threat assessment and target selection, some of the available methods found in the literature are: Bayesian optimization algorithm in Fu et al. (2021); backpropagation neural network in Yao (2021); combination of a genetic algorithm with deep learning in Li et al. (2020); zero-sum game in Ma et al. (2019); deep neural network in Dantas et al. (2021a); Case-Based Behavior Recognition proposed in Borck et al. (2015); and an algorithm that combines fuzzy logic and Bayesian network in Rao et al. (2011).

In the phase of selection and execution of tactical maneuvers, there are also many approaches in the literature: deep reinforcement learning in Hu et al. (2021); Bayesian networks in Du and Liu (2010); zero-sum differential game in Garcia et al. (2021); genetic algorithm in Kuroswiski (2020); reinforcement learning, artificial neural network and Markov decision processes in Piao et al. (2020); Hierarchical Multi-Objective Evolutionary Algorithm in Yang et al. (2020); decision algorithm based on the minimax method in Kang et al. (2019); Markov decision processes, reinforcement learning, a multilayer perceptron (MLP) neural network, and simulated annealing in Weilin et al. (2018); reasoning based on objectives in Floyd et al. (2017); finite state machines, rule-based scripts, and reinforcement learning in Toubman et al. (2016); and grammatical evolution and behavior trees in Yao et al. (2015).

Our work addresses the decision-making process of estimating the most effective moment for firing a missile in a BVR air combat in a specific scenario. The most decisive moment of firing is the one that guarantees the elimination of the target.

In Ha et al. (2018), the authors modeled the BVR air combat between two aircraft swarms as a zero-sum stochastic game. The firing moment estimation process was designed as a probabilistic function of the target's evasive ability, the missile's speed on the final approach, and the accuracy of the target's information to guide the missile. However, the methodology proposed has not been tested in simulations with higher fidelity concerning real BVR air combat. Also, significant simplifications were made in the process of modeling a BVR air combat: all aircraft in the same swarm fire at the same time, the missiles can pursue targets without the need for support from the radar aircraft that launched them, and the evasive ability of each aircraft is an input parameter.

In Dantas (2018) and Dantas et al. (2022), the authors designed a MLP neural network using data from constructive simulations to be employed in an embedded device to enhance the pilot's situational awareness in the in-flight decision-making process. Although obtaining promising results, only a single machine learning method was employed to analyze a reduced number of air combat scenarios simulation runs with only one aircraft on each team. Lima Filho et al. (2021) adopted a similar methodology but used data collected in real air combat exercises with computationally simulated shots.

The main contribution of our work is to compare the application of different machine learning methods to estimate the most effective moment for launching missiles during a BVR air combat, based on data from constructive simulations, which are run through a commercial off-the-shelf framework. Since running the simulations is computationally demanding, the machine learning methods can streamline the predictions regarding missile success to be used in real-time applications. Furthermore, it was observed that, during the simulations, the missiles could not hit their targets in most of the scenarios due to challenging shooting conditions within our experiment design, which led to an imbalanced dataset. Therefore, we employed resampling techniques to improve the predictive model, analyzing accuracy, precision, recall, and f1-score. To the best of our knowledge, this is the first work to address the imbalance in the missile launch results within air combat simulation .

The rest of this paper is organized as follows. The definition of a simulated BVR air combat scenario is presented in Section 2. Section 3 describes the methodology proposed to solve the problem of estimating the best moment for firing missiles using machine learning models. The analysis of the results obtained with the application of the machine learning models is presented in Section 4. Finally, Section 5 describes the conclusions of this work and shares ideas for future work.

2 SCENARIO DESCRIPTION

The scenario is formed by two forces that engage each other in a tropical area. The blue side performs a Combat Air Patrol (CAP), classified as a Defensive Counter Air mission. In contrast, the red side takes part in a fighter sweep (Offensive Counter Air) to neutralize the blue patrol, opening space for other types of tasks to be performed later, such as an air-to-ground attack. The red side always employs a 4-aircraft squadron formed by multi-role fighters, while the blue side can have either a 4- or a 6-aircraft squadron, which may also vary between two fighter concepts (defined as type 1 and 2). The concepts represent different classes of fighters; type 1 is a smaller single-engine aircraft (fourth-generation), while type 2 is a larger double-engine stealth aircraft (fifth-generation). These entities were defined within a framework for composable simulations called FLAMES (Ternion 2021), which provides several aspects of constructive simulation development and use, including customizable scenario creation, execution, visualization, and analysis, as well as interfaces to constructive, virtual, and live systems.

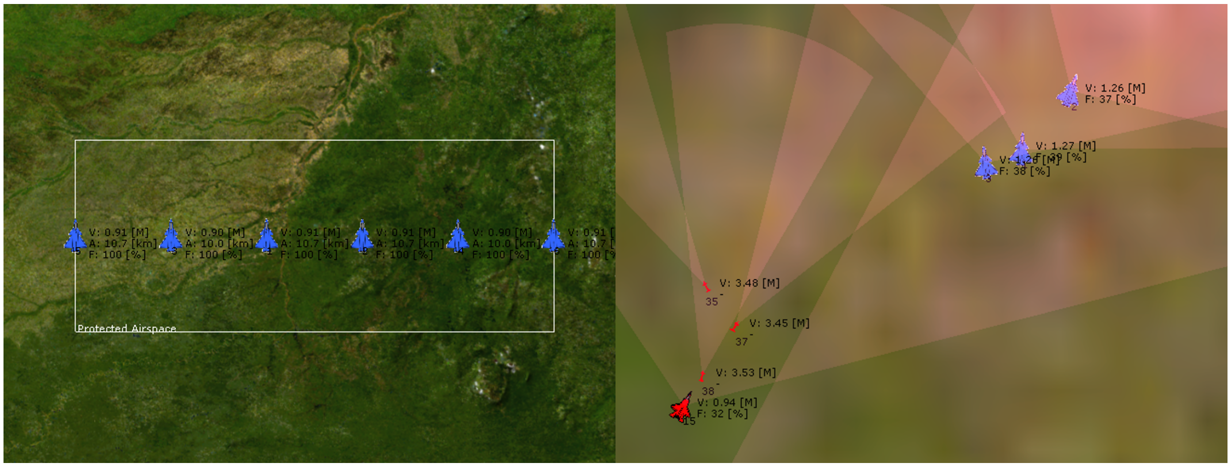
We modeled the BVR air combat behaviors of the aircraft, i.e., autonomous agents, through behavior trees structured within states of a finite state machine (Colledanchise and Ögren 2018). These behaviors include CAP, target selection, engagement, evasion, and missile firing. Also, the aircraft is equipped with several subsystems: controllers, trackers, datalinks, fusers, radars, RWR, antennas, and weapon systems. We will focus on the ones directly related to the variables used in our experimental design.

The red side employs a squadron formed by four twin-engine, mid-size fifth-generation fighters. These aircraft have internal weapons bays carrying up to 4 BVR air-to-air missiles (BVRAAMs). The blue side can have 4- and 6-aircraft squadrons of either type 1 or 2 aircraft. Type 1 is a light aircraft with a reduced cost, whereas type 2 is much larger. Both are single-engine multi-role fighters with stealth capabilities. The red and blue aircraft's main parameters can be found in Table 1.

Table 1: Main characteristics of the red and blue (type 1 and 2) aircraft.

Feature	Red	Blue 1	Blue 2	Feature	Red	Blue 1	Blue 2
Wing area	49.5 m^2	36 m^2	43 m^2	Mission fuel weight	6000 kg	3070 kg	5200 kg
Wing span	11.52 m	8.9 m	9.5 m	Maximum weight	26205 kg	13300 kg	22214 kg
Wing incidence	1°	0°	1°	Dry weight	17805 kg	9085 kg	14638 kg
Wing 25% sweep	27°	38.4°	42°	Maximum payload	8250 kg	6000 kg	8000 kg
Wing dihedral	-4°	0°	-2°	Radius of action	648 NM	1000 NM	700 NM
Wing twist	2.5°	2°	2.5°	Cruise altitude	11000 m	10668 m	11000 m
Length fuselage	17.28 m	15 m	18.96 m	Cruise Mach	0.8	0.9	0.8
Aspect ratio	2.68	2.2	2.1	Max Mach (sea level)	1.1	1.1	1.1
Taper ratio	0.21	0.2	0.2	Thrust dry	59038 N	64874 N	109642 N
Ultimate load factor	13.5	14.5	13.5	Thrust aferburner	91781 N	98022 N	173550 N
Number of missiles	4	3	6	Front RCS	-10 dBm^2	-10 dBm^2	-25 dBm^2

Even though each aircraft type had its own baseline front Radar Cross Section (RCS), an additive factor in dBm² was included throughout the design of experiments (DoE) so that different RCSs could be evaluated. Even though just the frontal value was provided, the RCS for each aircraft was determined by a table with values at each angle. Therefore, we applied the additive factor to all values within these tables. These aircraft types are both equipped with BVRAAM missiles with similar characteristics to those employed by the red side. However, different from what was modeled for the red missiles, the activation distance of the blue missiles varied to assess whether this would influence the shot's effectiveness. Additionally, during the different experiment cases, we changed the initial formation of the blue and red aircraft (distance between their CAP points, as in Figure 1a). Moreover, in the case of blue aircraft, we modified the radar ranges and the shot philosophy within their behavior trees. We altered flying altitudes and speeds according to the DoE. Figure 1b shows a representation of the radars and missiles employed during a simulation execution.



(a) Initial setting.

(b) Intermediate frame.

Figure 1: Scenario depictions with (a) 6 blue aircraft in wall formation within protected airspace and (b) radar and missile representations during the simulation execution.

The engagement distances for the aircraft's missiles are dynamically calculated based on factors such as the launcher's altitude and speed and the target's altitude, speed, and azimuth. Therefore, the aircraft's artificial pilot may decide whether to fire or not. The shot philosophy is defined as a percentage of the Weapon Engagement Zone (WEZ), calculated by the earlier parameters, stored on a table. For the red aircraft, this percentage is fixed at 60%. The WEZ, in simple terms, represents the range of a given weapon to be employed in a particular shooting stance (Dantas et al. 2021b).

Besides this percentage, the behavior considers other factors to choose to fire, such as whether the target is already engaged by another friendly aircraft. Additionally, it defines defensive maneuvers and any other action performed by the aircraft. The data that feed the behavior trees come mainly from the aircraft's sensors. The most important ones are the RWR and the radar, which provide the unit's tracklist, i.e., the combined list containing all its possible targets.

The radar could operate in two distinct modes: scan and track. In the scan mode, the radar can cover larger areas with a smaller range. This is used to detect the aircraft within the theater of operations. Diversely, the track mode focuses on a particular target (or set of targets) to follow its movements and prepare to fire. The track mode range is usually larger than the scan mode, which was therefore considered 60% of the track mode range. While tracking, the radar power is concentrated on more specific regions, providing more extensive ranges at the expense of situational awareness concerning the surrounding areas.

3 METHODOLOGY

We model the estimation of the most effective moment for firing missiles in BVR air combat simulations as a classification problem, a classic machine learning challenge. This problem consists of classifying a set of instances of features, independent variables, into two classes defined by a single dependent variable: value 1 indicating an effective shot; and value 0 meaning an ineffective shot. We employed some of the most relevant supervised machine learning methods to estimate the most effective moment for firing missiles in BVR air combat simulations: Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Naive Bayes (NB), Random Forest (RF), and Extreme Gradient Boosting (XGBoost); to the interested reader, we refer to Géron (2019). Concerning the resampling techniques, we applied oversampling methods such as Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al. 2002) and Adaptive Synthetic Sampling Approach (ADASYN) (He et al. 2008). Also, we introduced undersampling methods such as Tomek Links (TL) (Tomek 1976) and

Edited Nearest Neighbor (ENN) (Wilson 1972). Besides, we analyzed the datasets using hybrid techniques that use oversampling and undersampling together: SMOTE with Tomek Links (SMOTE-TL) (Batista et al. 2004) and SMOTE with Edited Nearest Neighbor (SMOTE-ENN) (Batista et al. 2004).

We proposed the following steps to solve this problem: design of a set of BVR air combat experiments (Subsection 3.1); acquisition of the shooting dataset, i.e., the training dataset, collected by performing the set of simulations (Subsection 3.2); specifying the variables used in the predictive models (Subsection 3.3); hyperparameters tuning process of all supervised machine learning models applied to the problem (Subsection 3.4); preprocessing of the training dataset (Subsection 3.5); and training and evaluation process of the machine learning models (Subsection 3.6).

3.1 Design of Experiments

Considering these scenarios and behavior characteristics, we create an experimental design using the Latin Hypercube Sampling (LHS) (McKay et al. 1979). This method is an alternative to using factorial strategies, presenting a solution for filling the sample space in a better fashion than what is done by a purely random process, such as the Monte Carlo sampling (Husslage et al. 2011). LHS divides the space into a prespecified number of sections from which it randomly samples one point. The variables in Table 2 form the sample space in this work, and each has a predefined interval to design the samples properly. This sampling method allows the user to specify the number of sample points desirable. In our work, we selected 240 cases as simulation inputs, each executed 30 times with different random seeds, which mainly interfered with missile probability of kill (set as 90% for both sides) and behavior evaluation delays since both were functions of these seeds. This probability value means that if the missile can reach a distance of at least 10 meters from the target, it has a 90% chance of destroying the target.

Table 2: Model input and output variables.

Description	Min	Max	Unit
Blue maneuvering altitude	27.5	42.5	kft
Red maneuvering altitude	27.5	42.5	kft
Blue maneuvering speed	0.9	1.5	Mach
Red maneuvering speed	0.9	1.5	Mach
Blue radar track range	150	300	km
Blue missile range multiplicative factor	1	2	-
Blue RCS	-10	10	dBm^2
Blue missile activation distance	15	30	km
Blue shot philosophy (in percentage of WEZ)	50	70	%
Initial distance between blue aircraft (in longitude)	0.1	1.0	°
Initial distance between red aircraft (in longitude)	0.1	1.0	°
Blue CAP speed	0.7	0.75	Mach
Red CAP speed	0.7	0.75	Mach
Blue aircraft concept (type)	1	2	-
Whether there are six blue aircraft (0) or not (1)	0	1	-

3.2 Simulation Results

With the 240 cases defined by the LHS, 7,200 simulations were carried out, generating the data reports for analysis. Each run stopped after all aircraft had been destroyed or a simulation time of 30 minutes had been reached, which is a regular time of BVR air combat engagements. Since the simulations ran faster than in real-time, these 30 minutes took only an average of 5 seconds to be run, totaling 10 hours for the whole experiment. The first dataset generated concerns the number of surviving aircraft after each run. It also contained the total number of missiles fired by the design case but no data concerning the firing conditions. In the second dataset, on the other hand, the focus was primarily on the firing conditions, presenting the positions of the shooter and the target at the moment of launch and the distance and the off-boresight angle between them (line of sight). Since the models used for the simulation are still restricted, the resulting datasets are also subject to restraints that preclude us from sharing them.

3.3 Variables

Using mutual information for selecting features in supervised models (Battiti 1994), we chose 12 variables from the 28 initial variables in the dataset after considering their distribution, correlation analysis, and operational importance as input and output variables of the proposed models. Table 3 describes the 11 features and 1 target variable used in this work's supervised machine learning models, considering the moment that the shooter aircraft launches the missile towards the target aircraft.

Table 3: Description of the model's input and output variables.

Variables	Unit	Description
radar_track_range	km	Radar track range
distance	km	Distance between aircraft
missile_act_dist	km	Missile activation distance
delta_altitude	m	Difference between aircraft altitudes
delta_speed	kt	Difference between aircraft speeds
missile_range	-	Missile range multiplicative factor
rcs	m^2	Radar cross section
firerange	%	Percentage of WEZ
angle_uni_to_tgt	°	Off-boresight angle between aircraft
delta_heading	°	Difference between aircraft headings
concept	-	Which blue aircraft concept type was employed (1 or 2)
kill	-	Whether the target aircraft was killed by the missile

3.4 Hypeparameters Tuning

We created all the models using the Scikit-learn library, except the XGBoost model that has its library (Chen and Guestrin 2016), and, unless otherwise stated, with its default settings for their hyperparameters (Pedregosa et al. 2011). We perform the grid search algorithm as the technique for tunning all models since we want to use our experience from previous works to find the best set of values, even though it is well-known that random search may avoid the drawbacks of regular intervals (Bergstra and Bengio 2012).

The LR model is using the default Scikit-learn hyperparameters except for C $= 100$, which is the inverse of regularization strength, after performing a grid search exploring in $\{10^{-3}, 10^{-2}, 10^{-1}, 10^{0}, 10^{1}, 10^{2}, 10^{3}\}$.

Regarding the KNN model, we chose 12 for its hyperparameter n_neighbors, which is the number of neighbors, after checking different values (from 1 to 50) and keeping track of the error rate for each of these models to find the minimum value.

Concerning the SVM model, we searched for C, which defines the amount of violation of the margin allowed, in $\{0.1, 1, 10, 100, 1000\}$ and gamma, a parameter that must be specified to the learning algorithm, in $\{1, 0.1, 0.01, 0.001, 0.0001\}$, resulting in C $= 10$ and gamma $= 0.1$ as the best set.

In the ANN model, we explored learning_rate_init, the initial learning rate, in $\{0.001, 0.01, 0.1\}$, activation, representing the activation function for the hidden layer, in {logistic,tanh,relu}, solver, which is the solver for weight optimization, in {sgd,adam}, and alpha, the strength of the L2 regularization term, in $\{0.0001, 0.001\}$. After that, we found learning_rate_init $= 0.001$, activation = relu, solver = adam and alpha = 0.001 as the best set.

The NB model is operating the default except for var_smoothing $= 0.002$, which represents the part of the most significant variance of all features that is added to variances for calculation stability, found after running the grid search trying 100 different values spaced evenly on a log scale from 10^{0} to 10^{-9}.

In the RF model, we searched for max_features, the number of features to consider when looking for the best split in the model, in $\{2, 3, 4, 5, 6, 7, 8, 9, 10\}$, min_samples_leaf, the minimum number of samples required to be at a leaf node, in $\{3, 5, 8\}$, and min_samples_split, the minimum number of samples required to split an internal node, in $\{4, 8, 12\}$. The best hyperparameters set found was max_features $= 5$, min_samples_leaf $= 8$, and min_samples_split $= 4$.

In the XGBoost model, we inspect the best hyperparameters between gamma, the minimum loss reduction required to make a further partition on a leaf node, in $\{0.5, 1, 1.5\}$, subsample, the subsample ratio of the training instances, in $\{0.6, 0.8\}$, `colsample_bytree`, the subsample ratio of columns when constructing each tree, in $\{0.6, 0.8, 1.0\}$, and `max_depth`, the maximum depth of a tree, in $\{3, 4, 5\}$. The best set was `gamma` $= 1.5$, `subsample` $= 0.8$, `colsample_bytree` $= 0.8$ and `max_depth` $= 5$.

After finding each model's best set of hyperparameters, we applied all of the resampling techniques in the dataset using the Imbalanced-learn library (Lemaître et al. 2017) with its default hyperparameters.

3.5 Preprocessing

The main goal of standardizing features is to help the convergence of the technique used for optimization (Laurent et al. 2016), which we perform to use the algorithms SVM, ANN, KNN, and NB. Data scaling was employed to equally distribute the importance of each input in the learning process (Priddy and Keller 2005). Standardization is not required for LR, RF, and XGBoost models. Besides, we performed Exploratory Data Analysis (EDA) to identify the general data behaviors. The methods employed in this analysis were correlation and descriptive statistics analysis.

The effectiveness of the training phase of machine learning models can deteriorate if the training dataset is imbalanced, i.e., if there is not an adequate number of samples relating the values of the features for each of the classes (target values). Through the EDA, we verified this problem, as there were many more samples of the occurrence of shots belonging to class `NO KILL`, indicating the non-elimination of the target. Thus, we used resampling methods to increase the number of class `KILL` samples.

3.6 Models Training and Evaluation Process

Before performing any training process, we conducted a train-validate-test split, randomly separating the data, allocating 85% for training and validation using a 5-fold cross-validation technique and 15% for testing. The test dataset will allow the evaluation of the machine learning models later. We try every combination of values from the grid search proposed, calculating the performance metric f1-score using 5-fold cross-validation. The grid point that best fits the dataset is the optimal combination of the hyperparameters. After running all the algorithms with the imbalanced training-validate dataset and evaluating it, we perform resampling techniques to improve the number of samples of the minority class. We again employed all the supervised learning algorithms using their best set of hyperparameters with these new balanced datasets. As the model deals with a classification problem, we evaluated the model by observing the metrics accuracy, precision, recall, and f1-score (Géron 2019). The metrics results were acquired by analyzing the models' predictions and actual values in the test dataset.

4 RESULTS AND ANALYSIS

This section examines the exploratory data analysis, the test dataset metrics, and time inference of the proposed supervised machine learning algorithms with and without resampling techniques.

4.1 Exploratory Data Analysis

Table 4 shows an overview of the descriptive statistics of these model's inputs numerical variables. All the model's input variables follow a uniform distribution since these variables were sampled using the LHS.

Remember that one of the features (`concept`) and the target variable (`kill`) are categorical. The distribution of the input variable `concept` is almost equal, presenting 67,238 (43.78%) samples as `Type 1` and 86,368 (56.22%) samples as `Type 2`. On the other hand, the output variable `kill` is very imbalanced, presenting only 18,397 (11.98%) samples as `KILL` and 135,209 (88.02%) samples as `NO KILL`. This imbalance is due to the fact that many of the 240 simulation cases have generated challenging shooting conditions, which degraded the missile envelope. These conditions could be aircraft with large altitude and speed differences or low aircraft RCS coupled with large missile activation distances, among others.

Table 4: Descriptive statistics of the model's input numerical variables.

Variables	Mean	Std	Min	25%	Median	75%	Max
`radar_track_range`	217,375.7	40,219.6	150,289.2	182,961.3	214,907.9	251,175.8	285,788.2
`distance`	40,841.9	16,529.9	3,023.6	29,319.6	38,078.3	50,553.9	100,717.4
`missile_act_dist`	22,442.6	4,353.8	15,197.3	18,742.0	22,735.8	26,224.3	29,828.1
`delta_altitude`	768.6	2,357.6	-14,168.3	-655.3	641.8	2,284.2	13,573.3
`delta_speed`	12.2	71.7	-232.4	-38.0	16.6	63.1	263.3
`missile_range`	1.5	0.3	1.0	1.2	1.5	1.8	2.0
`rcs`	-0.1	5.8	-9.9	-5.3	-0.1	5.0	9.7
`firerange`	60.2	5.7	50.2	55.4	60.6	65.2	69.9
`angle_uni_to_tgt`	-0.8	21.8	-44.9	-9.0	0.0	4.6	44.9
`delta_heading`	181.9	77.1	-42.8	140.5	180.0	220.0	401.5

Pearson's correlation analysis of the variables can be seen in the correlation matrix represented in Figure 2. Notice that none of the model's features has a strong correlation with each other, with the largest absolute value being only 0.33 between `delta_heading` and `angle_uni_to_tgt`, and 0.31 between `missile_range` and `distance`. The algorithm's performance may deteriorate if two or more variables are tightly related, called multicollinearity (Dantas et al. 2021b). We may also be interested in the correlation between input variables with the output variable (`kill`) to provide insight into which variables may or may not be relevant as input for developing a model. Only the variable `distance` has a slight correlation (-0.22) with the target variable. The missile launch analysis is a complex non-linear problem that depends on multiple variables with a low correlation that corroborates the application of supervised machine learning algorithms since they may relate to all these variables.

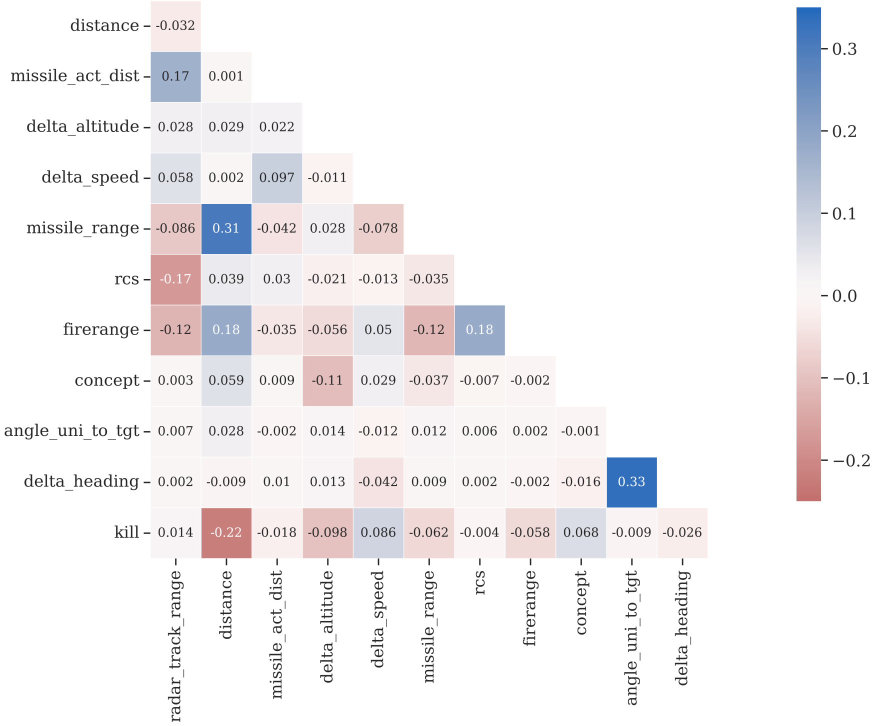


Figure 2: Pearson correlation matrix of all model variables.

4.2 Models Metrics

Table 5 shows the metrics, accuracy (ACC), precision (PREC), recall (REC) and F1-score (F1), and the inference time (IT) in milliseconds (ms) obtained after evaluating the test dataset on the supervised machine learning models using or not resampling techniques. Regarding the accuracy, we expect at least metrics better than 0.880, which is the proportion of the majority class in the imbalanced dataset. If the model consistently predicted the majority class, the accuracy would be 0.880. Thus, accuracy may not be the most appropriate metric for evaluating the models (Menardi and Torelli 2014). However, we notice a slight improvement in all models without resampling, except the LR model, with the RF models showing the best results with a low inference time regarding real-time applications (160.8 ms to predict the test dataset), as expected since this technique is quite suitable for imbalanced data (Khoshgoftaar et al. 2007). Precision, recall, and f1-score can better assess this problem (Jeni et al. 2013).

In general, the resampling techniques such as oversampling methods or hybrid approaches, using oversampling and undersampling techniques together, increased recall and f1-score with a slight decline in the accuracy and precision. Thus, considering it is an imbalanced dataset, each supervised machine learning model and the corresponding resampling technique must be applied in different situations, depending on the interest of having a greater precision or recall, which depends on the actual application of that model.

Low precision refers to cases where models are erroneously reporting that the missile would succeed if launched, but that does not happen in reality. Regarding costs associated with modern air combat, models with high precision avoid unnecessary missile launches and help maintain the aircraft's capability since there is a limit to the number of missiles to be loaded on the aircraft in a regular air combat operation.

Low recall refers to cases in which the model suggests that the missile would not hit the target aircraft if launched in a given condition, recommending not fire at that moment, though, in reality, that missile would have hit the target aircraft successfully if launched. As target neutralization is a critical factor in BVR air combat, not launching a missile that would probably hit a particular target is a massive issue that good pilots try to avoid, which shows the importance of having a high recall. The F1-score, the harmonic mean of precision and sensitivity, synthesizes the model's performance more broadly. The model using RF and SMOTE obtained the best f1-score overall with low inference time as well (108.3 ms), compared to the worst inference time from the model using KNN and SMOTE (5194.4 ms).

Therefore, we observe that the SVM model without resampling techniques presents the best precision results (0.716), even though it has one of the worst recall metrics. XGBoost and RF models also offer good precision, 0.648 and 0.686 respectively, and low recall, both around 0.250. Considering the analysis of the recall metric itself, in all the models, ADASYN and SMOTE-ENN brought the best increase in this metric. In ANN models, which showed the highest recall value, the ADASYN technique allowed a 224.30% increase in the recall, going from 0.251 to 0.814. In the LR models, the increase was from almost null recall values to values that reached 0.711 using SMOTE-ENN. Thus, resampling techniques demonstrated the capacity to increase the recall metric, even with a slight decrease in accuracy and precision.

Table 5: Supervised learning classification models metrics and inference time.

MODEL	ACC	PREC	REC	F1	IT[ms]	MODEL	ACC	PREC	REC	F1	IT[ms]
LR	0.877	0.421	0.003	0.006	1.4	ANN + SMOTE-TL	0.757	0.300	0.744	0.428	157.0
LR + SMOTE	0.655	0.215	0.685	0.327	1.1	ANN + SMOTE-ENN	0.730	0.283	0.784	0.416	35.7
LR + ADASYN	0.646	0.212	0.694	0.325	1.3	NB	0.884	0.672	0.096	0.168	4.3
LR + SMOTE-TL	0.661	0.217	0.676	0.328	1.3	NB + SMOTE	0.641	0.208	0.690	0.320	5.0
LR + SMOTE-ENN	0.625	0.204	0.711	0.317	1.1	NB + ADASYN	0.599	0.196	0.736	0.310	3.3
KNN	0.889	0.639	0.208	0.314	3903.1	NB + SMOTE-TL	0.641	0.208	0.691	0.320	3.3
KNN + SMOTE	0.763	0.296	0.678	0.412	5194.4	NB + SMOTE-ENN	0.590	0.194	0.743	0.307	3.2
KNN + ADASYN	0.730	0.272	0.721	0.395	4970.0	RF	0.895	0.686	0.262	**0.379**	**160.8**
KNN + SMOTE-TL	0.763	0.297	0.685	0.414	5090.1	RF + SMOTE	0.851	0.415	0.528	**0.465**	**108.3**
KNN + SMOTE-ENN	0.725	0.273	0.750	0.400	4632.8	RF + ADASYN	0.844	0.401	0.551	0.464	175.8
SVM	0.891	0.716	0.185	0.294	266.5	RF + SMOTE-TL	0.848	0.408	0.537	0.463	350.0
SVM + SMOTE	0.766	0.308	0.729	0.433	654.7	RF + SMOTE-ENN	0.809	0.351	0.664	0.459	35.2
SVM + ADASYN	0.722	0.276	0.785	0.409	752.8	XGBoost	0.892	0.648	0.255	0.366	17.1
SVM + SMOTE-TL	0.766	0.307	0.727	0.432	614.5	XGBoost + SMOTE	0.826	0.368	0.593	0.454	6.6
SVM + SMOTE-ENN	0.737	0.287	0.775	0.419	321.345	XGBoost + ADASYN	0.811	0.347	0.615	0.444	6.4
ANN	0.890	0.638	0.227	0.335	116.6	XGBoost + SMOTE-TL	0.825	0.369	0.609	0.459	6.2
ANN + SMOTE	0.765	0.308	0.735	0.434	94.4	XGBoost + SMOTE-ENN	0.791	0.332	0.699	0.450	6.8
ANN + ADASYN	0.703	0.267	0.814	0.402	163.1						

5 CONCLUSIONS AND FUTURE WORK

This work compares the application of supervised machine learning methods, using resampling techniques to improve the predictive model, on data from air combat constructive simulations to improve the effectiveness of missile launching, and demonstrates the differences in the performance of these several different models.

Without resampling, XGboost and RF brought the most consistent results considering the f1-score. Concerning all oversampling methods or hybrid techniques using oversampling and undersampling techniques, it is possible to indicate that these techniques increase recall and f1-score with a slight decline in accuracy and precision. The model with the best performance, considering the f1-score, without using any resampling techniques was RF which brought 0.379, with an inference time of 160.8 milliseconds regarding the time to predict the test dataset. After employing SMOTE, the RF model got 0.465, the best overall f1-score, increasing 22.69%.

Therefore, since obtaining real air combat data is quite problematic, we show through data obtained through constructive simulations that it is possible to develop decision support tools that may improve flight quality in BVR air combat since they are trying to support effective missile launches. We can use these models in the attempt to enhance the missile launching process by unmanned combat aerial vehicles or aid pilots in real air combat scenarios, increasing the effectiveness of offensive missions.

For future work, we suggest analyzing different scenarios with multiple aircraft equipped with other missiles, which can bring less deterministic simulations. Also, we recommend studying not just the missile launching moment but a sequence of several timeframes to understand better the coordination of the future events of a specific air combat scenario. Besides, since the hyperparameter space for the classifiers is not complete due to computational cost, we propose expanding the grid search space for all supervised machine learning models or, at least, for the models that delivered better results. Finally, we recommend developing more suitable design sampling strategies that allow the choice of other input variables with much more simulation runs to improve the dataset to be analyzed, which can bring more reliability and generalization to the results to enhance the pilot's in-flight situational awareness.

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