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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 beyond visual range air combat constructive simulations to estimate the most effective moment for launching missiles. We employed resampling techniques to improve the predictive model, and we could identify the remarkable performance of the models based on decision trees and the significant sensitivity of other algorithms. 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%, and with an appropriate time inference. 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 air combat, increasing the effectiveness of offensive missions to hit a particular target.

1 INTRODUCTION

We 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 run through a commercial off-the-shelf framework (FLAMES (Ternion 2022)). Since running the simulations is computationally demanding, machine learning methods can streamline the missile success predictions for 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.

We model the estimation of the most effective moment for firing missiles in BVR air combat simulations as a classification problem, employing some of the most relevant supervised machine learning methods: 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).

2 RESULTS

Table 1 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.

Table 1: 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						

Without employing resampling techniques, XGboost and RF brought the most consistent results considering the f1-score. Concerning all oversampling or hybrid methods, 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%.

3 CONCLUSIONS

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 an 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 not just the missile launching moment but a sequence of several timeframes to understand better the coordination of future events in the air combat scenario.

REFERENCES

Batista, G. E. A. P. A., R. C. Prati, and M. C. Monard. 2004. "A Study of the Behavior of Several Methods for Balancing Machine Learning Training Data". *SIGKDD Explorations Newsletter* 6(1):20–29.

Chawla, N. V., K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. 2002. "SMOTE: Synthetic Minority Over-Sampling Technique". *Journal of Artificial Intelligence Research* 16:321–357.

Géron, A. 2019. *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. 2nd ed. Sebastopol: O'Reilly Media, Inc.

He, H., Y. Bai, E. A. Garcia, and S. Li. 2008. "ADASYN: Adaptive Synthetic Sampling Approach for Imbalanced Learning". In *IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, June 1st–8th, Hong–Kong, China, 1322–1328.

Ternion 2022. "FLAMES Development Suite". https://flamesframework.com/. Last accessed 25 July 2022.

Tomek, I. 1976. "Two Modifications of CNN". *IEEE Transactions on Systems, Man, and Cybernetics* 6(11):769–772.

Wilson, D. L. 1972. "Asymptotic Properties of Nearest Neighbor Rules Using Edited Data". *IEEE Transactions on Systems, Man, and Cybernetics* 2(3):408–421.