Computer Vision Based Areal Photographic Rocket Detection using YOLOv8 Models

Luka Jovanovic[1], Milos Antonijevic[1,†], Jasmina Perisic[2,†], Marina Milovanovic[2,†], Zivkovic Miodrag[1,†], Nebojsa Budimirovic[1,†] and Nebojsa Bacanin[1,†,*]

[1]*Singidunum University, Danijelova 32, Belgrade, 11000, Serbia*

[2]*Faculty of Informatics and Computer Science, Union - Nikola Tesla University, Cara Dusana 62-64, Belgrade, 11000, Serbia*

Abtract: Advances in aerospace engineering and aerodynamics have pioneered space exploration and helped support telecommunication infrastructure. But these same developments have also aided in the creation of weapons of devastating impact. This necessitates the development of ways for detecting and tracking rockets. While several methods, mostly based on Doppler radar exist, the need for active radio emissions limits the applicability of these systems. A passive system has several advantages over traditional techniques, however their potential is largely unexplored. This work seeks to tackle this research gap by exploring the potential of emerging computer vision townies applied to rocket detection and tracking. The advantages of such a system are the relatively low cost as well as passive nature making observation stations harder to detect and easier to deploy. This work explores the potential of pre-trained, lightweight YOLOv8 architectures for rocket detection in real-world situations. A publicly available dataset is utilized and a comparative analysis is carried out between nano and small models. Both models demonstrate favorable outcomes with an accuracy of 0.90 for rocket body detection and 0.93 for engine flame detection. Nevertheless, rocket detection into space is still difficult, with a precision of 0.64 for this class. This paper indicates areas for additional refinement and demonstrates the potential of computer vision technology in passive rocket detection.

Keywords: Rocket detection, You only look once, Computer vision, Classification, Space.

1. INTRODUCTION

Rocket science, which is the study and application of rockets, plays a vital role in modern space exploration and satellite deployment. Through rocket engineering, mankind has been able to go beyond Earth and examine distant celestial planets thereby going beyond the boundaries of this planet. For instance, launching vehicles with scientific instruments to examine the Moon, Mars and further or farthest objects in outer space is dependent on it. Besides launching satellites that provide better pictures than those taken from the surface of Earth, rockets are also useful in positioning telescopes and other observational instruments into orbit. Apart from space research, satellite infrastructure establishment and maintenance depend on rocketry. Globally, satellites are used for communication systems serving numerous services like TV transmission, internet usage support, or global positioning systems (GPS). These satellites connect people on a global basis reducing distances between them thus enhancing international trade as well as collaboration. Furthermore, rocket technology developments have made rocket launches cheaper thereby expanding access to outer space for business ventures and facilitating growth of new industries such as asteroid mining and space tourism. Overall rocket technology is at the core of our efforts to discover outer space and improve intercontinental connectivity.

International rules precisely control rockets to guarantee their responsible and safe usage. These rules are meant to stop missile technology from expanding, safeguard the environment, and guarantee the safety of people living on Earth as well as of space missions. Furthermore, the Missile Technology Control Regime (MTCR)[1] seeks to stop the possible spread of missile and unmanned aerial vehicle technologies able to deliver a 500 kg payload at least 300km, therefore reducing the possibility for missile proliferation. Together with these international accords, national rules specify strict safety criteria and monitoring for rocket launches, therefore guaranteeing that operations in space are carried out with the best respect for environmental sustainability and international security.

Although they are essential for satellite deployment and space research, rockets are often used for less moral goals in military operations where they act as weapon delivery platforms. The great risks that rockets use in combat call for the creation of sophisticated defensive systems meant to offset these hazards. Developed to intercept and detonate incoming rockets,

*Address correspondence to this author at the Singidunum University, Danijelova 32, Belgrade, 11000, Serbia; E-mail: nbacanin@singidunum.ac.rs

[†]These authors contributed equally to this work.

[1]https://www.mtcr.info/en

anti-missile defense systems provide a vital layer of protection against missile strikes. However, the success of these defensive systems mostly depends on early, precise detection of rocket launches. Radar and satellite-based surveillance are among the advanced detection technologies that are most important for seeing and following rocket threats in real-time, therefore enabling quick and efficient countermeasures [1]. This emphasizes the need for identification in preventing the use of rocket technology and guaranteeing national security.

Although it is currently mostly unexplored, the use of computer vision in rocket detection offers a reasonably affordable substitute for costly systems depending on radio and radar technology. Conventional rocket detection systems depend on advanced radar and satellite monitoring equipment [2], which may be rather costly and demand major maintenance and running expenses. By use of cameras and sophisticated image processing techniques, computer vision-based systems also identify and track rockets. By using already-existing aerial or satellite imaging infrastructure, these technologies greatly lower the cost and maintenance complexity involved in implementation. Moreover, developments in machine learning, especially in object identification models (like YOLOv8), have improved the accuracy and speed of image-based detection systems, therefore making them practical for real-time uses. This makes computer vision an appealing choice for improving rocket detection capacities as it provides a scalable and reasonably priced solution that may either complement or even replace conventional radar-based systems. While several methods, mostly based on Doppler radar exist, the need for active radio emissions limits the applicability of these systems. A passive system has several advantages over traditional techniques, however their potential is largely unexplored. This motivated this work seeking to address the observed literature gap. The basic research question this work seeks to answer is whether YOLOv8 architectures have the capabilities needed for rocket detection and tracking from image data.

The scientific contributions of this work may be summarized as the following:

- Exploring the potential of emerging computer vision technologies for passive rocket detection.
- Investigating the use of the lightweight YOLOv8 architecture for rocket detection in images.
- Proposing a passive rocket detection system based on lightweight YOLOv8 architectures.

The remainder of this work follows the outline structure: Section 2 discusses preceding works in literature and outlines the observed literature gap addressed in this work. Section 3 presents a discussion of the methodology utilized in this work. The simulation setup is presented in Section 4 with outcomes presented and discussed in Section 5. The work is concluded with Section 6.

2. RELATED WORKS

Since Unmanned Aerial Vehicles (UAVs), also referred to as drones, started to be accessible for public usage, the risk of misuse is greatly increased. Many researchers in the literature investigated many methods and created hybrid and original systems to fight UAVs. In this research [3] the detection and localization using radar systems approach are addressed. Apart from widely used localization techniques for UAVs, this study also reviews the methods of hardware and software implementation. The increasing number of UAVs raises significant questions about how to do efficient and automated detection to stop illegal flying. The traditional constant false alarm rate-based detectors often experienced poor performance on tiny UAV identification owing to the weak signal, while they are highly reliant on certain human expertise like the ambient noise distribution estimate and the size selection of the detection windows. Authors in their work [4] investigate a DL-based UAV detection approach in pulse-Doppler radar. They suggest a two-head convolutional neural network (CNN) for the regression of offset between the target and the patch center and the categorization of the input range-Doppler map patch into target present or target missing. Whether natural orbital decay is in question or deliberate debris removal, precise information on the status of the target is very vital during deorbiting. Accurate determination of satellite and space debris orbits as well as comprehensive radar photographs of them is made possible by the Tracking and Imaging Radar (TIRA). In their paper [5], scholars analyze the state and attitude movements of satellites and space junk using 3D modeling of inverse synthetic aperture radar (ISAR) pictures collected with TIRA.

Effective rocket detection using radar and Doppler technologies frequently requires high-cost equipment. These systems make significant infrastructure expenditures, complex signal processing techniques, and powerful radar hardware. Such systems' creation, implementation, and maintenance might be excessively costly, therefore restricting their availability and general acceptance. The need for modern radar systems to generate signals for detection limits one major aspect of them. This radiance of radar waves might unintentionally expose the position of the radar system itself, therefore providing a target for countermeasures or strikes. For example, even if active radar systems provide real-time tracking and comprehensive knowledge about rocket trajectories, their signal emissions might be picked by enemies, therefore undermining the stealth and security of the monitoring system. Radar systems may also suffer from limited range, clutter from ambient elements, and trouble differentiating between many kinds of flying objects. These constraints force constant development and integration of artificial intelligence (AI) and machine learning (ML) methods to raise detection accuracy and lower false alarms.

Computer vision is the ability of computers to identify, evaluate, and comprehend visual data from their surroundings, like images and movies among other things [6]. Being a completely passive system, it only collects and interprets data gathered by sensors or cameras without changing the condition of the things it studies or directly interacting with them. There are several benefits of this passive character. First of all, computer vision retains the item's natural condition and function as it has no effect on it. This is vital in disciplines such as medical diagnostics and scientific research where object integrity is absolutely important. Furthermore, computer vision provides real-time analysis and constant monitoring, thereby enabling applications such as face identification, motion detection, and surveillance-free of human involvement, hence improving analytical accuracy and speed. At last, the ability of computer vision to examine intricate visual data may reveal important insights that would be hard for people to identify, therefore improving decision-making and providing more sensible answers in many different fields.

One of the main technologies driving contemporary transportation, autonomous driving, is gradually changing the modes of human movement. Vehicle detection is a major area of study in this field that spans many disciplines, including sensor technology and computer vision, interacting here. Authors in the paper [7] offer a thorough overview of current vehicle detection systems along with their pragmatic uses in the domain of autonomous driving. Including those based on machine vision, LiDAR, millimeter-wave radar, and sensor fusion, more than 200 classical and current vehicle detection methods are detailed. Using the YOLO-v5 architecture, another work [8] demonstrates vehicle identification and classification on publicly accessible datasets. The results of this work use the transfer learning theory by fine-tweaking the weights of the pre-trained YOLO-v5 architecture. Using the idea of transfer learning, the writers gathered large amounts of photographs and videos of the crowded traffic patterns. Using deep learning-based object detection is a good way to help visually challenged people avoid hazards. In other work [9], seven different YOLO object detection models-including YOLO-NAS (small, medium, large), YOLOv8, YOLOv7, YOLOv6, and YOLOv5 are evaluated with carefully tuned hyperparameters to examine how these models performed on images including common daily-life objects presented on roads and sidewalks. YOLOv8 turned out to be the best model. In their paper [10], authors evaluate the performance of the YOLOv8 model for drone identification issue. To find the ideal architectural size for this challenge, five different model sizes were investigated. Several recent applications of YOLOv8 models have been explored in recent literature as well [11-14].

Computer vision has multiple limitations even if it has amazing powers. Its huge processing power needs to provide one major obstacle. Especially when working with high-resolution photos or video streams, analyzing and understanding complex visual information often requires large processing resources. Furthermore, reliable outcomes with computer vision depend mostly on image quality and suitable labeling. Practically, getting high-resolution pictures and guaranteeing accurate labeling may be time-consuming and expensive, therefore perhaps restricting the system's efficiency. Selecting appropriate architectures and hyperparameters while training computer vision models will help to solve these constraints. The performance and efficiency of the system may be much improved by selecting the appropriate model architecture, such as convolutional neural networks (CNNs), and by fine-tuning hyperparameters such as learning rates and batch sizes. More efficient and useful computer vision applications result from better balancing of the trade-offs between processing power, picture quality, and labeling accuracy by appropriate model selection and optimization. More efficient and useful computer vision applications result from better balancing of the trade-offs between processing power, picture quality, and labeling accuracy by appropriate model selection and optimization.

In recent years several complex challenges have been effectively address though the application of AI algorithm [15-17]. Challenges associated with human readable text such as determining sentiment of comments and detecting phishing emails [18-20] are amount some of the more popular. Energy forecasting is yet another breach of computer science that has benefited form the integration of AI [21-23]. Additionally, sound analysis is an emerging branch of AI research [24-26]. Nevertheless the application of AI is not without challenges [27-29]. Algorithms are often designed and published with the goal of generalizability, with the goal being that many problems can be addressed in the defaults state of the algorithm [30, 31]. However, when applied to specific problems this can somewhat limit performance. Therefore hyperparameter tuning is often applied applied [32-34].

Using hybrid techniques that mix metaheuristics with machine learning models is one efficient way to solve the various optimization challenges [35-37]. Inspired by natural processes, such as swarm optimization or evolutionary algorithms, metaheuristics are optimization strategies meant to improve the performance and efficiency of machine learning models [38-40]. A hybrid method may, for instance, maximize the architecture and hyperparameters of a CNN used in computer vision applications using evolutionary algorithms [41-44]. The use of CNN has also found several applications outside of computer vision as well [45-47].

The use of computer vision for rocket detection remains little investigated in the present literature and shows a notable research gap. Though computer vision technologies have advanced and are used extensively in many other industries, there is a dearth of thorough research concentrating especially on rocket detection. Given the special difficulties presented by their fast-moving and frequently erratic trajectories, this discrepancy emphasizes the necessity of comprehensive research on how computer vision may be efficiently used to detect and track rockets. This paper attempts to close this discrepancy by building a baseline for rocket detection using computer vision methods. The objective is to provide a strong basis from which other researchers and practitioners may develop, thereby producing more accurate and dependable rocket detection systems.

3. METHODS

YOLO architecture-based solutions are fast and accurate. Their innovative technique predicts bounding boxes with probabilities for each class by just analyzing an image once [48]. This model predicts position and category using raw images, unlike two-stage detectors that make real-time applications practical. Data augmentation, transfer learning, and fine-tuning improve YOLO generalization. Use cases with great variety may be improved using these methods.

YOLO model object detection uses a single network to identify areas, orientations, and sizes without using distinct models. The backbone, neck, and head make up the single-stage YOLO detector. The backbone extracts low-level and high-level characteristics, the neck combines them, and the head predicts object location and class. The semantic information of characteristics increases with this approach. Grids in images anticipate item position and bounding boxes. This permits object identification with one inference by treating the issue as a single regression. Each bounding box outputs the object's potential coordinates and probability in five dimensions. The center point, width, height, and likelihood that the item is in that box are the dimensions. Transfer learning is crucial to YOLO architecture. These models are pre-trained in different sizes. Additionally, models may categorize, track, segment, and identify postures.

3.1. YOLOv8

New YOLO models are produced and improved fast. New features and approaches to increase performance, flexibility, and efficiency have been included in its upgraded forms. YOLOv8 supports computer vision tasks like object recognition, segmentation, posture estimate, tracking, and classification, the same as past models. The variety and freshness of this approach inspire people to try and implement it in other spheres. YOLOv8 boasts faster speed and more accuracy than earlier versions.

Comparing many model sizes allows one to assess this using mAP (mean average precision) value and inference speed. New models include YOLOv8-seg for segmentation tasks, YOLOv8-pose for pose estimation, and YOLOv8-cls for classification. YOLO became a more flexible tool because of this feature. One uniqueness is integrating with Roboflow, ClearML, Neural Magic, and Comet systems. Tasks related to dataset labeling, training, visualization, and model maintenance benefit from these platforms. Furthermore included is Ultralytics HUB, a brand-new tool offering a complete solution for data visualization, model training, and model implementation. Usually, pre-trained datasets are trained using Open Image V7 and COCO datasets. Variations exist in mAP levels and inference speeds.

Published in February 2024, the most recent YOLO version, the YOLOv9 model, is Rich in fresh ideas like the Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI), the new model Comparatively to the MS COCO dataset, the model architecture of YOLOv9 [49] achieves a higher mAP than current popular YOLO models including YOLOv8, YOLOv7 and YOLOv5.

4. EXPERIMENTAL SETUP

The introduced approach is evaluated on publicly available real-world data [50]. The utilized dataset consists of 28149 images total and constitutes a three-class problem. Detection of engine flames, labeled as class 0 in the dataset, rocket bodies labeled as 1 in the dataset, and "space" denoting tiny specks in the sky being rockets following Ascension into space. 24435 images are used to facilitate model training (around 89%), 2428 for validation (around 9%), and a total of 1286 images (around 5%) are reserved for model evaluation. The dataset comes with predefined data separations for each stage.

Partially pre-trained YOLOv8 model architectures are prepared using the data described above. Each model is trained using default training parameters with 15 allocated training epochs. Evaluations are carried out using the following metrics:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{1}$$

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{2}$$

$$mAP@50 = \frac{1}{n}\sum_{i=1}^{n} AP_i^{(50)} \tag{3}$$

$$mAP@95 = \frac{1}{n}\sum_{i=1}^{n} AP_i^{(95)} \tag{4}$$

where n denotes the number of classes, mAP@50 is the average precision for class i at a threshold of 0.5, and mAP@95 where the threshold is 0.95.

5. SIMULATION OUTCOMES

The following section describes the simulation outcomes. The outcomes of the nano architecture are presented first. These are followed by the outcomes attained by the small model architecture.

5.1. YOLOv8 Nano Model Simulations

Outcome metrics during training for the nano model are prided in Table **1**. Class loss stagnates around the 15th training epoch. Further detailed metrics in terms of precision, recall, mAP50, and mAP50-95 are provided

Table 1: YOLOv8 Nano Model Training and Validation Outcomes in each Epoch

epoch	train/box_loss	train/cls_loss	train/dfl_loss	val/box_loss	val/cls_loss	val/dfl_loss
1	1.6117	2.09110	1.20960	1.5004	1.27720	1.13890
2	1.5517	1.23020	1.19210	1.5076	1.14240	1.15230
3	1.5146	1.11470	1.17920	1.4294	0.99703	1.13890
4	1.4588	1.03310	1.14590	1.3937	0.91307	1.09170
5	1.3990	0.94683	1.11930	1.3346	0.83019	1.06060
6	1.3719	0.86985	1.09950	1.3009	0.81756	1.05110
7	1.3194	0.80643	1.07730	1.2974	0.77347	1.04030
8	1.2796	0.76251	1.05860	1.2227	0.71568	1.02110
9	1.2440	0.71949	1.03700	1.1815	0.68469	1.00440
10	1.2104	0.68530	1.02370	1.1766	0.66378	1.00540
11	1.1726	0.64564	1.00580	1.1381	0.63011	0.98908
12	1.1396	0.61856	0.99151	1.1216	0.61309	0.98202
13	1.1038	0.58686	0.97970	1.1015	0.58497	0.97739
14	1.0751	0.56003	0.96786	1.0929	0.57157	0.97192
15	1.0459	0.53685	0.95294	1.0753	0.55229	0.96608

Table 2: YOLOv8 Nano Model Detailed Metrics on Tasting Data in each Epoch

epoch	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)
1	0.59645	0.58013	0.60189	0.30233
2	0.58321	0.62473	0.64460	0.32373
3	0.69036	0.64193	0.68642	0.35526
4	0.74560	0.65727	0.71019	0.37728
5	0.70528	0.71309	0.73604	0.40247
6	0.78083	0.67954	0.73939	0.40853
7	0.75213	0.71370	0.76065	0.42624
8	0.79123	0.73057	0.77358	0.44084
9	0.78184	0.74419	0.78008	0.45429
10	0.80976	0.76031	0.80347	0.47087
11	0.83553	0.76214	0.80821	0.47931
12	0.84536	0.76699	0.82133	0.49132
13	0.85619	0.77653	0.82980	0.50257
14	0.84478	0.79327	0.82657	0.50569
15	0.85771	0.79670	0.84294	0.51542

in Table **2**. Precision peaks with a score of 0.85771 in the 15th iteration. Similarly recall recall a maximum of 0.79670. A MAP of 0.84294 is attained at a 0.51542 for mAP50-95. This is to be somewhat expected as the mAP50-95 has a much higher criterion for detection.

Visual plots of the training and validation metrics, as well as detailed metrics, are provided in Table **1**. A spike in early dfl_loss can be observed. However, this is resolved in later iterations. In terms of validation outcomes metrics in terms of precision recall and mAP50 and 96 show constant convergence during training reaching a precision exceeding 85%.

The PR curve and confusion matrix for the trained model are provided in Figure **2**. The confusion matrix suggests that the model performs well in detecting engine flames, attaining a precision of 0.92. Similarly, rocket bodies are detected with a precision of 0.90. Rockets in space are somewhat challenging for the

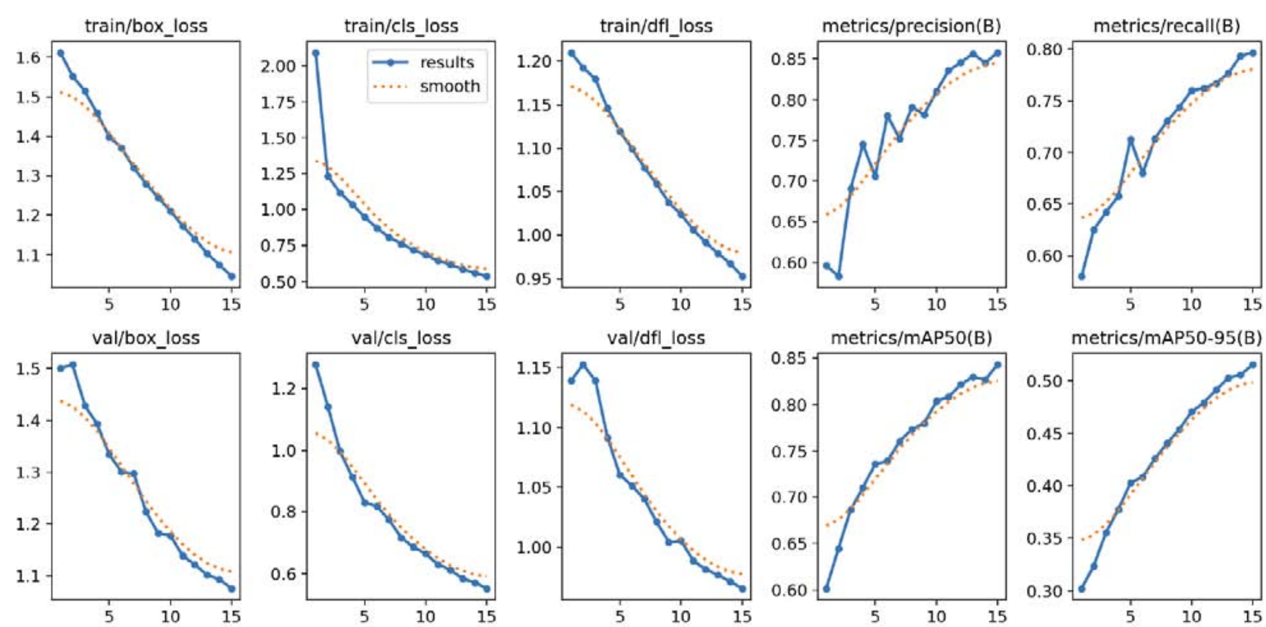

Figure 1: Nano model training and validation graphs.

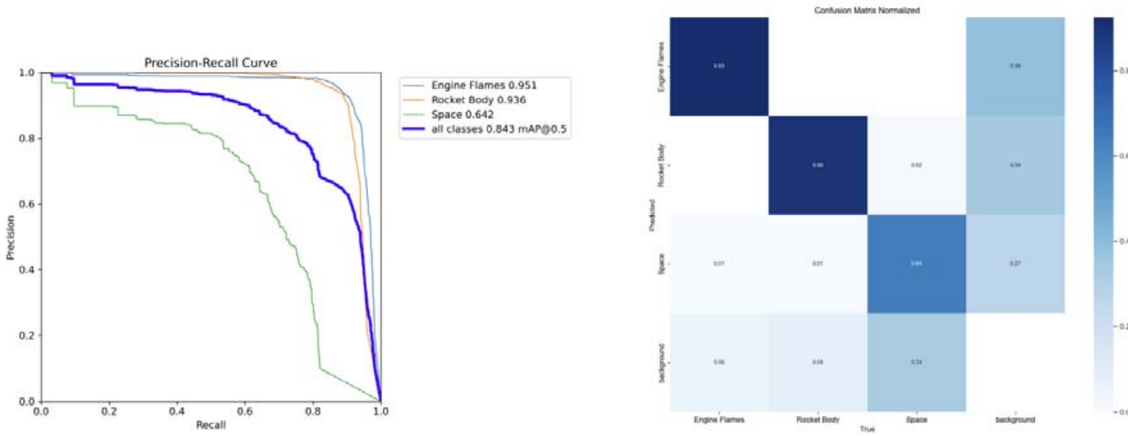

Figure 2: Nano model PR curve and confusion matrix.

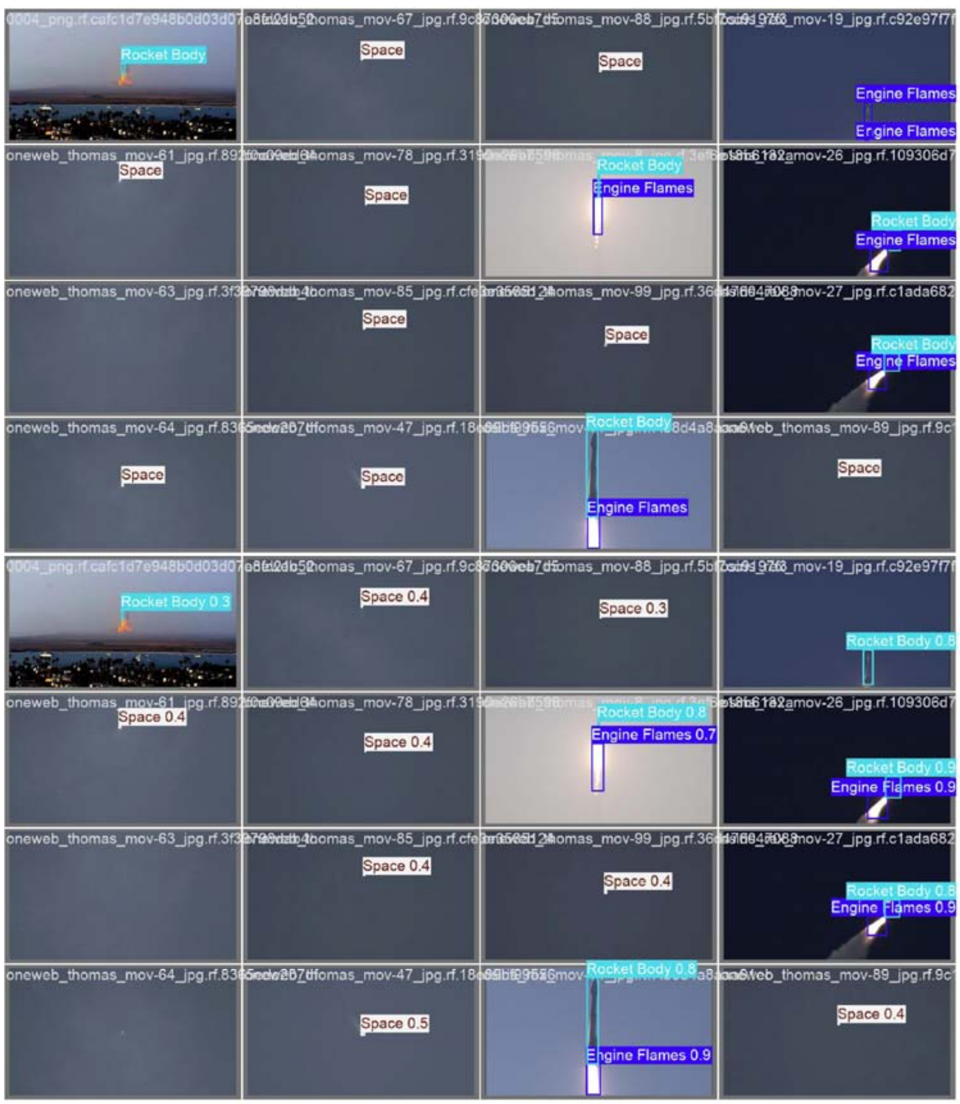

Figure 3: Nano model sample detection's and labels.

model attaining a precision of only 0.64. However, given the small dimension of the object in these cases, this is to somewhat be expected.

Samples of classifications with associated model confidence as opposed to ground truth labels are provided in Figure **3**.

Table 3: YOLOv8 Small Model Training and Validation Outcomes in each Epoch

epoch	train/box_loss	train/cls_loss	train/dfl_loss	val/box_loss	val/cls_loss	val/dfl_loss
1	1.5850	1.52820	1.27470	1.5691	1.51110	1.2783
2	1.5740	1.21440	1.27980	1.5478	1.15560	1.2723
3	1.5115	1.10950	1.24970	1.3894	0.96817	1.1854
4	1.4362	0.99644	1.20350	1.3475	0.85687	1.1447
5	1.3709	0.89933	1.16430	1.3250	0.80254	1.1121
6	1.3541	0.84220	1.16210	1.2669	0.75856	1.1062
7	1.3153	0.79147	1.14240	1.2908	0.74083	1.0898
8	1.2696	0.73841	1.11680	1.2104	0.69283	1.0644
9	1.2321	0.69871	1.09110	1.1618	0.65665	1.0545
10	1.1863	0.65938	1.07340	1.1263	0.62189	1.0380
11	1.1453	0.61158	1.05260	1.1052	0.59081	1.0336
12	1.1089	0.58096	1.03560	1.0814	0.57040	1.0272
13	1.0645	0.54645	1.01770	1.0672	0.54952	1.0164
14	1.0273	0.51621	1.00330	1.0516	0.53014	1.0105
15	0.9918	0.49134	0.98289	1.0400	0.51728	1.0099

5.2. YOLOv8 Small Model Simulations

Outcome metrics during training for the small model are prided in Table **3**. Class loss stagnates around the 15th training epoch. Further detailed metrics in terms of precision, recall, mAP50, and mAP50-95 are provided in Table **4**. Precision peaks with a score of 0.84701 in the 15th iteration. Similarly recall recall a maximum of 0.83300. A MAP of 0.86498 is attained at a 0.53888 for mAP50-95. An improvement in mAP scores can be observed over the outcomes attained by the nano model. Based on the attained outcomes further training is necessary to refine the small model and there is room for additional improvement in model outcomes.

Visual plots of the training and validation metrics, as well as detailed metrics, are provided in Table **4**. Due to the more complex architecture in comparison to the

Table 4: YOLOv8 Small Model Detailed Metrics on Tasting Data in each Epoch

epoch	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)
1	0.64730	0.48528	0.56456	0.28089
2	0.61515	0.56138	0.60788	0.30583
3	0.66877	0.66684	0.68195	0.35912
4	0.75531	0.68252	0.72662	0.39150
5	0.70574	0.70672	0.72807	0.40226
6	0.78040	0.73381	0.76945	0.43290
7	0.79730	0.73149	0.79158	0.44172
8	0.80060	0.75674	0.79038	0.45408
9	0.81648	0.76675	0.81106	0.47714
10	0.79882	0.76764	0.82525	0.49430
11	0.82246	0.77860	0.82680	0.50274
12	0.84899	0.79424	0.84732	0.51562
13	0.85054	0.81349	0.85163	0.52071
14	0.86119	0.80419	0.85947	0.53295
15	0.84701	0.83300	0.86498	0.53888

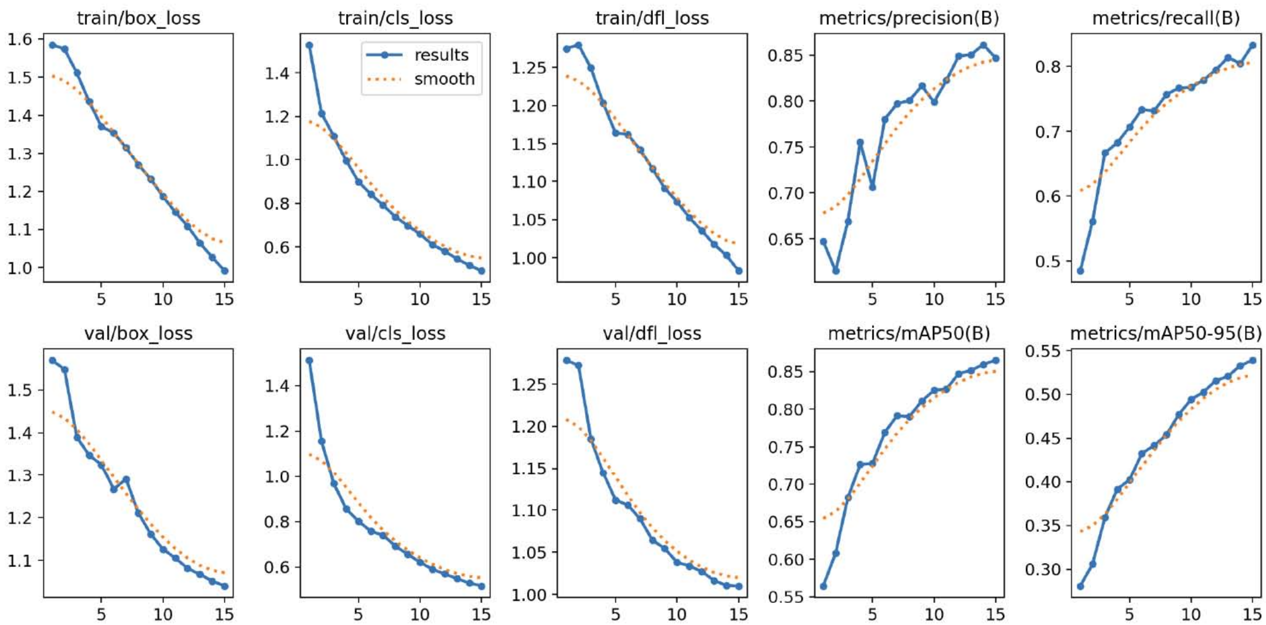

Figure 4: Small model training and validation graphs.

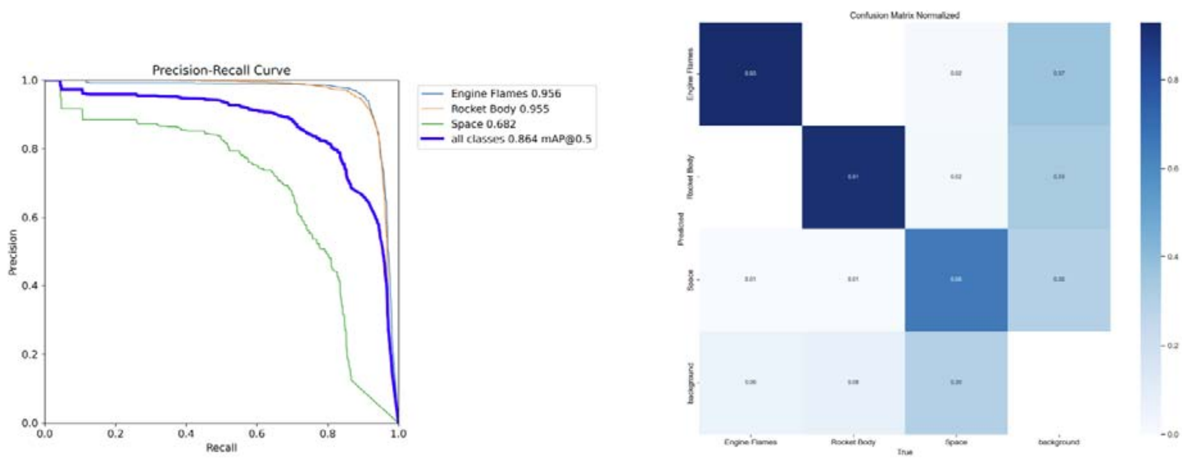

Figure 5: Small model PR curve and confusion matrix.

small model, training rates are somewhat stable with fewer spikes. However, several shifts in terms of precision on validation data. The model attains a precision score that is slightly below that of the nano model. While the complex architecture can address more subtle correlations in input data, it requires additional training epochs and additional training data to demonstrate favorable outcomes.

The PR curve and confusion matrix for the trained model are provided in Figure **5**. The model's precision for engine flames is matched between the nano and small models at 0.93. The small model performs marginally better for rocket body and space detection with respective scores of 0.91 and 0.66. While these results are somewhat better compared to the nano model, the increased computational costs for training and operations need to be considered when selecting a suitable model.

6. CONCLUSION

Advancements in rocketry have pioneered space exploration. Advances have helped push forward global telecommunications through satellite deployment. However, many of the same technologies that support these, can also be used as tools of conflict. Therefore, many tracking technologies have been developed to detect and identify rockets. Techniques such as Doppler radar have been in use since the Second World War with over-the-horizon radars developed since. Nevertheless, radio-based systems are active

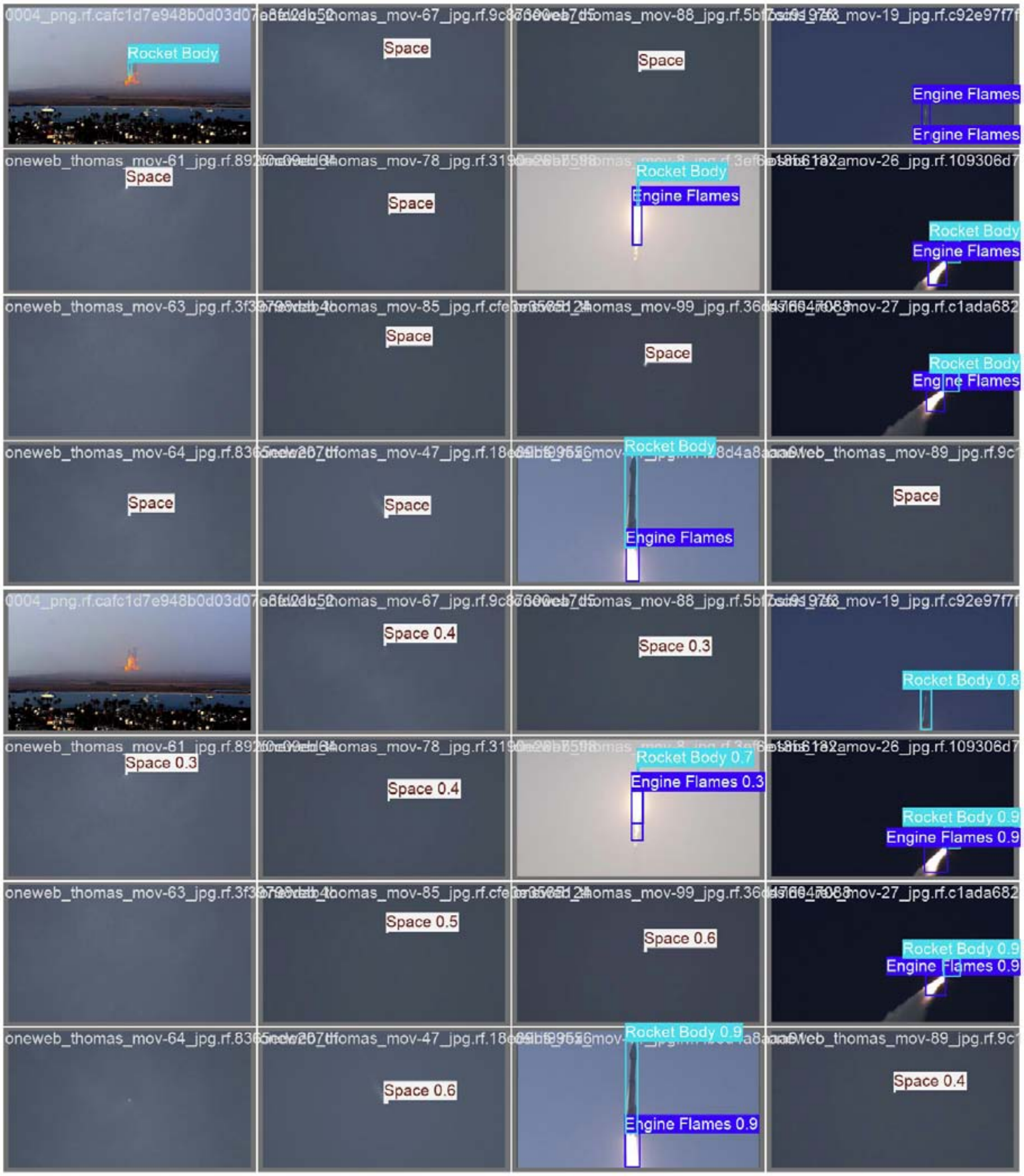

Figure 6: Small model sample detection's and labels.

transmission systems that give away their location in the radio spectrum, making them demanding in terms of power and easy to target. A passive computer vision-based system is a promising research topic as relatively cheap and simple cameras can potentially be used to track rockets in line of sight. This work explores the potential of emergent computer vision technologies for passive rockets and detection. The capabilities of lightweight pre-trained YOLOv8 architectures are evaluated on real-world data. Models demonstrate decent outcomes, with a precision of 0.93 for engine flame detection and 0.90 for rocket body detection. Rockets that have ascended into space can also be deleted as specks in images. This, however, is a tougher challenge with the model demonstrating a precision of 0.64 for the detection of this class.

As with any research this work faces certain limitations both practical and theoretical. Data availability, computational demands of training, and parameter optimization limit the extent of comparisons that can be conducted in a single study. Practical applications of the system are also limited by computational resource availability, image quality, and other external factors such as weather. Future works hope to explore how these factors influence the utilization of the porpoised system. Additionally, methods for optimizing model parameters improve training times as well as overall classification accuracy and outcomes.

REFERENCES

[1] Malanowski M, Borowiec K, Rzewuski S, Kulpa K. Detection of supersonic rockets using passive bistatic radar. IEEE Aerospace and Electronic Systems Magazine 2018; 33(1): 24-33. https://doi.org/10.1109/MAES.2017.160198

[2] Stone ML, Banner GP. Radars for the detection and tracking of ballistic missiles, satellites, and planets. Lincoln laboratory Journal 2000; 12(2): 217-244./

[3] Idhis SM, Dawdi T, Nasir Q, Talib MA, Omran Y. Detection and localization of unmanned aerial vehicles based on radar technology. In: Bianchini M, Piuri V, Das S, Shaw RN. (Eds.) Advanced Computing and Intelligent Technologies. Springer, Singapore 2022; pp. 429-452. https://doi.org/10.1007/978-981-16-2164-2_34

[4] Wang C, Tian J, Cao J, Wang X. Deep learning-based uav detection in pulse-doppler radar. IEEE Transactions on Geoscience and Remote Sensing 2022; 60: 1-12. https://doi.org/10.1109/TGRS.2021.3104907

[5] Karamanavis V, Dirks H, Fuhrmann L, Schlichthaber F, Egli N, Patzelt T, Klare J. Characterization of deorbiting satellites and space debris with radar. Advances in Space Research 2023; 72(8): 3269-3281. https://doi.org/10.1016/j.asr.2023.07.033

[6] Banerjee C, Nguyen K, Fookes C, George K. Physics-informed computer vision: A review and perspectives. ACM Comput Surv 2024. https://doi.org/10.1145/3689037

[7] Liang L, Ma H, Zhao L, Xie X, Hua C, Zhang M, Zhang Y. Vehicle detection algorithms for autonomous driving: A review. Sensors 2024; 24(10). https://doi.org/10.3390/s24103088

[8] Farid A, Hussain F, Khan K, Shahzad M, Khan U, Mahmood Z. A fast and accurate real-time vehicle detection method using deep learning for unconstrained environments. Applied Sciences 2023; 13(5). https://doi.org/10.3390/app13053059

[9] He C, Saha P. Investigating YOLO Models Towards Outdoor Obstacle Detection For Visually Impaired People 2023. https://doi.org/10.21203/rs.3.rs-3733857/v1

[10] Petrovic A, Bacanin N, Jovanovic L, Cadjenovic J, Kaljevic J, Zivkovic M, Antonijevic M. Computer-vision unmanned aerial vehicle detection system using yolov8 architectures. International Journal of Robotics and Automation Technology 2024; 11: 1-12. https://doi.org/10.31875/2409-9694.2024.11.01

[11] Jovanovic L, Bacanin N, Zivkovic M, Mani J, Strumberger I, Antonijevic M. Comparison of yolo architectures for face mask detection in images. In: 2023 16th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS), IEEE 2023; pp. 179-182. https://doi.org/10.1109/TELSIKS57806.2023.10316138

[12] Milanovic A, Jovanovic L, Zivkovic M, Bacanin N, Cajic M, Antonijevic M. Exploring pre-trained model potential for reflective vest real time detection with yolov8 models. In: 2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE 2024; pp. 1210-1216. https://doi.org/10.1109/ICAAIC60222.2024.10575617

[13] Jankovic P, Protic M, Jovanovic L, Bacanin N, Zivkovic M, Kaljevic J. Yolov8 utilization in occupational health and safety. In: 2024 Zooming Innovation in Consumer Technologies Conference (ZINC), IEEE 2024; pp. 182-187. https://doi.org/10.1109/ZINC61849.2024.10579310

[14] Protic M, Jovanovic L, Dobrojevic M, Cajic M, Zivkovic M, Shaker H, Bacanin N. Signals intelligence based drone detection using yolov8 models 2024. https://doi.org/10.2991/978-94-6463-482-2_6

[15] Djuric M, Jovanovic L, Zivkovic M, Bacanin N, Antonijevic M, Sarac M. The adaboost approach tuned by sns metaheuristics for fraud detection. In: Proceedings of the International Conference on Paradigms of Computing, Communication and Data Sciences: PCCDS 2022. Springer 2023; pp. 115-128. https://doi.org/10.1007/978-981-19-8742-7_10

[16] Stankovic M, Jovanovic L, Antonijevic M, Bozovic A, Bacanin N, Zivkovic M. Univariate individual household energy forecasting by tuned long short-term memory network. In: Inventive Systems and Control: Proceedings of ICISC 2023. Springer 2023; pp. 403-417. https://doi.org/10.1007/978-981-99-1624-5_30

[17] Cincovic J, Jovanovic L, Nikolic B, Bacanin N. Neurodegenerative condition detection using modified metaheuristic for attention based recurrent neural networks and extreme gradient boosting tuning. IEEE Access 2024; 12: 26719-26734. https://doi.org/10.1109/ACCESS.2024.3367588

[18] Kozakijevic S, Jovanovic L, Babic L, Kaljevic J, Zivkovic M, Bacanin N. Machine learning for company review sentiment analysis interpretation. In: International Conference on Multi-Strategy Learning Environment. Springer 2024; pp. 647-659. https://doi.org/10.1007/978-981-97-1488-9_47

[19] Jovanovic L, Bacanin N, Ravikumar R, Antonijevic M, Radic G, Zivkovic M. Generative adversarial networks for synthetic training data replacement in phishing email detection using natural language processing. In: International Conference on Smart Data Intelligence. Springer 2024; pp. 607-618. https://doi.org/10.1007/978-981-97-3191-6_46

[20] Kumpf K, Protic M, Jovanovic L, Cajic M, Zivkovic M, Bacanin N. Insider threat detection using bidirectional encoder representations from transformers and optimized adaboost classifier. In: 2024 International Conference on Circuit, Systems and Communication (ICCSC). IEEE 2024; pp. 1-6. https://doi.org/10.1109/ICCSC62074.2024.10616526

[21] Salb M, Jovanovic L, Bacanin N, Kunjadic G, Antonijevic M, Zivkovic M, Devi VK. The long short-term memory tuning for multi-step ahead wind energy forecasting using enhanced sine cosine algorithm and variation mode decomposition. In: International Conference on Paradigms of Communication, Computing and Data Analytics. Springer 2023; pp. 31-43. https://doi.org/10.1007/978-981-99-4626-6_3

[22] Jovanovic L, Kljajic M, Petrovic A, Mizdrakovic V, Zivkovic M, Bacanin N. Modified teaching-learning-based algorithm tuned long short-term memory for household energy consumption forecasting. In: International Conference on Worldwide Computing and Its Applications. Springer 1997; pp. 347-362. https://doi.org/10.1007/978-981-99-5881-8_28

[23] Zivkovic M, Jovanovic L, Pavlov M, Bacanin N, Dobrojevic M, Salb M. Optimized recurrent neural networks with attention for wind farm energy generation forecasting. In: 2023 16th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS). IEEE 2023; pp. 187-190. https://doi.org/10.1109/TELSIKS57806.2023.10316047

[24] Bozovic A, Jovanovic L, Desnica E, Radovanovic L, Zivkovic M, Bacanin N. Direct current motor malfunction detection through metastatic optimized audio analysis and classification. In: 2024 International Conference on Inventive Computation Technologies (ICICT). IEEE 2024; pp. 1471-1478. https://doi.org/10.1109/ICICT60155.2024.10544852

[25] Jovanovic L, Bacanin N, Simic V, Pamucar D, Zivkovic M. Audio analysis speeding detection techniques based on metaheuristic-optimized machine learning models. Engineering Applications of Artificial Intelligence 2024; 133: 108463. https://doi.org/10.1016/j.engappai.2024.108463

[26] Babic L, Jovanovic L, Petrovic A, Zivkovic M, Zivkovic T, Bacanin N. Leveraging metaheuristic optimized machine learning classifiers to determine employee satisfaction. In: International Conference on Multi-Strategy Learning Environment. Springer 2024; pp. 337-352. https://doi.org/10.1007/978-981-97-1488-9_26

[27] Jovanovic L, Kljajic M, Mizdrakovic V, Marevic V, Zivkovic M, Bacanin N. Predicting credit card churn: Application of xgboost tuned by modified sine cosine algorithm. In: 2023 3rd International Conference on Smart Data Intelligence (ICSMDI). IEEE 2023; pp. 55-62. https://doi.org/10.1109/ICSMDI57622.2023.00018

[28] Jovanovic L, Zivkovic M, Bacanin N, Dobrojevic M, Simic V, Sadasivuni KK, Tirkolaee EB. Evaluating the performance of metaheuristic-tuned weight agnostic neural networks for crop yield prediction. Neural Computing and Applications 2024; 1-30. https://doi.org/10.1007/s00521-024-09850-4

[29] Todorovic M, Petrovic A, Toskovic A, Zivkovic M, Jovanovic L, Bacanin N. Multivariate bitcoin price prediction based on lstm tuned by hybrid reptile search algorithm. In: 2023 16th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS). IEEE 2023; pp. 195-198. https://doi.org/10.1109/TELSIKS57806.2023.10316108

[30] Jovanovic L, Gajevic M, Dobrojevic M, Budimirovic N, Bacanin N, Zivkovic M. Tackling iot security challenge by metaheuristics tuned extreme learning machine. In: International Conference on Intelligent Sustainable Systems. Springer 2023; pp. 507-522. https://doi.org/10.1007/978-981-99-1726-6_39

[31] Golubovic S, Jovanovic L, Radomirovic B, Njegus A, Zivkovic M, Bacanin N. Evolving deep neural network architectures by sine cosine algorithm for healthcare 4.0. In: 2023 IEEE International Conference on Contemporary Computing and Communications (InC4). IEEE 2023; vol. 1: pp. 1-6. https://doi.org/10.1109/InC457730.2023.10263180

[32] Radomirovic B, Jovanovic L, Stoean C, Zivkovic M, Njegus A, Bacanin N. Solar flare classification using modified metaheuristic optimized xgboost. In: 2023 25th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC). IEEE 2023; pp. 287-292. https://doi.org/10.1109/SYNASC61333.2023.00049

[33] Bozovic A, Jovanovic L, Desnica E, Bacanin N, Zivkovic M, Antonijevic M, Mani JP. Metaheuristic optimized extreme gradient boosting milling maintenance prediction. In: Congress on Intelligent Systems. Springer 2023; pp. 361-374. https://doi.org/10.1007/978-981-99-9037-5_28

[34] Bisevac P, Toskovic A, Salb M, Jovanovic L, Petrovic A, Zivkovic M, Bacanin N. Solar flare classification via modified metaheuristic optimized extreme gradient boosting. In: International Conference for Information and Communication Technologies. Springer 2023; pp. 81-95. https://doi.org/10.1007/978-3-031-62624-1_7

[35] Mani J, Shaker H, Jovanovic L, *et al*. Sunspot occurrence forecasting with metaheuristic optimized recurrent neural networks. Theoretical and Applied Computational Intelligence 2023; 1(1): 15-26. https://doi.org/10.31181/taci1120231

[36] Jovanovic L, Jovanovic D, Antonijevic M, Zivkovic M, Budimirovic N, Strumberger I, Bacanin N. The xgboost tuning by improved firefly algorithm for network intrusion detection. In: 2022 24th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC). IEEE 2022; pp. 268-275. https://doi.org/10.1109/SYNASC57785.2022.00050

[37] Jovanovic L, Hajdarevic Z, Jovanovic D, Jassim HS, Strumberger I, Bacanin N, Zivkovic M, Antonijevic M. Tuning extreme learning machine by hybrid planet optimization algorithm for diabetes classification. In: Congress on Intelligent Systems. Springer 2022; pp. 23-36. https://doi.org/10.1007/978-981-19-9379-4_3

[38] Jovanovic L, Petrovic A, Zivkovic T, Antonijevic M, Bacanin N, Zivkovic M. Exploring the potential of generative adversarial networks for synthetic medical data generation. In: 2023 31st Telecommunications Forum (TELFOR). IEEE 2023; pp. 1-4. https://doi.org/10.1109/TELFOR59449.2023.10372727

[39] Zivkovic M, Vesic A, Bacanin N, Strumberger I, Antonijevic M, Jovanovic L, Marjanovic M. An improved animal migration optimization approach for extreme learning machine tuning. In: International Conference on Intelligent and Fuzzy Systems. Springer 2022; pp. 3-13. https://doi.org/10.1007/978-3-031-09176-6_1

[40] Jovanovic L, Bacanin N, Antonijevic M, Tuba E, Ivanovic M, Venkatachalam K. Plant classification using firefly algorithm and support vector machine. In: 2022 IEEE Zooming Innovation in Consumer Technologies Conference (ZINC). IEEE 2022; pp. 255-260. https://doi.org/10.1109/ZINC55034.2022.9840579

[41] Cuk A, Bezdan T, Jovanovic L, Antonijevic M, Stankovic M, Simic V, Zivkovic M, Bacanin N. Tuning attention based long-short term memory neural networks for parkinson's disease detection using modified metaheuristics. Scientific Reports 2024; 14(1): 4309. https://doi.org/10.1038/s41598-024-54680-y

[42] Jovanovic L, Bacanin N, Zivkovic M, Antonijevic M, Jovanovic B, Sretenovic MB, Strumberger I. Machine learning tuning by diversity oriented firefly metaheuristics for industry 4.0. Expert Systems 2024; 41(2): 13293. https://doi.org/10.1111/exsy.13293

[43] Jovanovic L, Bacanin N, Jovancai A, Jovanovic D, Singh D, Antonijevic M, Zivkovic M, Strumberger I. Oil price prediction approach using long shortterm memory network tuned by improved seagull optimization algorithm. In: International Conference on Sustainable and Innovative Solutions for Current Challenges in Engineering & Technology. Springer 2022; pp. 253-265. https://doi.org/10.1007/978-981-99-1431-9_20

[44] Jovanovic L, Strumberger I, Bacanin N, Zivkovic M, Antonijevic M, Bisevac P. Tuned long short-term memory model for ethereum price forecasting via an arithmetic optimization algorithm. International Journal of Hybrid Intelligent Systems 2023; 19(1, 2): 27-43. https://doi.org/10.3233/HIS-230003

[45] Jovanovic L, Damaševičius R, Matic R, Kabiljo M, Simic V, Kunjadic G, Antonijevic M, Zivkovic M, Bacanin N. Detecting parkinson's disease from shoe-mounted accelerometer sensors using convolutional neural networks optimized with modified metaheuristics. Peer J Computer Science 2024; 10: 2031. https://doi.org/10.7717/peerj-cs.2031

[46] Bacanin N, Jovanovic L, Stoean R, Stoean C, Zivkovic M, Antonijevic M, Dobrojevic M. Respiratory condition detection using audio analysis and convolutional neural networks

optimized by modified metaheuristics. Axioms 2024; 13(5): 335.
https://doi.org/10.3390/axioms13050335

[47] Salb M, Jovanovic L, Bacanin N, Antonijevic M, Zivkovic M, Budimirovic N, Abualigah L. Enhancing internet of things network security using hybrid cnn and xgboost model tuned via modified reptile search algorithm. Applied Sciences 2023; 13(23): 12687.
https://doi.org/10.3390/app132312687

[48] Jiang P, Ergu D, Liu F, Cai Y, M, B. A review of yolo algorithm developments. The 8th International Conference on Information Technology and Quantitative Management (ITQM 2020 & 2021): Developing Global Digital Economy after COVID-19. Procedia Computer Science 2022; 199: 1066-1073.
https://doi.org/10.1016/j.procs.2022.01.135

[49] Wang C-Y, Yeh I-H, Liao H-YM. YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information 2024.

[50] NASASpaceflight: Rocket Detect Dataset. Roboflow. visited on 2024-08-11 2023. https://universe.roboflow.com/nasaspaceflight/rocket-detect

Received on 04-08-2024 Accepted on 30-08-2024 Published on 09-09-2024

https://doi.org/10.31875/2409-9694.2024.11.03