Computer-Vision Unmanned Aerial Vehicle Detection System Using YOLOv8 Architectures

Aleksandar Petrovic[1,*], Nebojsa Bacanin[1], Luka Jovanovic[1], Jelena Cadjenovic[1], Jelena Kaljevic[1], Miodrag Zivkovic[1] and Milos Antonijevic[1]

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

Abstract: This work aims to test the performance of the you only look once version 8 (YOLOv8) model for the problem of drone detection. Drones are very slightly regulated and standards need to be established. With a robust system for detecting drones the possibilities for regulating their usage are becoming realistic. Five different sizes of the model were tested to determine the best architecture size for this problem. The results indicate high performance across all models and that each model is to be used for a specific case. Smaller models are suited for lightweight system approaches where some false identification is tolerable, while the largest models are to be used with stationary systems that require the best precision.

Keywords: UAV, Computer vision, Object detection, YOLOv8.

1. INTRODUCTION

The popularity of unmanned aerial vehicles (UAV) is on the rise as commercial drones are becoming more available. With the advancement of technology, more efficient hardware was made available, making the use of miniature drones possible. With such scale modifications, the real-world application of drones has significantly broadened. The applications range from recreational to industrial use. The use of UAVs for military purposes has defined modern warfare. The training of fighter pilots is expensive and more importantly time-consuming. Furthermore, human error is inevitable and in air warfare scenarios it makes the difference between life and death. Lastly, the biggest savings come from the equipment itself. The price of manufacturing a fighter jet can be five times the price of a UAV depending on which models are compared. The effectiveness of UAVs in combat has been proven, making them a very dangerous asset. However, the introduction of regulations for UAV use is required and their lack of creates potentially dangerous scenarios and even complete drone takeover.

Therefore, a robust system for drone detection is required. The first step in better drone usage regulations is creating a method to track their movement for which they need to be precisely identified beforehand. Traditional detection systems that are radar-based struggle with drone detection due to their condensed operating frequency profile. On the other hand, systems that rely on radio frequencies for detection are not precise enough for the task and can prove to be substantially less cost-efficient. Aside from military use, real-world use of drone detection can massively improve the organization and security of public gatherings such as concerts for example. During public gatherings, drones can be used to comb through the masses for problematic behavior. However, during such gatherings, the number of private drones in the sky from the goers is on the rise. People tend to use drones to capture footage or just get a better view of the event they are attending. The lack of regulations means that anyone can purchase and fly a drone which poses a risk to public safety.

This problem can be solved by applying computer vision (CV). A system for detecting and tracking drones can be relatively cheaply created. With such a system, it will be possible to identify each drone as well as track their behavior which should result in a more controlled and safer environment. For this purpose, this work employs the YOLOv8 model. The popularity of you only look once (YOLO) models is due to a couple of reasons. Most importantly, they are very lightweight and provide a range of different architecture sizes based on the user's needs. Furthermore, they employ transfer learning and are pre-trained for object detection. By exploiting these principles, YOLO models can be a very efficient solution for the CV use case. A real-world dataset containing photographs of drones in various scenarios is applied to test different YOLO architectures.

The main contributions of this work are highlighted:

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

E-ISSN: 2409-9694/24

– Efficient solution for detecting and tracking UAVs based on CV.

– Analysis of YOLOv8 architectures for the drone detection problem.

– Real-world dataset YOLOv8 predictions comparison.

A brief overview of the paper's structure is as follows: Section 2 introduces necessary concepts for this research and provides a literature review, Section 3 describes the applied methodology, Section 4 provides information for experiments recreation, Section 5 follows with the results of performed experiments along with discussion about simulation outcomes, while Section 6 concludes the paper.

2. RELATED WORKS

The application spectrum of CV systems is broad and depending on the technologies used in combination with them different frameworks can be constructed. Che *et al*. [12] analyze the use of CV in robotics. This use case is one of the most important ones as the robotics field is already applied widely across the industry. By giving sight to already employed robotics systems the increases in efficiency, precision, and generally the amount of possible actions increases. Additionally, Bacanin *et al*. [10] explore the potential of CV for quality control in plants.

The role of CV in modern traffic is paramount for the smart systems in vehicles and the infrastructure as well. Medicine is one of the most important fields of human survival, and in the work of Zivkovic *et al*. [?] the use of computer vision was applied for separating cases of healthy lungs, pneumonia, and lungs affected by COVID-19. Ren [34] explores an approach to tackle traffic violations. The need for a robust system to detect violations like speeding and running stop signs is important not only for general safety but for the safety of usage of the smart systems that will soon be applied everywhere. The system struggles to regulate the violations performed by autonomous cars in the current traffic setting and hence this only raises the importance of application of such CV systems. Furthermore, Petrovic *et al*. [31] propose a metaheuristic-based hybrid solution for pedestrian detection.

Sminek *et al*. [37] highlight the importance of CV in agriculture by performing a study concerning real-time cattle identification. The authors deployed a system on edge devices for cattle identification called Read My Cow which is rooted in the YOLO version 5 model. Jaramillo-Hernández *et al*. [18] tackle the issue of precision farming. The authors explored the use of CV on low-cost devices which is crucial for use cases where large areas have to be covered like with crop fields.

As per the no free lunch (NFL) theorem [43], CV has advantages and disadvantages depending on the use case. Lower resolutions are depicted through CV use and for cases where the highest precision is required the neural network approach is much more suited [28]. In terms of use alongside UAVs, CV struggles with regions of weak GPS signals and environmental conditions can greatly affect its precision [2]. Petropoulou *et al*. [30] tackle the problem of CV precision in greenhouse environments due to changing light conditions.

Outstanding performance for computer vision tasks has been exhibited with CNN use [1]. The architecture of CNNs is based on the brain's visual cortex which is made of multiple layers [26]. The first layer extracts low-level features from the input, called the convolutional layer. Each additional layer filters the data further by reducing its size. The activation function follows which provides transformed non-linear output. Afterward, a pooling layer is to be applied for dimensionality reduction of the data which results in faster processing. The last type of layer that is used are the dense layers which flatten and classify data. This type of network is usually trained with gradient-descent-based methods [17]. The loss function is to be minimized over epochs through optimizing functions. For each epoch, the network biases and weights are adjusted with this goal. There are different loss functions and some of the most common ones are binary and categorical cross-entropy. As with other deep learning structures, CNNs require tuning. This process is described as hyperparameter optimization. This process is required to be performed by trial and error method since there is no clear indication of which parameters work the best for each case. This is inefficient and in most cases not feasible at all. For this reason, algorithms for the optimization of hyperparameters are introduced and this problem is considered NP-hard.

Moreover, hybrid methods between machine/deep learning and metaheuristics excel in other application domains as well, as evidenced by numerous successful recent applications including medicine [22, 13, 8, 27, 32, 6, 24], agriculture [25], environmental monitoring [5, 20], economy [13, 41, 38] and power grids [29, 14, 3, 39, 45]. Other notable applications include weather forecasting [21], cloud computing [7, 33, 4, 9], wireless sensor networks [46, 11, 44] and intrusion detection [35, 36, 23, 15]. Also, it is worth mentioning that there are also many applications of enhanced metaheuristics methods [40, 42].

The YOLO architectures are not employed enough in practice and require further experimentation. The literature gap is observed for the YOLOv8 architecture for drone detection use case. In this work, the goal is to bridge that gap by experimenting with different YOLOv8 architectures on a real-world dataset.

3. MATERIALS AND METHODS

This work applies YOLO models for drone detection. Firstly, general information on the YOLO models is provided followed by the YOLOv8 which is the main predictor applied in this research.

3.1. YOLO Models

High accuracy and speed attribute the YOLO architecture-based solutions. This is possible due to their unique mechanism to only look once at an image with the goal of predicting bounding boxes with the probabilities for each class [19]. This type of model uses raw pixels for location and category predictions, unlike the traditional two-stage detectors which make real-time applications realistic. The techniques applied in YOLO that increase generalization performance are data augmentation, transfer learning, and fine-tuning. With the use of these techniques use cases with high diversity can benefit from such improvements as well.

The YOLO model object detection avoids the use of different models for regions, orientations, and scales and is performed by a single YOLO network. The YOLO network is a single-stage detector comprised of the backbone, neck, and head. Low-level and high-level features are extracted by the backbone, while the neck fuses them, and the location and class of the object are predicted by the head. By applying such a process, the features' semantic information is increased.

Images are divided into grids which are used to predict the object's location and its bounding boxes. By doing so, the object detection problem can be treated as a single regression, which allows for object detection with only one inference. Five-dimensional output is provided by each bounding box which represents the object's possible coordinates and the probability for it to be true. The dimensions are the center point depicted by two coordinates, the width and height, and the probability that the object is in that box.

Transfer learning has a key role in YOLO architecture. These models come pre-trained in various sizes. The model is trained on images of 640×640 pixels.

The models are trained for general object detection. Aside from this, the models can classify, track, segment, and detect a pose. After the model is obtained from the developer the user needs to train the model on its own data. Transfer learning helps as it avoids training generic features which increases the training speed.

3.2. YOLOv8 Model

The YOLOv8 model provides impressive performance in terms of speed and accuracy with an accent on real-time application. By incorporating advanced methods like path aggregation networks and focus spatial attention object detection performance is increased. A trade-off between accuracy and speed can be achieved with the use of five different sizes provided by the YOLO developers. The version 8 of the YOLO model exhibits improved performance in terms of real-time application especially with small and overlapping objects. The model is versatile as it can be applied to different use cases due to its transfer learning capabilities. The model can be applied on edge devices as well as on more powerful machines when required to have the highest precision.

The most important features of the YOLOv8 model are provided in the following paragraph. Firstly, the improvements to the architecture are responsible for improved efficiency in image processing. The version 8 of the YOLO model uses CSPDarknet53 as its backbone network. This network is used since version 4 and it aids the feature extraction process. Advanced data augmentation techniques and optimization algorithms provide faster conversion in training. Lastly, the generalization capabilities are improved, which improves the models' performance in real-world use cases.

4. EXPERIMENTAL SETUP

The dataset [16] used for this research is publicly available at https://universe. roboflow.com/military-drone/drone_mil-u8fqk/dataset/1. The dataset consists of 5238 training images, 1345 validation images, and 678 images left for testing with a total of 7261 images in the dataset. The images include different scenarios of drone usage as well as images of drones on a plain background. The dataset can be downloaded from the link in various versions prepared for different frameworks. For this work, the YOLOv8 format is applied and other available formats include Pascal VOC XML and COCO JSON among others.

Five different experiments are performed, one for each YOLO architecture. The testing begins from the smallest nano model, over the small, medium, large, and lastly the extra-large model with standard hyperparameters.

4.1. Metrics

The precision metric is used to evaluate the ratio of true positive (TP) predictions to all predictions that were classified to be positive including false positives (FP). This metric is described in Eq. 1.

$$P = \frac{TP}{TP + FP} \tag{1}$$

The recall metric depicts the ratio of correctly made predictions to all positive predictions including false negatives (FN).

$$R = \frac{TP}{TP + FN} \tag{2}$$

The harmonic mean and of precision and recall is depicted by the f1 score and described in Eq. 3. The range of scores is from 0 to 1, where 1 indicates perfect precision and recall.

$$F1 = 2 * (precision * recall)/(precision + recall) \tag{3}$$

The main evaluation index for the detection task performance evaluation is the mAP described in Eq. 4.

$$mAP = \frac{1}{n}\sum_{i=0}^{n} AP_i \tag{4}$$

The average accuracy for all categories at an intersection over union (IoT) threshold of 0.5 is represented by the mAP50 metric. Higher values indicate better detection and recognition. Ten mAP values distributed in intervals of 0.0 from an IoU threshold of 0.5 to an mAP threshold of 0.95 averaged represent the mAP 50:95 metric.

5. SIMULATION OUTCOMES AND DISCUSSION

The results are provided in the following text. Firstly, the results for the smallest model which is the nano model are shown followed by the small, medium, large, and extra-large YOLO architectures.

5.1. Nano YOLO Model Results

The precision-recall (PR) curve is exhibited alongside the confusion matrix for the nano YOLOv8 architecture in Figure **1**. The nano model is the fastest predictor of the five tested architectures and its use is optimal for edge devices. However, bigger architecture sizes prove to be more robust. Actual predictions are exhibited in Figure **2**, where on the left side of the figure labels are provided. Very high accuracy is exhibited with an average over 90%.

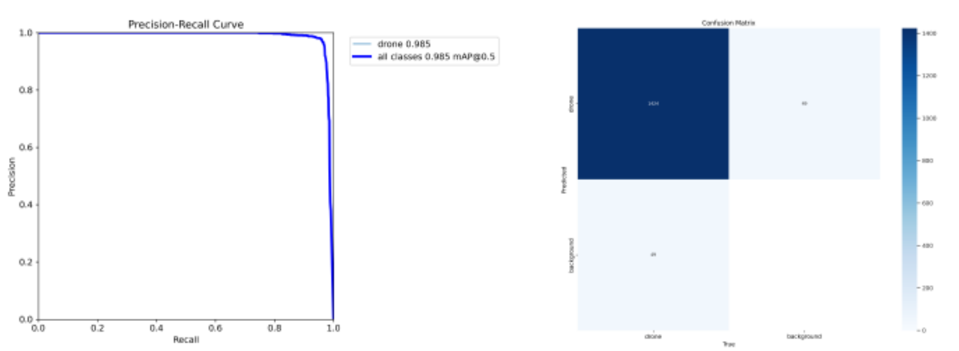

Figure 1: Nano YOLOv8 model PR curve and confusion matrix.

Figure 2: Nano YOLOv8 model predictions.

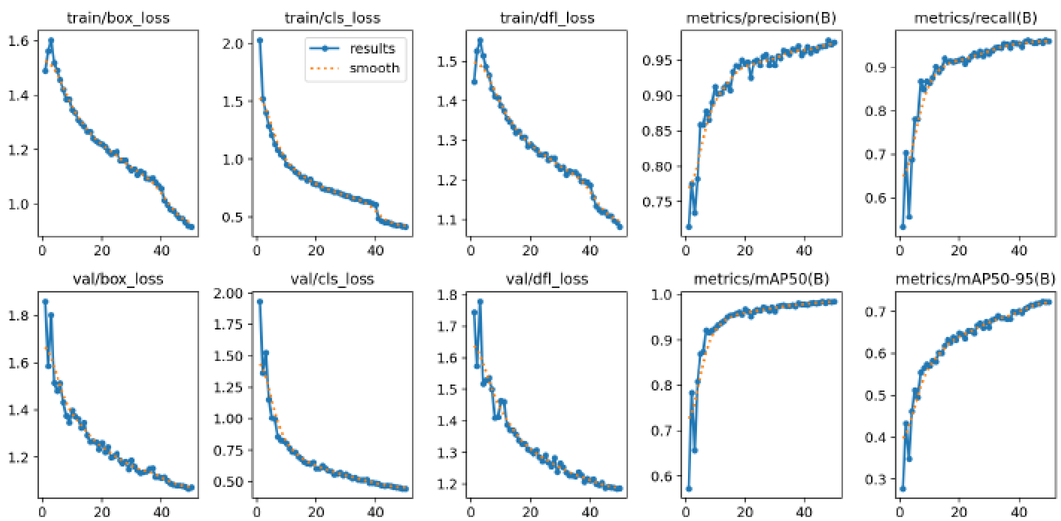

Figure 3: Nano YOLOv8 model results.

Evaluated metrics convergences are provided in Figure **3**.

5.2. Small YOLO Model Results

The small YOLO architecture exhibits a slightly more robust performance with fewer false negatives

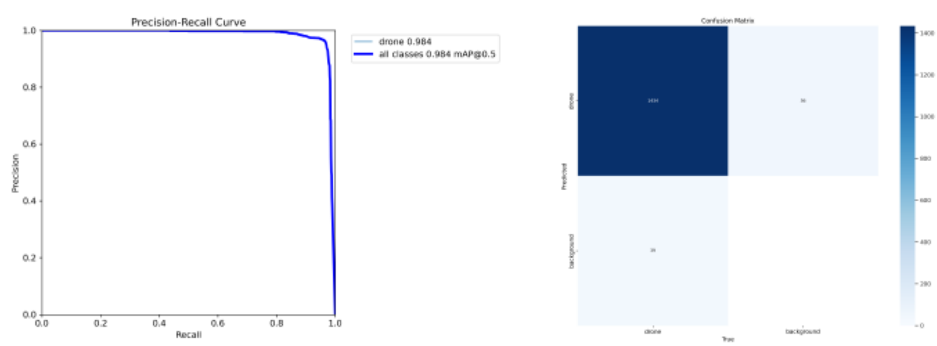

Figure 4: Small YOLOv8 model PR curve and confusion matrix.

Figure 5: Small YOLOv8 model predictions.

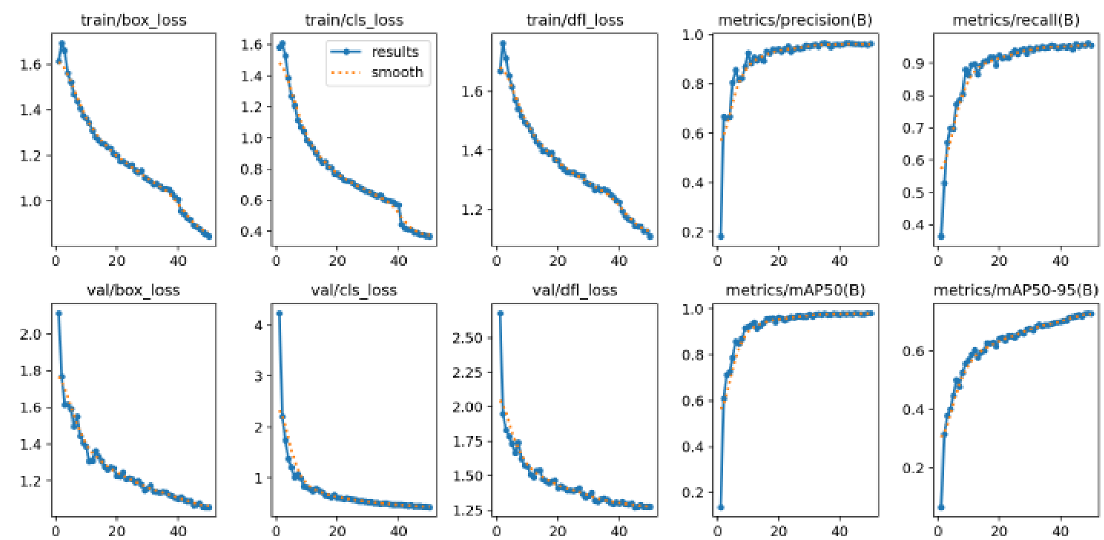

Figure 6: Small YOLOv8 model results.

but with slightly more false positives as seen in Figure **4**. From Figure **5** where the actual predictions are exhibited it can be seen that the small model did not falsely classify a bridge as a drone in the third image in the second row, unlike the small model. The nano model barely converges faster than the small model. For detailed convergence speeds refer to Figure **6**.

5.3. Medium YOLO Model Results

The medium model provided the most robust performance of the five models. This indicates that this model is optimal for most use cases where there is no need for lightweight devices or for the highest possible precision. The PR curve and the confusion matrix are exhibited in Figure **7** while the convergences for all metrics are provided in Figure **9**. Actual predictions are shown in Figure **8** where slightly better performance than the small model is observed.

5.4. Large YOLO Model Results

The large model indicates even higher confidence in predictions in Figure **11** in comparison to the medium model, but worse convergence times compared to smaller models exhibited in Figure **15**. The PR curve and the confusion matrix are provided in Figure **10**.

5.5. Extra Large YOLO Model Predictions

The largest model exhibits the highest precision in its task but the slowest convergence speed exhibited

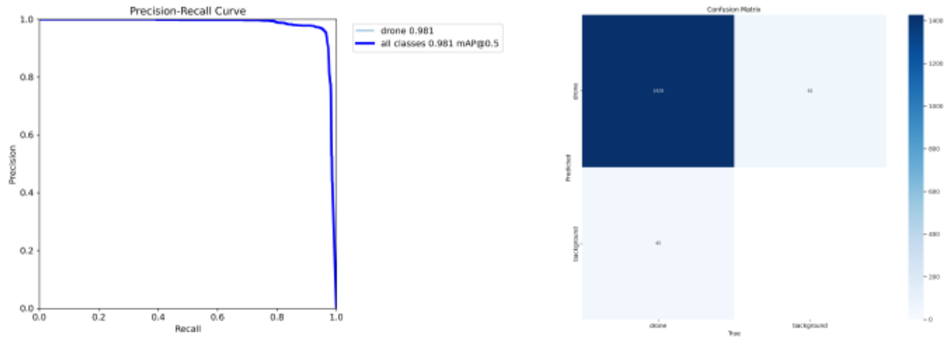

Figure 7: Medium YOLOv8 model PR curve and confusion matrix.

Figure 8: Medium YOLOv8 model predictions.

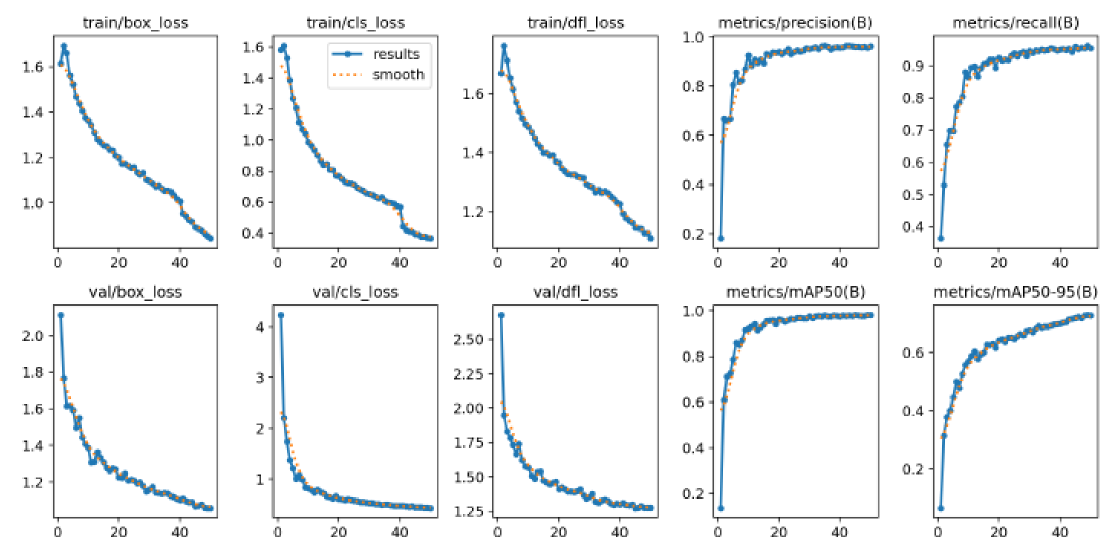

Figure 9: Medium YOLOv8 model results.

in Figure **15**. The actual predictions indicate the robustness of the model in Figure **14** and that this model is to be used with high-powered hardware for the cases where the highest precision is required. The PR curve and confusion matrix are provided in Figure **7**.

Experiments were performed for nano, small, medium, large, and extra-large architectures of the

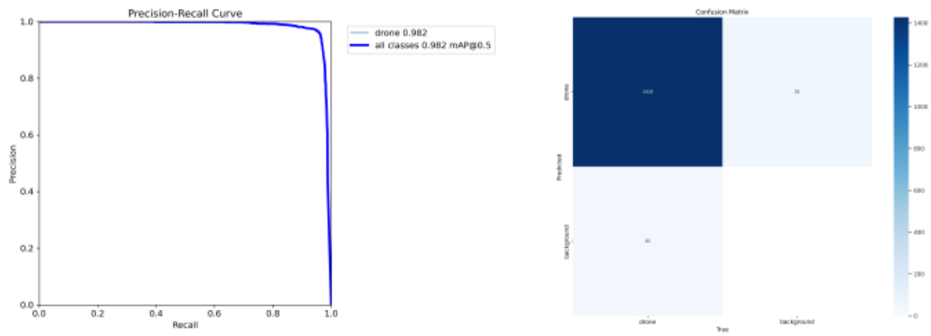

Figure 10: Large YOLOv8 model PR curve and confusion matrix.

Figure 11: Large YOLOv8 model predictions.

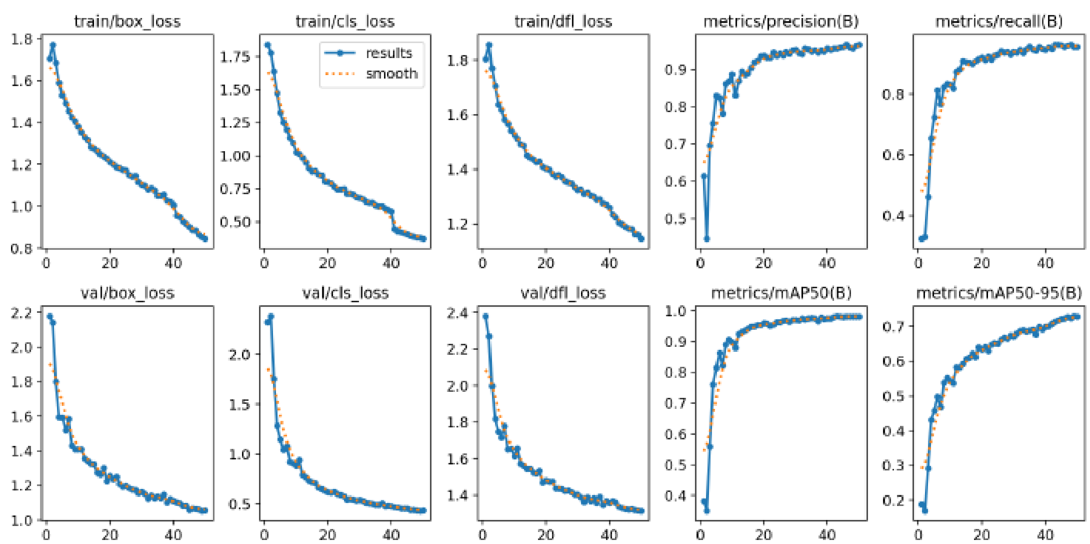

Figure 12: Large YOLOv8 model results.

YOLOv8 models. The models are prebuilt and pretrained for object detection and this research aimed to test their performance on the problem of drone detection. The best performance considering the trade-off between speed and accuracy is exhibited by the model of medium size. This model provides the most robust performance while not sacrificing speed like the larger models.

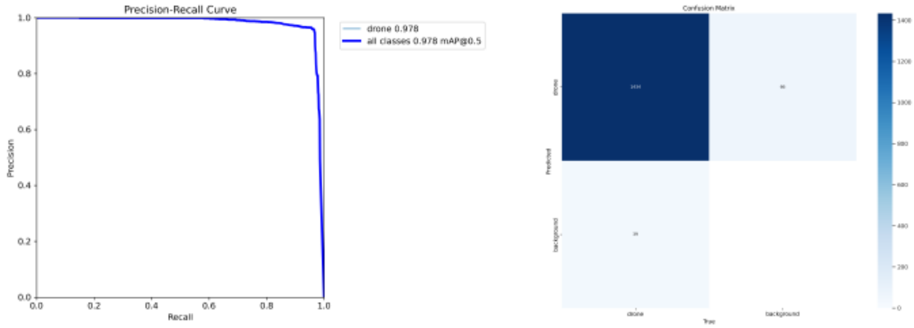

Figure 13: Extra large YOLOv8 model PR curve and confusion matrix.

Figure 14: Extra large YOLOv8 model predictions.

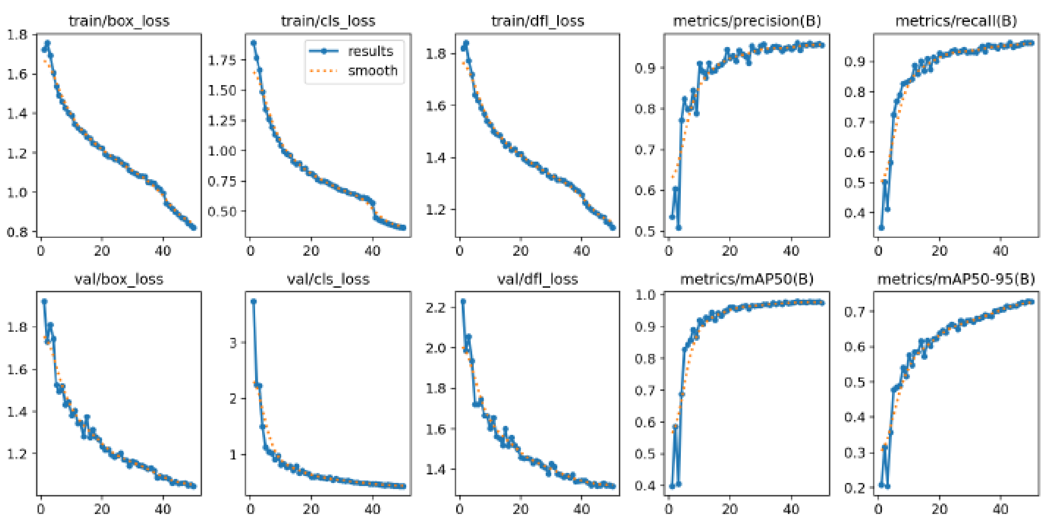

Figure 15: Extra large YOLOv8 model results.

The large and extra-large models exhibit the highest precision and are the most robust when not considering the speed. These models can be used where the time is not a factor, as well as with cases that require absolute precision.

The small and nano models are to be used with lightweight devices of modest processing power. These models provide very high confidence in detection but with the decrease in architecture's size, for example, the nano model can misclassify the background as a drone.

To conclude, the medium model is the best overall model and is suited for most use cases. The model is more precise than the smaller model versions, while not lacking too far behind the higher models. On the other hand, the model is not the fastest, but its convergence speed is significantly better than with larger models.

6. CONCLUSION

The aim of this research was to test the YOLOv8 model for the problem of drone detection. This issue is of importance to the increased drone usage as it becomes more affordable. The lack of regulations is a massive issue for safe drone use and this research benefits that cause. With a robust drone detection system regulations can be enforced towards everyone's safety. The research indicates the best performance by the medium-sized YOLOv8 model, while the large and extra- large models are to be used with cases where the highest precision is required and the nano and small models are to be used for edge computing. Further endeavors in drone detection will include other use cases as well as experimentation with possible optimization techniques.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

REFERENCES

[1] Al Bataineh, A., Kaur, D., Al-khassaweneh, M., Al-sharoa, E.: Automated cnn architectural design: A simple and efficient methodology for computer vision tasks. Mathematics 11(5), 1141 (2023) https://doi.org/10.3390/math11051141

[2] Arafat, M.Y., Alam, M.M., Moh, S.: Vision-based navigation techniques for un-manned aerial vehicles: Review and challenges. Drones 7(2), 89 (2023) https://doi.org/10.3390/drones7020089

[3] Bacanin, N., Jovanovic, L., Zivkovic, M., Kandasamy, V., Antonijevic, M., Deveci, M., Strumberger, I.: Multivariate energy forecasting via metaheuristic tuned long- short term memory and gated recurrent unit neural networks. Information Sciences 642, 119122 (2023) https://doi.org/10.1016/j.ins.2023.119122

[4] Bacanin, N., Jovanovic, L., Zivkovic, M., Salb, M., Elsadai, A., Sarac, M.: De- composition aided cloud load forecasting with optimized long-short term memory networks. In: 2023 16th International Conference on Advanced Technologies, Sys- tems and Services in Telecommunications (TELSIKS). pp. 191-194. IEEE (2023) https://doi.org/10.1109/TELSIKS57806.2023.10316036

[5] Bacanin, N., Perisic, M., Jovanovic, G., Damaševičius, R., Stanisic, S., Simic, V., Zivkovic, M., Stojic, A.: The explainable potential of coupling hybridized meta- heuristics, xgboost, and shap in revealing toluene behavior in the atmosphere. Science of The Total Environment 929, 172195 (2024) https://doi.org/10.1016/j.scitotenv.2024.172195

[6] Bacanin, N., Petrovic, A., Jovanovic, L., Zivkovic, M., Zivkovic, T., Sarac, M.: Parkinson's disease induced gain freezing detection using gated recurrent units optimized by modified crayfish optimization algorithm. In: 2024 5th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI). pp. 1-8. IEEE (2024) https://doi.org/10.1109/ICMCSI61536.2024.00006

[7] Bacanin, N., Simic, V., Zivkovic, M., Alrasheedi, M., Petrovic, A.: Cloud computing load prediction by decomposition reinforced attention long short-term memory network optimized by modified particle swarm optimization algorithm. Annals of Operations Research pp. 1-34 (2023) https://doi.org/10.1007/s10479-023-05745-0

[8] Bacanin, N., Stoean, C., Markovic, D., Zivkovic, M., Rashid, T.A., Chhabra, A., Sarac, M.: Improving performance of extreme learning machine for classification challenges by modified firefly algorithm and validation on medical benchmark datasets. Multimedia Tools and Applications pp. 1-41 (2024) https://doi.org/10.1007/s11042-024-18295-9

[9] Bacanin, N., Zivkovic, M., Bezdan, T., Venkatachalam, K., Abouhawwash, M.: Modified firefly algorithm for workflow scheduling in cloud-edge environment. Neu- ral computing and applications 34(11), 9043-9068 (2022) https://doi.org/10.1007/s00521-022-06925-y

[10] Bacanin, N., Zivkovic, M., Sarac, M., Petrovic, A., Strumberger, I., Antonijevic, M., Petrovic, A., Venkatachalam, K.: A novel multiswarm firefly algorithm: An application for plant classification. In: International Conference on Intelligent and Fuzzy Systems. pp. 1007-1016. Springer (2022) https://doi.org/10.1007/978-3-031-09173-5_115

[11] Bezdan, T., Zivkovic, M., Antonijevic, M., Zivkovic, T., Bacanin, N.: Enhanced flower pollination algorithm for task scheduling in cloud computing environment. In: Machine learning for predictive analysis: proceedings of ICTIS 2020. pp. 163-171. Springer (2021) https://doi.org/10.1007/978-981-15-7106-0_16

[12] Che, C., Zheng, H., Huang, Z., Jiang, W., Liu, B.: Intelligent robotic control system based on computer vision technology. arXiv preprint arXiv:2404.01116 (2024) https://doi.org/10.54254/2755-2721/64/20241373

[13] 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 14(1), 4309 (2024) https://doi.org/10.1038/s41598-024-54680-y

[14] Damaševičius, R., Jovanovic, L., Petrovic, A., Zivkovic, M., Bacanin, N., Jovanovic, D., Antonijevic, M.: Decomposition aided attention-based recurrent neural net- works for multistep ahead time-series forecasting of renewable power generation. PeerJ Computer Science 10 (2024) https://doi.org/10.7717/peerj-cs.1795

[15] Dobrojevic, M., Zivkovic, M., Chhabra, A., Sani, N.S., Bacanin, N., Amin, M.M.: Addressing internet of things security by enhanced sine cosine metaheuristics tuned hybrid machine learning model and results interpretation based on shap approach. PeerJ Computer Science 9, e1405 (2023) https://doi.org/10.7717/peerj-cs.1405

[16] military drone: drone_mil dataset. https://universe.roboflow.com/ military-drone/drone_mil-u8fqk (dec 2023), https://universe.roboflow. com/military-drone/drone{_}mil-u8fqk, visited on 2024-05-06

[17] Hinton, G., Deng, L., Yu, D., Dahl, G.E., Mohamed, A.r., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T.N., *et al.*: Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal processing magazine 29(6), 82-97 (2012) https://doi.org/10.1109/MSP.2012.2205597

[18] Jaramillo-Hernández, J.F., Julian, V., Marco-Detchart, C., Rincón, J.A.: Appli- cation of machine vision techniques in low-cost devices to improve efficiency in precision farming. Sensors 24(3), 937 (2024) https://doi.org/10.3390/s24030937

[19] Jiang, P., Ergu, D., Liu, F., Cai, Y., Ma, B.: A review of YOLO algorithm developments. Procedia Computer Science 199, 1066-1073 (2022) https://doi.org/10.1016/j.procs.2022.01.135

[20] Jovanovic, G., Perisic, M., Bacanin, N., Zivkovic, M., Stanisic, S., Strumberger, I., Alimpic, F., Stojic, A.: Potential of coupling metaheuristics-optimized-xgboost and shap in revealing pahs environmental fate. Toxics 11(4), 394 (2023) https://doi.org/10.3390/toxics11040394

[21] Jovanovic, L., Bacanin, N., Simic, V., Mani, J., Zivkovic, M., Sarac, M.: Optimiz- ing machine learning for space weather forecasting and event classification using modified metaheuristics. Soft Computing pp. 1-20 (2023) https://doi.org/10.1007/s00500-023-09496-9

[22] 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 10, e2031 (2024) https://doi.org/10.7717/peerj-cs.2031

[23] Jovanovic, L., Jovanovic, D., Antonijevic, M., Nikolic, B., Bacanin, N., Zivkovic, M., Strumberger, I.: Improving phishing website detection using a hybrid two-level framework for feature selection and xgboost tuning. Journal of Web Engineering 22(3), 543-574 (2023) https://doi.org/10.13052/jwe1540-9589.2237

[24] 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). pp. 1-4. IEEE (2023) https://doi.org/10.1109/TELFOR59449.2023.10372727

[25] Jovanovic, L., Zivkovic, M., Bacanin, N., Dobrojevic, M., Simic, V., Sadasivuni, K.K., Tirkolaee, E.B.: Evaluating the performance of metaheuristic-tuned weight agnostic neural networks for crop yield prediction. Neural Computing and Appli- cations pp. 1-30 (2024) https://doi.org/10.1007/s00521-024-09850-4

[26] LeCun, Y., Bengio, Y., *et al.*: Convolutional networks for images, speech, and time series. The handbook of brain theory and neural networks 3361(10), 1995 (1995)

[27] Minic, A., Jovanovic, L., Bacanin, N., Stoean, C., Zivkovic, M., Spalevic, P., Petrovic, A., Dobrojevic, M., Stoean, R.: Applying recurrent neural networks for anomaly detection in electrocardiogram sensor data. Sensors 23(24), 9878 (2023) https://doi.org/10.3390/s23249878

[28] Nizovtseva, I., Palmin, V., Simkin, I., Starodumov, I., Mikushin, P., Nozik, A., Hamitov, T., Ivanov, S., Vikharev, S., Zinovev, A., *et al.*: Assessing the mass trans- fer coefficient in jet bioreactors with classical computer vision methods and neural networks algorithms. Algorithms 16(3), 125 (2023) https://doi.org/10.3390/a16030125

[29] Pavlov-Kagadejev, M., Jovanovic, L., Bacanin, N., Deveci, M., Zivkovic, M., Tuba, M., Strumberger, I., Pedrycz, W.: Optimizing long-short-term memory models via metaheuristics for decomposition aided wind energy generation forecasting. Arti- ficial Intelligence Review 57(3), 45 (2024) https://doi.org/10.1007/s10462-023-10678-y

[30] Petropoulou, A.S., van Marrewijk, B., de Zwart, F., Elings, A., Bijlaard, M., van Daalen, T., Jansen, G., Hemming, S.: Lettuce production in intelligent green- houses-3d imaging and computer vision for plant spacing decisions. Sensors 23(6), 2929 (2023) https://doi.org/10.3390/s23062929

[31] Petrovic, A., Strumberger, I., Antonijevic, M., Jovanovic, D., Mladenovic, D., Chabbra, A.: Firefly-xgboost approach for pedestrian detection. In: 2022 IEEE Zooming Innovation in Consumer Technologies Conference (ZINC). pp. 197-202. IEEE (2022) https://doi.org/10.1109/ZINC55034.2022.9840700

[32] Pilcevic, D., Djuric Jovicic, M., Antonijevic, M., Bacanin, N., Jovanovic, L., Zivkovic, M., Dragovic, M., Bisevac, P.: Performance evaluation of metaheuristics- tuned recurrent neural networks for electroencephalography anomaly detection. Frontiers in Physiology 14, 1267011 (2023) https://doi.org/10.3389/fphys.2023.1267011

[33] Predić, B., Jovanovic, L., Simic, V., Bacanin, N., Zivkovic, M., Spalevic, P., Budimirovic, N., Dobrojevic, M.: Cloud-load forecasting via decomposition-aided attention recurrent neural network tuned by modified particle swarm optimization. Complex & Intelligent Systems 10(2), 2249-2269 (2024) https://doi.org/10.1007/s40747-023-01265-3

[34] Ren, Y.: Intelligent vehicle violation detection system under human-computer in- teraction and computer vision. International Journal of Computational Intelligence Systems 17(1), 40 (2024) https://doi.org/10.1007/s44196-024-00427-6

[35] 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 13(23), 12687 (2023) https://doi.org/10.3390/app132312687

[36] Savanović, N., Toskovic, A., Petrovic, A., Zivkovic, M., Damaševičius, R., Jo- vanovic, L., Bacanin, N., Nikolic, B.: Intrusion detection in healthcare 4.0 internet of things systems via metaheuristics optimized machine learning. Sustainability 15(16), 12563 (2023) https://doi.org/10.3390/su151612563

[37] Smink, M., Liu, H., Döpfer, D., Lee, Y.J.: Computer vision on the edge: Individual cattle identification in real-time with readmycow system. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. pp. 7056-7065 (2024) https://doi.org/10.1109/WACV57701.2024.00690

[38] Stankovic, M., Jovanovic, L., Bacanin, N., Zivkovic, M., Antonijevic, M., Bisevac, P.: Tuned long short-term memory model for ethereum price forecasting through an arithmetic optimization algorithm. In: International Conference on Innovations in Bio-Inspired Computing and Applications. pp. 327-337. Springer (2022) https://doi.org/10.1007/978-3-031-27499-2_31

[39] Stoean, C., Zivkovic, M., Bozovic, A., Bacanin, N., Strulak-Wójcikiewicz, R., Antonijevic, M., Stoean, R.: Metaheuristic-based hyperparameter tuning for recurrent deep learning: application to the prediction of solar energy generation. Axioms 12(3), 266 (2023) https://doi.org/10.3390/axioms12030266

[40] Strumberger, I., Bacanin, N., Tuba, M.: Enhanced firefly algorithm for constrained numerical optimization. In: 2017 IEEE congress on evolutionary computation (CEC). pp. 2120-2127. IEEE (2017) https://doi.org/10.1109/CEC.2017.7969561

[41] Todorovic, M., Stanisic, N., Zivkovic, M., Bacanin, N., Simic, V., Tirkolaee, E.B.: Improving audit opinion prediction

accuracy using metaheuristics-tuned xgboost algorithm with interpretable results through shap value analysis. Applied Soft Computing 149, 110955 (2023) https://doi.org/10.1016/j.asoc.2023.110955

[42] Tuba, M., Bacanin, N.: Jpeg quantization tables selection by the firefly algo- rithm. In: 2014 International Conference on Multimedia Computing and Systems (ICMCS). pp. 153-158. IEEE (2014) https://doi.org/10.1109/ICMCS.2014.6911315

[43] Wolpert, D.H., Macready, W.G., *et al*.: No free lunch theorems for search. Tech. rep., Citeseer (1995)

[44] Zivkovic, M., Bacanin, N., Zivkovic, T., Strumberger, I., Tuba, E., Tuba, M.: En- hanced grey wolf algorithm for energy efficient wireless sensor networks. In: 2020 zooming innovation in consumer technologies conference (ZINC). pp. 87-92. IEEE (2020) https://doi.org/10.1109/ZINC50678.2020.9161788

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

[46] Zivkovic, M., Zivkovic, T., Venkatachalam, K., Bacanin, N.: Enhanced dragonfly algorithm adapted for wireless sensor network lifetime optimization. In: Data Intelligence and Cognitive Informatics: Proceedings of ICDICI 2020. pp. 803-817. Springer (2021) https://doi.org/10.1007/978-981-15-8530-2_63

Received on 14-04-2024 Accepted on 20-05-2024 Published on 22-05-2024

DOI: https://doi.org/10.31875/2409-9694.2024.11.01