



# Vision-based Propeller Damage Inspection Using Machine Learning

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**Abstract**—Unmanned Aerial Vehicles (UAVs) play an increasingly pivotal role in day-to-day rescue operations, offering crucial aerial support in challenging terrain and emergencies, such as drowning. Drone hangars are strategically deployed to ensure swift response in remote locations, overcoming range-limiting constraints posed by battery capacity. However, the UAV's airworthiness, typically ensured through conventional inspections by a technical individual, is paramount to guarantee mission safety. Over time, UAVs are prone to degradation through contact with the external environment, with propellers often being the cause of flight instability and potential crashes. This paper presents an innovative approach to automate UAV propeller inspection to avert incidents preemptively. Leveraging visual recordings and deep learning methodologies, we train a Convolutional Neural Network (CNN) model using both passive and active learning strategies. Our approach successfully detects physical damage on propellers with an impressive accuracy of 85.8%, promising a significant improvement in maintaining UAV flight safety and effectiveness in rescue operations.

**Keywords**— UAV diagnostics, propeller inspection, image processing, deep learning, active learning, passive learning

## I. INTRODUCTION

Today, unmanned aerial vehicles (UAVs) are increasingly being used in day-to-day rescue operations. According to the German Life Saving Association (DLGR), around 355 death cases happened in Germany during 2022 due to drowning [1]. It is estimated that two thirds of these deaths occur during the summer season, with approximately 41 percent of the cases happening in lakes as shown in Fig. 1.

In fact, the World health organization has disclaimed that the drowning mortality rate represents 2.1 per 100000 population in Europe, compared to 3.1 deaths per 100000 population as the global rate [2]. Therefore, the quick response of authorities to emergency calls is necessary to reduce fatalities. To ensure this, unmanned aerial vehicles are an effective solution to support the rescue operations since they allow the authorities to reach the victim in record times. This allows for a range of quick actions (such as throwing a

flotation devices) that can be performed to save the victim until the responders arrive at the location.

The RescueFly research project is a joint cooperation of an interdisciplinary team of scientists and companies in Germany, which aims to use decentralized, autonomous drones to enable fast and practical help in unguarded water emergencies, specifically in the remote Lusatian Lake District which spans across Brandenburg and the Free State of Saxony in Germany.

The project encapsulates several research themes, from which we can mention the design and development of an UAV hangar, where UAVs can be stored. The UAVs will be deployed after receiving the emergency call, and locates the drowning victim before assisting him with a flotation device. Therefore, RescueFly project encompasses a range of topics, from the conception and creation of the intelligent UAV hangar, to the secure and effective missions plan. It also includes the autonomous identification of individuals in need, the automatic release of life-saving flotation devices, and the seamless integration of these operations into the into the two federal states' already established emergency response systems.

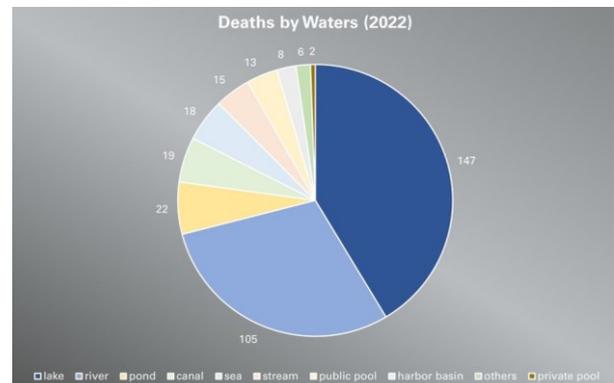


Fig. 1 The number of death by water during 2022 [1]

In order to guarantee the automated aspect of the mission, the UAV must always be ready to respond to emergency calls.

However, the readiness of the UAV depends heavily on its airworthiness, which is defined by examining the main components of the UAV. Conventionally, a technician on site is necessary to identify any issues with the UAV before the flight. While these traditional methods effectively detect defects, they are still very costly and time-consuming. In the case of drone hangars, the manual inspection requires the displacement of the concerned persons to remote locations, simply to evaluate the airworthiness of an UAV. This process might require a considerable amount of time and may also be a waste of money, since in most of the cases, the UAV is healthy.

This paper addresses the aspect of automation in examining the UAV propeller health. The context of this project demands the automation of this process to remove the human-dependency factor surrounding UAV diagnostics. The proposed method leverages the camera sensors inside the drone hangar and uses of an AI trained model to predict the need for maintenance calls. The remaining of this paper is outlined as follows. Section 2 surveys the SOA approaches dealing with UAV propeller inspection. In section 3, we present the adopted methodology before discussing the experiment setup in section 4. In section 5, the obtained results are evaluated and surveyed. Finally, the paper discusses the future challenges surrounding propeller visual inspections.

## II. LITERATURE REVIEW

Propeller defects, such as cracks, deformations, and wear, can significantly reduce the efficiency and safety of drone operations and even lead to catastrophic failures [3].

The traditional methods for inspecting drone propellers, such as manual visual inspection, are time-consuming and labor-intensive. Lately, methods based on machine learning algorithms are gaining more and more interest due to the robustness that they bring to the detection problem.

### A. Propeller Fault Inspection

Lee et al. [4] proposed a technique for detecting faults in UAV motors using a steady-state model and an infrared sensor to measure angular speed. The classification and diagnostics of motors is tested based on the predicted nonlinear parameters of a steady-state model. DC motor are used to simplify the model assumption due to the facility of removing derivatives. According to their results, the model performance is unstable due to the transient state and is very sensitive to sensor noise.

In the same direction, Ciaburro et al. [5] proposed a model based on the audio signal processing of the propeller sound. The measurements of the noise emitted by a UAV were used to build a classification model to detect unbalanced blades in a UAV propeller with an accuracy reaching 97.63%. A similar study [6] has also leveraged the audio signal for fault detection. The detection algorithm is a data-driven approach that uses of an artificial neural network to classify characteristic features of acoustic signals (Mel Frequency Spectrum Coefficients) and accurately detect the presence of anomalies.

Guo et al. [7] also proposed a hybrid feature model and deep learning-based fault diagnosis for UAV sensors. Their model makes use of residual signals of different sensor faults,

including a global positioning system (GPS), an inertial measurement unit (IMU), and an air data system (ADS).

Bondyra [8] et al. adopted a three-stage method based on signal processing and machine learning. The method aims to identify a rotor fault's occurrence and detect its scale and type. The proposed method uses the measurements of acceleration from an inertial measurement unit (IMU) sensor to detect the fault. Unbalanced rotating parts are sources of vibrations in mechanical systems, noticeable in the acceleration signal.

Li et al. [9] developed a model based on a deep Gaussian-Bernoulli Boltzmann machine (GDBM) that uses a statistical approach using vibration measurements of rotating machines. The recorded signals of the vibration sensors by rotating mechanical systems are represented in the time, frequency and time frequency domains. The statistical approach can detect several defects with a minimum accuracy of 91%.

### B. Passive vs. Active Learning

The usage of deep learning in computer vision tasks have been a trending topic in the last decade. In fact, the vision inspection systems have noticed a tremendous increase in their robustness thanks to breakthrough in neural networks. Deep learning architectures and their training strategy play an essential role in ensuring the model quality.

Active learning is a machine learning approach that aims to improve model accuracy while minimizing the labeling effort required. It involves selecting the most informative samples from a large unlabeled dataset and presenting them to a human expert for labeling. The labeled samples are then used to train the model, and the process is repeated iteratively. Compared to passive deep learning tasks, active learning can significantly reduce labeling effort while achieving comparable or better model accuracy [10], [11].

Active learning can be beneficial approach for inspection tasks, especially when labeled data is limited or costly. It offers the advantage of reducing the annotation effort and achieving comparable performance to deep passive learning with a smaller labeled dataset. However, passive deep learning can also be a suitable choice if a large labeled dataset is readily available and annotation costs are not a significant concern. The selection between the two approaches depends on the specific constraints, available resources, and desired trade-offs in terms of data efficiency and annotation costs.

## III. METHODOLOGY

The study introduces a robust methodology to enhance the reliability and safety of Unmanned Aerial Vehicles (UAVs) by applying Deep Learning (DL) techniques. Focused primarily on the critical aspect of propeller inspection, our approach employs a comprehensive process encompassing data collection, data augmentation, duplicate removal, and the training based on both passive and active learning strategies. We aim is to fortify UAV's operational lifespan and flight performance through the creation of an automated, efficient, and accurate propeller inspection mechanism.

### A. Dataset Collection

At the time of the experiment, no publicly available dataset included propeller defects. Identification of the appropriate dataset for training the deep learning model is essential step to solving the task. The dataset's quality is also a critical aspect

to guarantee a high-quality model. It is proven that the dataset's quality directly affects the performance and quality of the trained model [12]. Therefore, collecting a quality dataset for the training and testing phases (Fig. ). To achieve this, we collected, using a camera mounted on top of the UAV, a total of 1216 images split fairly into two main classes: healthy, and broken. Due to the limited number of broken propellers, the background of the captured frames has been changed to diversify the samples in our dataset. In addition, the frames were captured under different illumination conditions. The propellers were also classified depending on the severity of the defect. Three categories were taken into consideration: fully broken, partially broken, and healthy. This helps the model distinguish between defect types and also allows it to generalize easily to new or unseen data.



Fig. 2 Samples from the collected image dataset

### B. Data Augmentation and Preprocessing

Data augmentation is a strategy that permits diversifying the feature elements that could be fed to the model during training [13]. It enhances the capabilities of a model to improve its resilience to object transition, and prevent overfitting. The augmentation strategy bolsters the model's capacity to detect propeller defects under various conditions, such as changes in texture, orientation, or illumination. To reduce training time and resource consumption, we opted for offline augmentation rather than its online counterpart. We applied a range of augmentation techniques (Fig. ) which allowed us to collect approximately 5000 images. While traditional data augmentation includes techniques such as rotation, flipping, gray scaling, noise, and scaling, we also opted as well for negative transformation. The negative transformations are formed by inverting the image with the point processing operation. In image inversion, the original pixel value is replaced by the subtraction between the maximum pixel value and each pixel value. In our study, it plays a vital role due to the object color and darker background in the image. It helps extract information from the image's dark areas [14]. Therefore, we used color negative and gray negative images for our dataset.

Since data augmentation increases the number of samples in the dataset, it sometimes causes the generation of duplicate images. Therefore, we developed a duplicate detector based on calculating of the mean square error difference, which allows us to compare identical images. This method is enormously flexible to resist noises and considerably robust in recognizing the image [15]. This phase aims to guarantee the

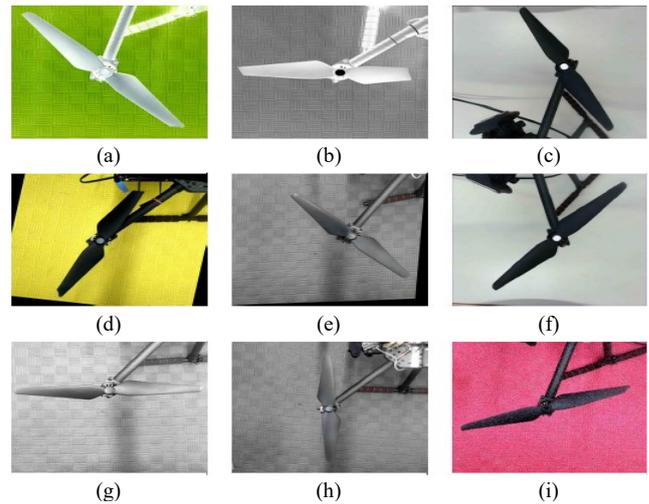


Fig. 3 Illustration of several data augmentation techniques applied to propellers (a) color negative (b) gray negative (c) 90° rotation (d) 10° rotation (e) 10° shear (f) flipping (g) grayscale (h) blur (i) noise

collection of a balanced dataset with diversified samples and without duplicates.

### C. Deep Learning Frameworks

Our research employed two prominent deep learning paradigms: passive learning and active learning, each providing unique strengths and posing different challenges. These learning strategies dictate how our model interacts with the training data and consequently influence the model's learning efficiency and performance.

#### 1) Passive Learning

Passive deep learning, also known as traditional supervised learning, involves the training on the labeled dataset. In this learning paradigm, the training is performed only once without any interaction or modification during the training phase. In this regard, the dataset is split in a 80:20 ratio, where 80% is reserved for the training and 20% for the testing phase. The YOLOv5 model is therefore trained and fine-tuned with a validation set representing about 20% of the training set. The primary purpose behind the fine-tuning is to increase the obtained accuracy from the training and help the model generalize.

#### 2) Active Learning

Active learning is a machine learning technique that involves selecting the most informative data samples to be labeled by a human expert, thus reducing the amount of labeled data required for training. As it can be seen in Fig. 2, the methodology of the active deep learning used for the propeller damage inspection was based on the proposed approaches [10], [16] and it incorporates the following steps:

- a. Determination of the types of propeller damages to be inspected.
- b. Initial dataset compilation: 15% of the dataset was manually labelled, categorized into three distinct groups according to the extent of propeller damage, as will be further elaborated.
- c. Initial model training: The YOLOv5 model was initially trained on the 15% labelled dataset to acquire baseline performance metrics.

- d. Informative sample selection: 5% of the unlabeled original dataset was selected using an uncertainty and query-based selection method, allowing the model to earmark the most informative propeller images for labelling.
- e. Labeling of selected samples: An expert manually labelled the chosen samples, which were then incorporated into the training dataset.
- f. YOLOv5 model retraining: The model was retrained again with the 5% of labelled dataset to upgrade its knowledge base.
- g. Steps d to g were executed in a repeated cycle until the model's performance attained a satisfactory level.

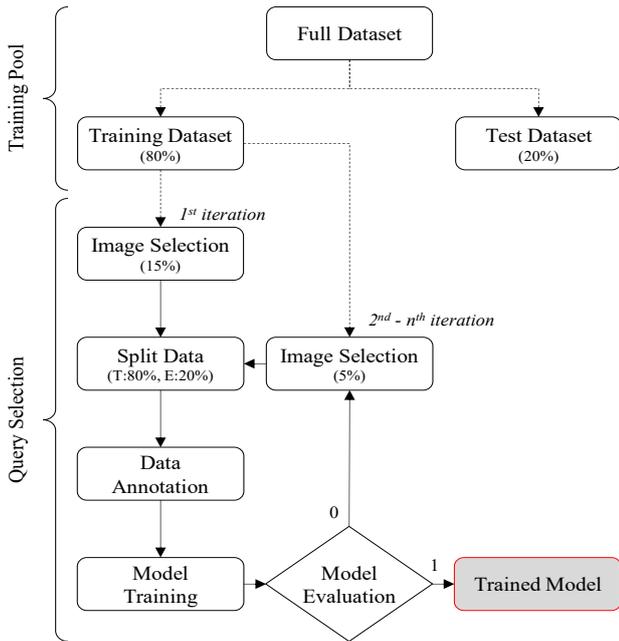


Fig. 2 Proposed Active Learning Workflow

Another essential aspect of the active learning framework is the query selection strategy. There are several popular strategies to sample the data in active learning. Uncertainty sampling is one of these strategies. It uses the most informative samples, about which the model is most certain. In the case of this research, the model performs a binary classification to predict the presence of a defect. Therefore, choosing the right query strategy is essential to obtain optimal results in the shortest amount of time. As discussed earlier in the report, the dataset is split into three main categories depending on the degree of the propeller damage. This leads to three degrees of confidence as explained below:

- High Confidence: This category includes images where the propeller damage is most severe or even fully broken. Our model demonstrates a high level of confidence when dealing with such images, as the distinguishing features of such severe damage are typically clear and straightforward to detect.
- Average Confidence: Images falling into this category show propellers with only partial damage. The level of confidence here is somewhat intermediate, as the damages are less conspicuous compared to the high confidence category. It's also a more challenging

classification task since it involves distinguishing between minor defects and normal wear and tear.

- Low Confidence: This category is comprised of images that depict healthy propellers. These images typically elicit a lower level of confidence from the model as there is often a fine line between a perfectly healthy propeller and one with minor, yet significant, damage. Ensuring that the model correctly identifies healthy propellers is crucial for avoiding false positives.

#### D. Model Training

The passive learning strategy involves training the model for a total of 150 epochs, with a batch size of 16, using the Stochastic Gradient Descent (SGD) optimizer. This process is implemented on a Tesla T4 GPU, ensuring optimal computational efficiency. We used the YOLOv5m architecture to focus on accuracy rather than performance. Unlike the active learning approach, where training involves iteratively selecting, labeling, and introducing samples into the training set based on their confidence levels (high, average, and low), the passive learning strategy maintains a fixed training dataset and uses consistent hyper-parameters. This distinct approach to model training offers valuable insight into the effectiveness and efficiency of both passive and active learning methodologies in propeller defect detection.

## IV. RESULTS AND DISCUSSION

Following the model training, the results were assessed for both the passive and the active approaches. The evaluation was performed on the same test data. In order to assess the performance and effectiveness of our model in the task of propeller damage classification, we leveraged a set of widely-used metrics. This includes precision, recall, and mean average precision (mAP).

The mean average precision clearly assesses the model's performance, specifically for the YOLO family. It is evaluated based on model prediction's intersection over union (IoU) and the ground truth. In the case of @0.5, the intersection represents 50% of the union. The precision and the recall are measured using the formula in (1) and (2), which are calculated using the confusion matrix results.

$$Recall = \frac{TP}{TP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

TABLE I represents the obtained results from the passive learning approach. We trained two versions of the YOLOv5 model, where YOLOv5s is lightweight but less accurate than YOLOv5m. In addition, we compared the obtained results with the YOLOv7 model, for testing purposes. As depicted in the table, the performance of the YOLOv5m overcomes both

TABLE I Model performance comparison using passive learning

Models	Precision	Recall	mAP @0.5	mAP @0.5-0.95
YOLOv5s	0.769	0.823	0.798	0.663
<b>YOLOv5m</b>	<b>0.798</b>	<b>0.849</b>	<b>0.853</b>	<b>0.737</b>
YOLOv7	0.777	0.810	0.847	0.725

other YOLO versions, allowing us to detect the presence of defects on propellers accurately. Therefore, the active learning approach was performed on the YOLOv5m model to compare the results of both strategies.

Although the passive learning scored a mAP reaching 85%, it required the entire dataset and longer times to train the model. On the other hand, the active learning, which iteratively feeds chunks of selected datasets to train the model further, obtained the same mAP after 10 phases. Furthermore, it required only 60% percent of the entire dataset and less time to train the model. TABLE II showcases the aforementioned results and Fig. 3 depicts the model predictions.

TABLE II Performance Evaluation between passive and active learning for YOLOv5m

Learning methods	Datasets	Training Data	Dataset [%]	Precision	Recall	mAP @0.5
Active	Training Set 1	754	15%	0.314	0.261	0.316
	Training Set 2	968	20%	0.368	0.303	0.402
	Training Set 3	1172	25%	0.423	0.350	0.499
	Training Set 4	1364	30%	0.482	0.402	0.573
	Training Set 5	1548	35%	0.545	0.464	0.728
	Training Set 6	1722	40%	0.608	0.529	0.781
	Training Set 7	1888	45%	0.695	0.666	0.827
	Training Set 8	2046	50%	0.761	0.734	0.845
	Training Set 9	2198	55%	0.816	0.797	0.836
	Training Set 10	2340	60%	0.823	0.816	0.858
Passive	Full dataset	4092	100%	0.798	0.849	0.853

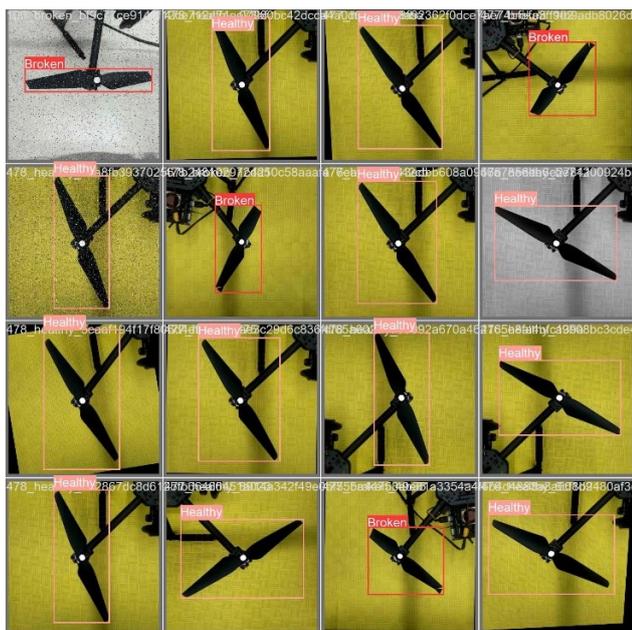


Fig. 3 YOLOv5m model predictions on the test data

## V. CONCLUSION

This research takes on the task of propeller damage identification on UAVs, despite the challenge related to the size of the dataset. We have constructed two deep learning models, following both passive and active learning strategies, to assess propeller health accurately. Both models harness the power of YOLOv5 medium architecture, delivering around 30 FPS, which makes them apt for the inspection applications.

When comparing the two strategies, our results suggest that active learning can potentially enhance efficiency in

object inspections, mainly when the available dataset is limited. Although it is efficient in the learning process, active learning still demands increased human interaction.

On the other hand, when a rich and varied dataset is available, and the variability in propeller conditions is less, passive learning appears to be more suitable. This study represents an initial step in inspecting aircraft propellers using image datasets. As we look ahead, future endeavors will involve refinement of our models to boost their generalizability. This would enable the models to tackle a broader range of propeller conditions and further enhance performance metrics. Additionally, improved deployment strategies will be a key focus to ensure practical real-time application of these models.

## ACKNOWLEDGMENT

The research presented is part of the project 'RescueFly', number 45ILM1016D, which is funded by the German Federal Ministry for Digital and Transport.

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