International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

YOLO vs RCNN for Real Time Aerial Survey: A Review

Mudasir Ashraf

Manipa Global Nxt University

Abstract: ***This article reviews the effectiveness of two prominent object detection algorithms, YOLO (You Only Look Once) and RCNN (Region - based Convolutional Neural Networks), specifically in the context of real - time aerial surveys. YOLO is known for its speed and ability to process data in real - time, making it ideal for applications where rapid decision - making is required. In contrast, RCNN offers higher detection accuracy by using a multi - step process, which is particularly beneficial in tasks that demand precise object identification, though it requires more computational resources. This review explores the strengths and limitations of each algorithm to guide researchers and practitioners in selecting the most suitable approach for aerial data collection.***

Keywords: aerial survey, YOLO, RCNN, real - time detection, object detection

1. Introduction

In the field of aerial monitoring, improvements in computer vision have led to the use of advanced object detection methods, which improve both the speed and accuracy of data gathering. Among these techniques, the You Only Look Once (YOLO) system and the Region - based Convolutional Neural Networks (RCNN) stand out as top options, each offering unique benefits suited for different operational settings. While YOLO is noted for its exceptional speed and capability to handle real - time video feeds, RCNN is known for providing higher accuracy by carefully refining object suggestions through a multi - step detection process. This review outlines the comparative benefits and drawbacks of YOLO and RCNN, with the goal of helping users and researchers choose the best method for real - time aerial surveys. By examining existing research and practical uses, the results will highlight how these methods can transform the area of aerial data collection and analysis.

a) Background on Aerial Survey Technologies

The development of aerial survey tools has changed how data is collected in different fields, especially in farming, environment checks, and city planning. Using drones, researchers can carry out accurate and quick evaluations of land and resources. These improvements have created many uses, ranging from monitoring crop health with live images to using advanced algorithms for better data analysis. Importantly, deep learning models like the YOLO series have become key in improving how objects are detected in aerial surveys. Comparing YOLO with other detection methods, like RCNN, is important due to the performance differences caused by the quality of images from UAVs ((Tian et al., 2023)). This examination shows how choosing the right algorithm affects the effectiveness and accuracy of aerial surveys, emphasizing the need for creating optimized systems for real - time use ((Badgujar et al., 2024)).

b) Importance of Real - time Object Detection

The skill to detect objects in real - time is more important now in many areas, especially in aerial observation and checking the environment. With new tools like drones, being able to quickly find and identify objects like sharks can greatly improve safety at beaches or in marine parks. For example, projects that use cloud - based machine learning to warn officials about sharks' presence may face problems due to internet connection issues; therefore, it is essential to have a strong on - device solution (Moore et al., 2020). Additionally, the history of object detection systems shows a move towards quicker and more precise methods that meet real - time needs, especially in changing environments (Guo et al., 2019). As these systems become more reliable, the areas where they can be used widen, resulting in better use of resources and decision - making in emergencies. Therefore, advancing real - time detection methods will improve public safety and operational effectiveness.

c) Overview of YOLO and RCNN Frameworks

Many object detection frameworks have come up to meet the important need for fast applications, especially in fast - moving areas like aerial surveys. The YOLO (You Only Look Once) design has become well - liked due to its great speed and precision, making it a good fit for situations where quick choices matter. Unlike older models that use region proposal networks, YOLO looks at images all at once, finding and locating objects together, which greatly improves how well it works. On the other hand, the R - CNN (Region - based Convolutional Neural Network) system, known for its strong detection skills, works in several steps that involve first generating region proposals and then classifying them, leading to high accuracy but slower speeds. While R - CNN systems have been effective in spotting complicated features—like road markings in aerial images (Kimollo et al., 2023) —the need for real - time results in aerial surveys makes the lighter YOLO architecture better for performance and flexibility in different field situations.

2. Overview of YOLO (You Only Look Once)

A major step forward in object detection is the launch of YOLO (You Only Look Once), which changes how images are processed by providing real - time detection. Unlike older methods that use convolutional neural networks (CNNs) in a step - by - step way for proposals and classification, YOLO treats detection as one problem, predicting bounding boxes and class probabilities from entire images at once. This design greatly cuts down on processing time, which is crucial for tasks needing quick responses, like real - time aerial surveys.

The mix of efficiency and speed makes YOLO a better choice when computing power is limited, such as on UAVs, making it useful in environments like coastal monitoring or infrastructure assessment, where quick decisions and accuracy are vital. Using YOLO could help fix the issues seen in systems like SSD MobileNet and enhance object detection in challenging aerial datasets (Moore et al., 2020) (Qurishee et al., 2019).

a) Architecture and Design Principles

Understanding architecture and design principles in object detection frameworks is very important for improving performance in real - time use cases like aerial surveys. The architecture choices in these frameworks, especially between YOLO and RCNN, significantly affect their efficiency and accuracy. YOLO's end - to - end learning method shows a simple architecture that notably boosts real - time processing, making it suitable for applications like agricultural monitoring and surveillance (Badgujar et al., 2024). On the other hand, the RCNN framework, although more accurate in some situations, often uses a lot of computational resources due to its multi - stage processing, impacting its speed and real - time use (Guo et al., 2019). This comparison of fast detection versus accuracy highlights the need for a well - thought - out design that meets the unique needs of aerial surveys, supporting ongoing research into hybrid models that combine the strengths of both architectures for better results in the field.

b) Advantages of YOLO in Real - time Applications

The YOLO (You Only Look Once) algorithm has clear benefits for real - time uses, especially in aerial surveys where quick decisions are needed. By combining object detection into one neural network, YOLO significantly cuts down on processing time compared to older methods like RCNN, which need several steps for detection and classification. This real - time ability is highlighted by its capacity for high frame rates, such as 53 FPS in UAV situations, making it suitable for tasks that need fast visual assessments (Hu et al., 2023). Also, the recent updates in the YOLO series, including improvements like the transformer and GhostBottleneck, not only boost accuracy but also lessen resource use, enabling efficient edge computing setups (Tian et al., 2023). Therefore, YOLO emerges as a very effective choice in situations where quick reactions and accurate object identification are important, especially in tough conditions like low light.

c) Limitations and Challenges of YOLO

In real - time aerial surveys, the YOLO (You Only Look Once) model has some limits that can make it less effective. Even though it is fast, the quality of detection can be poor, especially with images from unmanned aerial vehicles (UAVs) where environmental factors might lead to low - quality images. YOLO relies on high - resolution images and has trouble accurately identifying overlapping objects. This creates a big problem in situations where precise object localization and classification are important (Tian et al., 2023). Additionally, YOLO's design does not do well with different scales and aspect ratios, leading to misdetections when surveying complex areas like forests or cities. Overall, these issues indicate that while YOLO provides some operational benefits, these drawbacks need to be thought about carefully, particularly in tasks that need higher accuracy and reliability, like aerial surveying (Guo et al., 2019).

3. Overview of RCNN (Region - based Convolutional Neural Networks)

The change in object detection methods has greatly affected how well aerial surveys work, especially with the introduction of Region - based Convolutional Neural Networks (RCNNs). Unlike older techniques, RCNNs use deep learning to pull detailed features from certain areas of images. This leads to better accuracy in finding and pinpointing objects, which is especially useful for things like monitoring the environment and planning cities. Additionally, combining RCNNs with systems like Faster RCNN helps make things faster and more efficient, which is important for applications that need real - time results. In aerial situations, where images often have low quality and noise, using advanced models like RCNN has proven to be very helpful; they boost the detection of small objects and improve key measures like intersection over union (IoU) and precision (Chao et al., 2020). Therefore, RCNNs are a significant step forward, serving as strong alternatives to faster models like YOLO in aerial survey situations (Oleksii Rubel et al., 2024).

a) Architecture and Design Principles

Understanding how to design and build object detection systems is important for making tools for real - time uses like aerial surveys. Good designs need to balance how fast they run and how accurately they detect things, especially when used in places with limits, like edge - computing devices. For example, the YOLO design is popular for its quickness and effectiveness, shown in aerial monitoring systems where quick decision - making is key during important tasks (Weill et al., 2018). On the other hand, designs like Faster R - CNN may be better in terms of precision but usually require more computing power and time, making them less ideal for situations that need quick reactions. The ongoing changes in design ideas must take these trade - offs into account, adjusting to the different needs of uses from watching over areas to self - driving navigation, as seen in the two - pronged strategy for finding ships with satellite images (Nina Choquehuayta et al., 2020).

b) Advantages of RCNN in Object Detection

In object detection, RCNN (Region - based Convolutional Neural Networks) has many benefits that make it a strong option, especially for tasks needing accuracy. A key advantage of RCNN is its ability to create region proposals and then classify these areas, enabling careful attention to detail in an image. This multi - step method improves the model's ability to identify small objects, which can be difficult in aerial surveys. For instance, the YOLO - Drone model, though advanced, continues to struggle with image quality and timing issues when spotting small items (Hu et al., 2023). On the other hand, RCNN's design is naturally equipped to handle these problems, yielding better outcomes in conditions with changing light and complex settings, as shown by advancements in datasets like UAVDT and VisDrone (Tian et al., 2023). In summary, the strength and accuracy of RCNN make it an important option in the ongoing progress of object detection methods, making it a crucial technology for real - time aerial surveys.

c) Limitations and Challenges of RCNN

The Region - based Convolutional Neural Network (RCNN) has been an important step in object detection, but it has notable drawbacks that limit its use in real - time situations, especially in aerial surveys. A major issue is its computational inefficiency. This inefficiency stems from the systematic way it proposes regions and then classifies them separately, which requires a lot of processing power and time, making it not ideal for time - sensitive needs. This problem is even more noticeable in changing environments, like those found in agricultural monitoring. While RCNN has helped improve detection accuracy, it is often outperformed by newer models, such as You Only Look Once (YOLO), which offer real - time speed and better efficiency (Badgujar et al., 2024). Therefore, although RCNN is historically important in object detection (Guo et al., 2019), the growing need for quick and effective algorithms in real - time use highlights its shortcomings and calls for newer, better solutions.

4. Comparative Analysis of YOLO and RCNN

Choosing the right object detection model is very important for improving UAVs' performance during real - time aerial surveys. YOLO (You Only Look Once) and RCNN (Region - based Convolutional Neural Networks) are two different types that meet different operational needs. YOLO has a big benefit in speed, allowing for real - time detection, which is very important in fast - changing situations where quick decisions must be made. This ability to keep high frame rates is, as mentioned, especially essential when using technologies like edge computing, as it boosts processing efficiency while still keeping accuracy (Tian et al., 2023). On the other hand, RCNN and its versions, like Fast RCNN and Faster RCNN, focus more on accuracy using region proposal methods, but they usually have longer processing times (Babu et al., 2023). In the end, choosing between YOLO and RCNN depends on the specific needs of the survey job and finding the right balance between speed and precision in detecting objects.

a) Performance Metrics in Aerial Surveys

In the area of aerial surveys, checking how well object detection algorithms work requires strict measures that show both accuracy and how well they operate. Important measures, such as precision, recall, and F1 - score, are essential for judging the effectiveness of models like YOLO and R - CNN in finding target objects in difficult settings. These measures help researchers see not just how good the system is at spotting objects but also how well it reduces false positives and false negatives. Also, temporal efficiency is important, mainly in real - time situations where quick analysis is necessary for making decisions. Recent studies have shown that aerial surveys using models like SSD MobileNet have had issues with detecting smaller objects, pointing out the need for special anchor box setups to improve performance under certain flight and viewing conditions (Moore et al., 2020). Additionally, a full review of past developments in object detection reveals ongoing progress and challenges these algorithms encounter, stressing the need for standardized performance measures to make comparisons between different methods easier (Guo et al., 2019).

b) Use Cases and Practical Applications

Object detection algorithms like YOLO and RCNN are very useful in many practical situations, especially in aerial surveys. Drones with these detection systems are now more often used in precision farming and monitoring the environment, giving important information about crop health and changes in land use. For example, YOLO can analyze images quickly, allowing stakeholders to respond fast to changing conditions (Tian et al., 2023). Also, these technologies are useful beyond farming; using aerial photos for disaster assessments shows how they can improve understanding during crises (Tian et al., 2023). These uses show the significant impact of these algorithms, as shown by studies of over 400 object detection papers that demonstrate their growth and new methods. Therefore, using YOLO and RCNN for real - time aerial surveys has important effects, encouraging proactive decision - making in different fields.

c) Future Trends and Developments in Object Detection

New trends in object detection are likely to change the abilities of applications in different fields, especially in agriculture and aerial monitoring. The growth of deep learning frameworks like YOLO and RCNN shows a major move towards models that are more efficient and accurate. This makes real - time processing possible, which is important for changing environments. YOLO's approach of learning from start to finish allows for quick object detection with little delay, making it more appealing for automated systems in farming ((Badgujar et al., 2024)). Additionally, better datasets and improved detection measures have led to mixed models that use the benefits of both YOLO and RCNN, improving accuracy and flexibility in tough situations ((Guo et al., 2019)). Future work will probably aim to connect these models with new technologies like drones and edge computing, which will make operations smoother and promote better resource management. Overall, these developments point to an important change in automated monitoring methods.

5. Conclusion

This review shows how using advanced deep learning methods, especially YOLO and RCNN types, can change real - time aerial surveys. By adding these technologies to UAV systems, there have been notable improvements in finding structural problems, like cracks in concrete bridges. The study highlights how UAVs help not just with speeding up inspections but also with dealing with issues from changing environments, like lighting, mentioned in (Babu et al., 2023). Additionally, the new YOLO - Drone algorithm shows marked enhancements in object detection in tough situations, such as low - light areas, as noted in (Hu et al., 2023). In conclusion, this review points out the need to use these advanced methods to improve structural health monitoring, which helps ensure safety in key infrastructure. The findings of this research go beyond just technology, suggesting a move towards a more efficient and dependable future in aerial surveying.

a) Summary of Key Findings

The comparison of YOLO and RCNN for real - time aerial surveys shows important information about the use and effectiveness of these advanced object detection methods.

YOLO's ability to process data quickly and its lower resource needs make it very effective for tasks that require quick decisions, as shown in various studies (Tian et al., 2023). On the other hand, RCNN and its versions, while providing better detection accuracy, often require more computational power, which can limit their use in urgent situations, like monitoring buildings in UAV tasks (Babu et al., 2023). This contrast reveals the need to balance performance and efficiency, particularly when analyzing UAV images, which often face issues like changing lighting and small target sizes. In the end, the results emphasize the need to choose the right algorithm for specific project needs, with YOLO performing well in speed and efficiency, and RCNN focusing on accuracy when there are enough computational resources.

b) Implications for Future Research

Developments in UAV tech and deep learning methods make good space for future study in live aerial surveys, especially in structural health checking and ecological reviews. The combining of deep learning tools, like YOLO and RCNN, seems good for better crack spotting in buildings (Babu et al., 2023), but changes are needed to use these tools in changing settings. Next research should look at creating light, on - device detection systems that can work by themselves in remote areas, much like projects for shark spotting that show how useful local processing is (Moore et al., 2020). Moreover, studies could look into tailoring anchor box setups to boost detection accuracy for smaller items, which is important for uses from building monitoring to managing wild animals. Together, these efforts not only help the growth of UAV uses but also meet the urgent need for effective and trusted monitoring systems in many areas.

c) Final Thoughts on YOLO vs RCNN in Aerial Surveying

In the changing field of aerial surveying, the choice between YOLO (You Only Look Once) and R - CNN (Region - based Convolutional Neural Networks) depends on specific needs and limitations of the application. YOLO has clear benefits in situations that need real - time processing, as its single architecture allows for quicker predictions, making it especially useful for fast - paced environments where quick decisions are important. On the other hand, R - CNN, known for its higher accuracy due to a more complicated process that includes region proposal networks, performs better in static situations where detail and accuracy are more important than speed. Therefore, the effectiveness of each model relies on the deployment context; so, users must carefully consider whether they need fast response times or thorough analysis. In the end, the different strengths of YOLO and R - CNN highlight the importance of a careful choice in model selection in aerial surveying.

References

[1] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[2] Badgujar, Chetan M, Gan, Hao, Poulose, Alwin (2024). "Agricultural Object Detection with You Look Only Once (YOLO) Algorithm: A Bibliometric and Systematic Literature Review". http: //arxiv. org/abs/2401.10379

[3] Moore, Daniel (2020). "Towards On - Device Detection of Sharks with Drones". DigitalCommons[at]CalPoly. https: //core. ac. uk/download/491317625. pdf

[4] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[5] Moore, Daniel (2020). "Towards On - Device Detection of Sharks with Drones". DigitalCommons[at]CalPoly. https: //core. ac. uk/download/491317625. pdf

[6] Kimollo, Michael (2023). "Extracting road surface marking features from aerial images using deep learning". UNF Digital Commons. https: //core. ac. uk/download/604296936. pdf

[7] Chao, Dennis, Chowdhury, Subir, Rabbi, Jakaria, Ray, Nilanjan, Schubert, Matthias (2020). "Small - Object Detection in Remote Sensing Images with End - to - End Edge - Enhanced GAN and Object Detector Network". http: //arxiv. org/abs/2003.09085

[8] Oleksii Rubel, Rostyslav Tsekhmystro, Vladimir Lukin (2024). "Study of methods for searching and localizing objects in images from aircraft using convolutional neural networks". National Aerospace University «Kharkiv Aviation Institute». https: //core. ac. uk/download/614738340. pdf

[9] Babu, Bandla Pavan, Bingi, Kishore, Gargote, Saurach, Khandagale, Sarah, Shinde, Vedashree (2023). "Enhancing Infrastructure Safety: A UAV - Based Approach for Crack Detection". Faculty of Engineering, Chulalongkorn University. https: //core. ac. uk/download/595328752. pdf

[10] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[11] Hu, Hanzheng, Jiang, Zhengnan, Xiong, Feng, Xiong, Jiahui, Zhu, Li (2023). "YOLO - Drone: Airborne real - time detection of dense small objects from high - altitude perspective". http: //arxiv. org/abs/2304.06925

[12] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[13] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[14] Badgujar, Chetan M, Gan, Hao, Poulose, Alwin (2024). "Agricultural Object Detection with You Look Only Once (YOLO) Algorithm: A Bibliometric and Systematic Literature Review". http: //arxiv. org/abs/2401.10379

[15] Moore, Daniel (2020). "Towards On - Device Detection of Sharks with Drones". DigitalCommons[at]CalPoly. https: //core. ac. uk/download/491317625. pdf

[16] Qurishee, Murad Al (2019). "Low - cost deep learning UAV and Raspberry Pi solution to real time pavement condition assessment". UTC Scholar. https: //core. ac. uk/download/215400573. pdf

[17] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV

applications". https: //core. ac. uk/download/613186057. pdf

[18] Babu, Bandla Pavan, Bingi, Kishore, Gargote, Saurach, Khandagale, Sarah, Shinde, Vedashree (2023). "Enhancing Infrastructure Safety: A UAV - Based Approach for Crack Detection". Faculty of Engineering, Chulalongkorn University. https: //core. ac. uk/download/595328752. pdf

[19] Hu, Hanzheng, Jiang, Zhengnan, Xiong, Feng, Xiong, Jiahui, Zhu, Li (2023). "YOLO - Drone: Airborne real - time detection of dense small objects from high - altitude perspective". http: //arxiv. org/abs/2304.06925

[20] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[21] Badgujar, Chetan M, Gan, Hao, Poulose, Alwin (2024). "Agricultural Object Detection with You Look Only Once (YOLO) Algorithm: A Bibliometric and Systematic Literature Review". http: //arxiv. org/abs/2401.10379

[22] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[23] Badgujar, Chetan M, Gan, Hao, Poulose, Alwin (2024). "Agricultural Object Detection with You Look Only Once (YOLO) Algorithm: A Bibliometric and Systematic Literature Review". http: //arxiv. org/abs/2401.10379

[24] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[25] Babu, Bandla Pavan, Bingi, Kishore, Gargote, Saurach, Khandagale, Sarah, Shinde, Vedashree (2023). "Enhancing Infrastructure Safety: A UAV - Based Approach for Crack Detection". Faculty of Engineering, Chulalongkorn University. https: //core. ac. uk/download/595328752. pdf

[26] Hu, Hanzheng, Jiang, Zhengnan, Xiong, Feng, Xiong, Jiahui, Zhu, Li (2023). "YOLO - Drone: Airborne real - time detection of dense small objects from high - altitude perspective". http: //arxiv. org/abs/2304.06925

[27] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[28] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[29] Tian, Yikun (2023). "Effective image enhancement and fast object detection for improved UAV applications". https: //core. ac. uk/download/613186057. pdf

[30] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055

[31] Babu, Bandla Pavan, Bingi, Kishore, Gargote, Saurach, Khandagale, Sarah, Shinde, Vedashree (2023). "Enhancing Infrastructure Safety: A UAV - Based Approach for Crack Detection". Faculty of Engineering, Chulalongkorn University. https: //core. ac. uk/download/595328752. pdf

[32] Moore, Daniel (2020). "Towards On - Device Detection of Sharks with Drones". DigitalCommons[at]CalPoly. https: //core. ac. uk/download/491317625. pdf

[33] Weill, Edwin Lee (2018). "Edge - Computing Deep Learning - Based Computer Vision Systems". Clemson University Libraries. https: //core. ac. uk/download/268676963. pdf

[34] Nina Choquehuayta, Wilder (2020). "Detección de embarcaciones utilizando Deep Learning e imágenes satelitales ópticas". 'Baishideng Publishing Group Inc. '. https: //core. ac. uk/download/559499670. pdf

[35] Moore, Daniel (2020). "Towards On - Device Detection of Sharks with Drones". DigitalCommons[at]CalPoly. https: //core. ac. uk/download/491317625. pdf

[36] Guo, Yuhong, Shi, Zhenwei, Ye, Jieping, Zou, Zhengxia (2019). "Object Detection in 20 Years: A Survey". http: //arxiv. org/abs/1905.05055