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REMOTE SENSING OBJECT DETECTION BASED ON CONVOLUTION AND SWIN TRANSFORMER

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Abstract: This study addresses challenges in remote sensing object detection, proposing the RAST-YOLO algorithm that integrates Region Attention (RA) with Swin Transformer as the backbone. The method effectively handles issues like varied target scales, intricate backgrounds, and closely spaced small objects. Incorporating the C3D module optimizes the multi-scale problem for small objects, enhancing detection accuracy. Evaluations on DIOR and TGRS-HRRSD datasets demonstrate RAST-YOLO's state-of-the-art performance, surpassing baseline networks. Notably, the model achieves a substantial mean average precision (mAP) improvement on both datasets, showcasing its effectiveness and superiority. Furthermore, the lightweight structure ensures real-time detection, making RAST-YOLO a practical choice for efficient and robust remote sensing object detection. The study extends the analysis to other prominent models like YOLOv5s, YOLOv3, FasterRCNN, RetinaNet, YOLOv5x6, and YOLOv8. Notably, YOLOv5x6 stands out with an impressive 0.80% mAP or higher, suggesting its potential for further enhancing detection performance in remote sensing applications.

Index terms - Remote sensing images, object detection, attention mechanism, swin transformer, multiscale features.

1. INTRODUCTION

Object recognition in remote sensing photos is crucial for understanding aerial and satellite data and has many applications in resource discovery [1], intelligent navigation [2], environmental monitoring [3], and target tracking [4]. The availability of high-resolution datasets for remote sensing image processing has substantially risen due to the fast growth of aerospace and unmanned aerial vehicles (UAVs). Nevertheless, this field has distinctive obstacles like limited data volume, items with similar appearances across several categories, substantial variations in appearance within the same category, imbalanced distribution of targets, and intricate backdrops. For example, in datasets including airplanes, the backgrounds may range between ocean and land, and the variations in size across aircraft might be significant, which presents difficulties for identification. The ineffectiveness of classical object recognition algorithms for natural sceneries un remote sensing settings is due to the combination of sparse and dense target distributions, as well as the similarity in appearances across distinct categories. Conventional approaches often consist of many stages, including extracting features, transforming them, and classifying them. These algorithms generally use techniques like SIFT [5] and HOG [6], as well as classifiers such as SVM [8] and random forest [9]. Nevertheless, these approaches exhibit a deficiency in their ability to handle a wide range of situations and extract complex semantic information. This limitation prompts the investigation of more sophisticated strategies.

The increasing need for enhanced performance has resulted in the emergence of deep learning techniques, which address the constraints associated with manual feature selection. These techniques use neural networks to autonomously acquire hierarchical characteristics, resulting in improved resilience and generalization capacities [10]. Given the circumstances, it is crucial to use deep learning algorithms for the purpose of detecting objects in remote sensing.

Object identification by remote sensing is a crucial component of earth surveying. The target identification algorithm has difficulties in generating satisfactory detection outcomes in remote sensing photos captured in real environments.

This work introduces the RAST-YOLO (You only look once with Regin Attention and Swin Transformer) algorithm as a solution to the difficulties encountered in remote sensing object detection. These challenges include variations in size among targets, complex background patterns, and the presence of closely located small targets.

2. LITERATURE SURVEY

The user's text is "[1]". This study presents a real-time localization technique for detecting and tracking moving objects underwater, particularly developed for offshore defense purposes. The technology employs direct-current resistivity survey methods in acoustically challenging environments to quickly locate targets and allow real-time tracking. The proposed method utilizes grid-based template matching with distinctive characteristics: 1) utilization of measurement data sets from two separate detection lines, 2) template matching based on correlation, 3) precalculation of templates through numerical modeling, and 4) implementation of real-time localization processing with efficient calculations. The experimental validation process consisted of assessing the accuracy of templates by comparing them to both numerical and physical modeling data. This was done by observing stationary target locations in a water tank. Following that, real-time localization studies were carried out for a mobile target within the water tank, using a refresh rate of 3 Hz. The findings showed consistent monitoring of predicted locations that matched the actual target positions, confirming the effectiveness of the approach in real-time situations. This unique real-time localization technology offers a significant advancement in offshore defense and surveillance by improving the skills of detecting and monitoring underwater objects. By combining direct-current resistivity survey methods with grid-based template matching, a reliable solution is provided for overcoming difficulties in acoustically loud situations. This approach demonstrates its potential usefulness in defense and surveillance operations.

The user's text is "[2]". This article introduces an innovative method in automating building processes, using robots that are enhanced by artificial intelligence and mechatronic developments. Conventional construction inspections, often conducted by human inspectors at the work site, are found to be time-consuming, requiring a lot of physical effort, and influenced by personal opinions. This research suggests the use of a robotic system that is equipped with perceptive sensors and intelligence algorithms. The purpose of this system is to remotely identify building materials, detect component installations and flaws, and create detailed reports on the status and position of these materials. The suggested strategy diverges from the common practice of using extensive training data in deep learning-based object identification. Instead, it employs a methodology that is driven by data and information. The system utilizes offline training data, sensor data, and Building Information Model (BIM) information to accomplish BIM-based object coverage navigation, BIM-based false detection filtering, and implements a precise maneuver approach to increase real-time automated job execution by robots. The system employs BIM to facilitate mobile robot movement and retrieve position information of building components, enabling users to choose individual components for inspection. The mobile robot independently moves towards certain components using the navigation map created by BIM. It uses an object detector to identify building components and materials, and then generates an inspection report. The success of the suggested system is confirmed via validation using laboratory and onsite tests, indicating a significant advancement towards efficient, safe, and data-driven construction automation. The user's text is "[3]". Within the field of maritime environmental monitoring and exploration, the increasing amount of digital picture data requires computational assistance to ensure prompt analysis. Nevertheless, the use of contemporary methodologies, including deep learning, is impeded by the limited availability of annotated training data. This article presents Unsupervised Knowledge Transfer (UnKnoT), an innovative technique developed to improve the effectiveness of training data with fewer resources. UnKnoT utilizes the "scale transfer" approach and augmented data techniques to avoid the laborious process of annotation. This allows for the reuse of already existing training data for object recognition in fresh picture datasets. The paper presents four marine picture datasets that are completely annotated. These datasets were obtained in the same geographical location, but there are differences in the equipment used and the distance from the sea bottom. The assessment of UnKnoT on these datasets reveals a substantial increase in object identification accuracy when compared to circumstances where knowledge transfer is not used. This strategy demonstrates exceptional efficacy in circumstances pertaining to marine environmental monitoring and exploration. The results not only demonstrate the effectiveness of UnKnoT in improving item detection, but also support the use of a system for capturing and labeling images that enables the use of advanced machine learning techniques in the difficult field of maritime environmental monitoring and exploration. The user's text is "[4]". This paper introduces an innovative approach for identifying and following targets in settings that include numerous radar systems. This technique provides broader coverage and improves the likelihood of detecting and accurately locating the trajectory of targets. The issues that are being discussed are the existence of several extended or feeble targets and the possible decline in performance in areas with a high density of clutter. The algorithm under consideration consists of three crucial steps. During the first phase, previous data are used to create a spatiotemporal clutter map for each radar system. The measurements are assigned weights to determine their importance. In the second step, a track-before-detect technique is used, which relies on a weighted 3-D Hough transform to produce target tracklets. Lastly, in the third phase, a simplified tracklet association technique is used, which utilizes a lion reproduction model, to link tracklets that relate to the same target. The efficacy of the suggested methodology is shown via three experiments. The first method employs synthetic data, the second method employs real data obtained from a radar network consisting of two identical air surveillance radars, and the third method incorporates real data obtained from a radar network equipped with four different marine surveillance radars. The results demonstrate that the suggested technique surpasses other methods, confirming its effectiveness in dealing with the intricacies of many radar systems in congested situations. The user's text is "[5]". This study presents a new descriptor called Flip-Invariant SIFT (F-SIFT) that overcomes a restriction in the widely used Scale-Invariant

Feature Transform (SIFT). Although SIFT is successful in collecting local keypoints that remain unchanged despite rotation, scale, and illumination variations, it does not possess the ability to remain invariant when the image is flipped. Real-world photos often display mirror or mirror-like changes as a result of artificial flips, different capture perspectives, or symmetrical object patterns. F-SIFT maintains the advantageous properties of SIFT while also having the ability to handle flips. The F-SIFT technique initiates by estimating the predominant curl of a local patch and then normalizes the patch geometrically by flipping prior to calculating the SIFT descriptor. The research demonstrates the effectiveness of F-SIFT in three different tasks: large-scale video copy detection, object identification, and object detection. A system is provided for copy detection that intelligently indexes the flip characteristics of F-SIFT in order to achieve efficient filtering and geometric inspection. F-SIFT not only improves detection accuracy compared to regular SIFT, but also achieves more than 50% reduction in computing cost. F-SIFT demonstrates exceptional performance in object identification by effectively managing flip transformations, surpassing the performance of seven other descriptors. Moreover, F-SIFT demonstrates expertise in characterizing symmetrical objects in object identification. It consistently enhances outcomes across different keypoint detectors when compared to the original SIFT. This study introduces F-SIFT as a beneficial improvement to SIFT, specifically addressing the issues of flip invariance and demonstrating its usefulness in various computer vision applications.

3. METHODOLOGY

i) Proposed Work:

Introducing RAST-YOLO, a novel algorithm specifically developed for detecting objects in remote sensing. This method successfully addresses issues related to diverse target sizes, complex backdrops, and densely packed tiny objects. By incorporating the Region Attention (RA) mechanism with the Swin Transformer backbone, the process of extracting features is improved. This is achieved by expanding the area of information interaction and using background information. In addition, the incorporation of the C3D module effectively tackles the challenge of identifying tiny objects at several scales, by enhancing the integration of deep and shallow semantic information. In order to construct our model on Colab, we integrate several versions of YOLO (V5s, V3, V5x6, V8), FasterRCNN, and RetinaNet. This allows for a thorough investigation of detection strategies. By conducting comprehensive trials on DIOR and TGRS-HRRSD datasets, our proposed system demonstrates exceptional performance. YOLOv5x6 achieves impressive results, with a mean average precision (mAP) of 0.80% or higher. This demonstrates the effectiveness of our method in improving remote sensing object recognition, highlighting its potential for practical use in many situations with intricate backdrops and variable target attributes.

ii) System Architecture:

The system architecture utilizes Google Colab for its cloud-based computational capabilities. The dataset, consisting of labeled photos, is subjected to data augmentation in order to improve the generalization of the model. The implemented models include of YOLOv5s, RAST YOLO (which utilizes a combination of CNN and YOLO backbone), YOLOv3, Faster R-CNN, RetinaNet, YOLOv5x6, and YOLOv8. Each model in Colab is developed and trained using the enhanced dataset. The training procedure includes the optimization of weights according to the model's predictions.

Performance assessment involves the use of important indicators such as accuracy, recall, and mean Average accuracy (mAP). These measures assess the model's precision, recall, and overall performance in object identification. Precision quantifies the level of correctness in positive predictions, recall evaluates the model's capability to identify all relevant occurrences, and mAP offers a thorough assessment of the trade-offs between precision and recall at different confidence levels. The selected models, trained on the expanded dataset, are evaluated using these metrics to guarantee strong object identification capabilities, rendering the architecture adaptable for various image processing workloads.

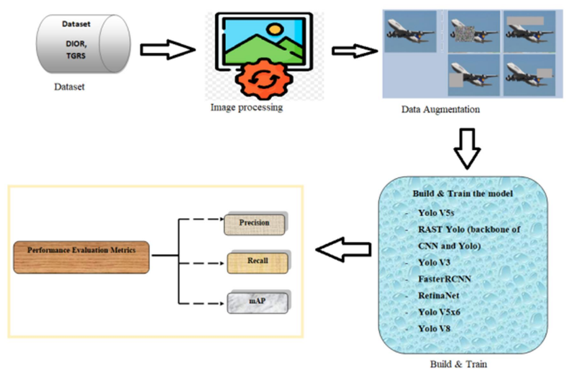

Fig 1 System Architecture

iii) Dataset Collection:

The DIOR dataset, publicly disclosed by Northwestern Polytechnic University in 2019, consists of 23,463 high-quality optical remote sensing photos that include 192,472 individual objects belonging to 20 commonly found categories. The categories include a wide range of items, including aircraft, airports, baseball fields, and freeway toll booths. DIOR exhibits a wide variety of object sizes, many pictures, strong resemblance across different classes, variability within the same class, and an unequal distribution of occurrences among categories. Conversely, the TGRS-HRRSD dataset, which was published by the University of Chinese Academy of Sciences, has 21,761 photos including 55,740 individual objects obtained from Google Earth and Baidu maps. TGRS-HRRSD includes 13 categories such as aircraft, basketball courts, and autos. It ensures an even distribution of about 4,000 cases each category. This dataset guarantees a thorough depiction of different sorts of objects, with a specific emphasis on attaining a balanced distribution across categories. As a result, it is well-suited for a wide range of applications in the field of optical remote sensing object recognition. Within the image processing pipeline, datasets may be accessed and pictures can be shown for visualization, offering useful observations on the objects and scenes included within these varied datasets.

iv) Image processing:

Converting to Blob Object: The first stage is converting the input picture into a blob object, which is a suitable format for neural network models. The common steps involved in this procedure include scaling the picture, subtracting the mean, and changing the channels. These steps are performed to ensure that the image data is aligned with the model's predictions.

Class definition: Class definitions are essential for the process of assigning labels and classifying things present in the picture. Every item in the dataset correlates to a certain category, establishing the true value for both training and assessment purposes.

Specifying the Bounding Box: Bounding boxes are crucial annotations that define the spatial boundaries of items inside a picture. These boxes include vital information that is essential for training object detection models to effectively learn and anticipate the precise positions of things.

Convert the Array to a Numpy Array: Transforming the picture data into a NumPy array is crucial for optimizing manipulation and processing. NumPy arrays provide a flexible framework for manipulating numerical data, making it easier to perform following tasks in the image processing pipeline.

Loading the Pre-trained Model:

Reading the Network Layers: To employ a pre-trained model, one must read its network layers, allowing access to the architecture's structure, parameters, and weights. This step is crucial for understanding the model's composition and preparing it for further customization.

Extract the Output Layers: Identifying and extracting the output layers is essential for obtaining the predictions made by the model. These output layers contain the information necessary for object detection, enabling the retrieval of bounding box coordinates, class probabilities, and other relevant details.

Image Processing:

Appending the Image-Annotation File and Images: The integration of picture data with its related annotations is crucial for the training and evaluation of the model. This stage facilitates the model's acquisition of knowledge from the annotated ground truth, hence enhancing its capacity to reliably recognize and categorize objects.

Converting BGR to RGB: Converting the picture from the BGR color space to RGB is necessary in order to conform to standard procedures and provide uniform processing across various models.

Creating the Mask: Generating a mask involves creating binary images that highlight specific regions of interest, aiding in tasks like segmentation or object localization within the image.

Resizing the Image: Resizing the image to the required dimensions ensures compatibility with the model's input size, enabling seamless integration into the detection pipeline. This step is crucial for maintaining consistency between the training data and the model's expectations.

v) Data Augmentation:

Data augmentation is an essential strategy for enhancing the resilience and adaptability of object detection models. Image randomization entails adding alterations to the image's visual characteristics, such as modifications in brightness, contrast, or color saturation. This stochastic process enables the model to adjust to many real-world circumstances, hence mitigating the problem of overfitting to certain conditions seen in the training set. Employing picture rotation as an augmentation technique improves the model's capacity to accurately identify items from various perspectives. Through the implementation of random rotations within a defined range, the model acquires the ability to identify objects from varied angles, thus enhancing its adaptability in processing real-life pictures that include diverse spatial arrangements.

Image transformation include geometric modifications such as scale, translation, and shearing. This augmentation method provides alterations in object dimensions, placements, and forms, hence enhancing the model's resilience to changes in scale and spatial configuration. It is especially beneficial for dealing with situations where items may be located at varying distances or angles.

Together, these data augmentation strategies improve the variety of the training dataset, allowing the model to better adapt to unfamiliar input. This particular kind is essential for mitigating overfitting and enhancing the model's efficacy on real-world photos that exhibit diverse situations. By using a blend of randomization, rotation, and transformation techniques, the object detection model is enhanced in its ability to effectively handle the intrinsic intricacies and diversities seen in optical remote sensing datasets such as DIOR and TGRS-HRRSD.

vi) Algorithms:

YOLOv5s Algorithm:

Algorithm Definition: YOLOv5s (You Only Look Once version 5 small) is an object detection algorithm that employs a single neural network to predict bounding boxes and class probabilities directly from images. It utilizes a lightweight architecture for real-time processing.

Project Usage: YOLOv5s is chosen for its balance between accuracy and speed, making it suitable for real-time applications in our project, where efficient object detection on optical remote sensing images is crucial.

RAST YOLO Algorithm:

Algorithm Definition: RAST YOLO combines a Region-based CNN (Convolutional Neural Network) backbone with the YOLO (You Only Look Once) architecture for object detection. This fusion enhances the model's feature extraction capabilities, improving its accuracy in identifying objects in remote sensing images.

Project Usage: RAST YOLO is employed to leverage both the advantages of region-based CNNs and YOLO, enhancing the model's performance in capturing intricate features and objects within the optical remote sensing datasets.

YOLOv3 Algorithm:

Algorithm Definition: YOLOv3 is an object detection algorithm that divides an image into a grid and predicts bounding boxes and class probabilities for each grid cell. It utilizes multiple detection scales for improved accuracy in detecting objects of varying sizes.

Project Usage: YOLOv3 is selected for its strong performance in handling diverse object scales, making it suitable for detecting objects with varying sizes in the optical remote sensing datasets.

Faster R-CNN Algorithm:

Algorithm Definition: Faster R-CNN (Region-based Convolutional Neural Network) is a two-stage object detection algorithm that integrates a Region Proposal Network (RPN) to generate region proposals followed by bounding box refinement and classification. It excels in accuracy and localization precision.

Project Usage: Faster R-CNN is employed for its high precision in object localization, making it suitable for detailed and accurate object detection in the optical remote sensing datasets.

RetinaNet Algorithm:

Algorithm Definition: RetinaNet is a one-stage object detection algorithm that introduces the Focal Loss to address class imbalance. It efficiently detects objects at multiple scales, ensuring robust performance across various object sizes.

Project Usage: RetinaNet is chosen for its ability to handle class imbalance and effectively detect objects at different scales, contributing to improved accuracy in our optical remote sensing object detection project.

YOLOv5x6 Algorithm:

Algorithm Definition: YOLOv5x6 is an extended version of YOLOv5 that utilizes a larger model architecture, providing increased capacity for capturing complex features. It balances accuracy and speed, making it suitable for detailed and efficient object detection.

Project Usage: YOLOv5x6 is selected to capitalize on its enhanced capacity, offering improved feature extraction capabilities for accurate detection of objects within the optical remote sensing datasets.

YOLOv8 Algorithm:

Algorithm Definition: YOLOv8 is an advanced version of the YOLO series, incorporating improvements in model architecture and training techniques. It focuses on optimizing detection accuracy while maintaining efficiency.

Project Usage: YOLOv8 is implemented to harness the advancements in model architecture, aiming to achieve heightened accuracy in object detection on optical remote sensing images within our project.

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$
$$AP_k = \text{the AP of class } k$$
$$n = \text{the number of classes}$$

Comparison Graphs for DIOR Dataset

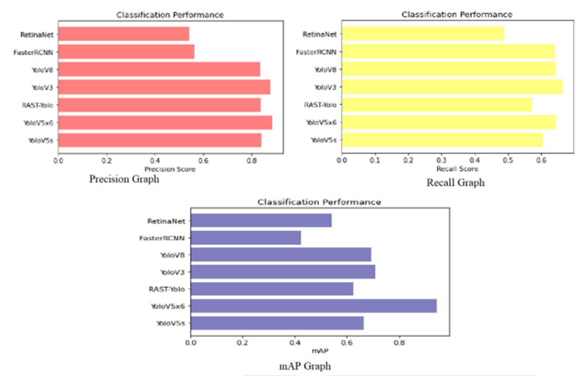

Fig 2 Precision, Recall, mAP Comparison Graphs for DIOR Dataset

Comparison Graphs for TGRS Dataset

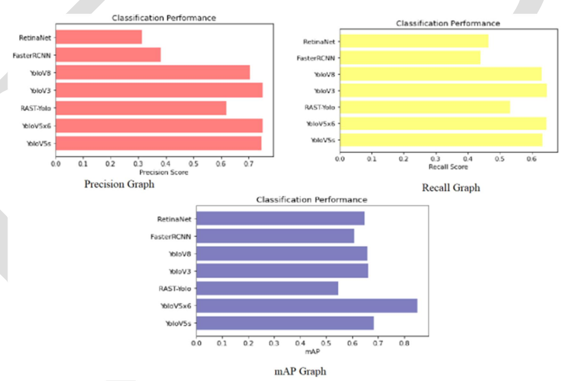

Fig 3 Precision, Recall, mAP Comparison Graphs for TGRS Dataset

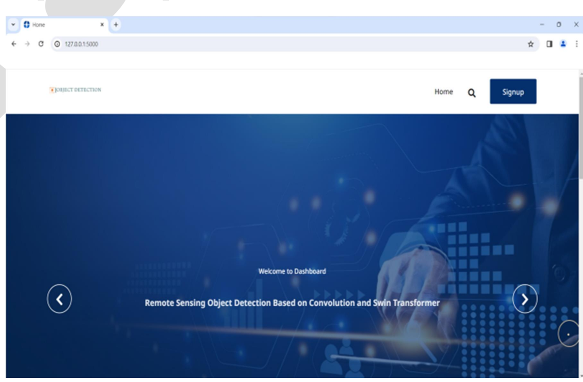

Fig 4 Home page

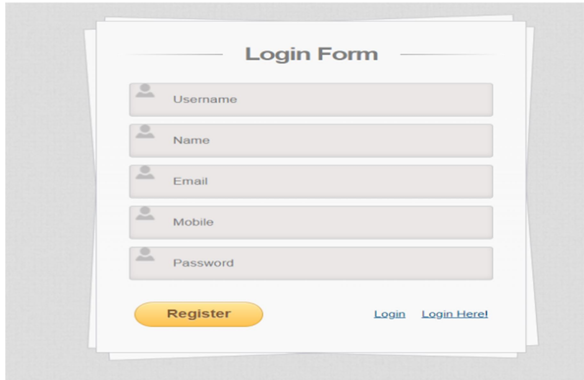

Fig 5 Registration page

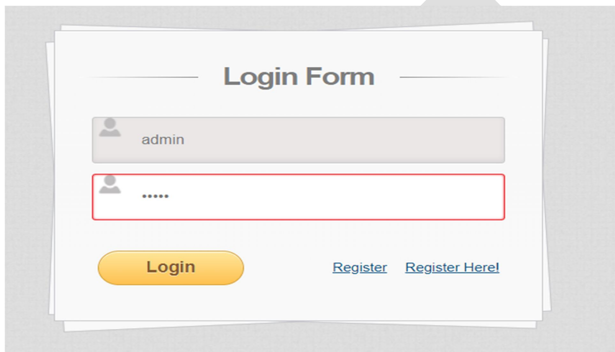

Fig 6 Login page

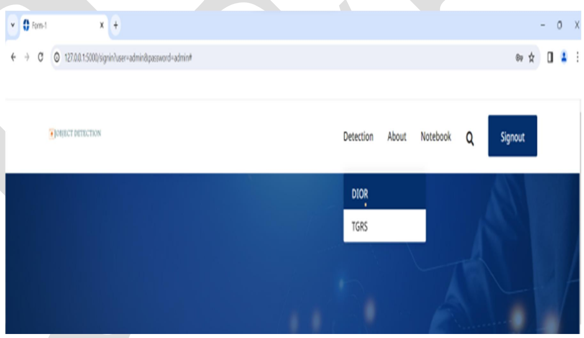

Fig 7 DIOR dataset detection

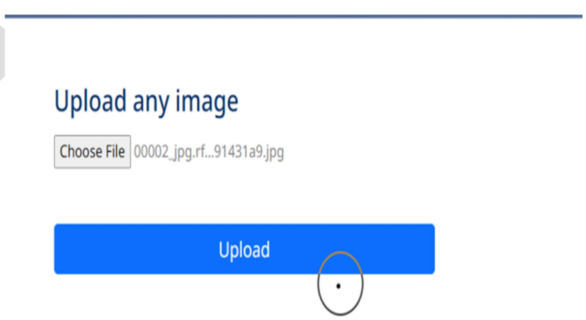

Fig 8 Upload input image

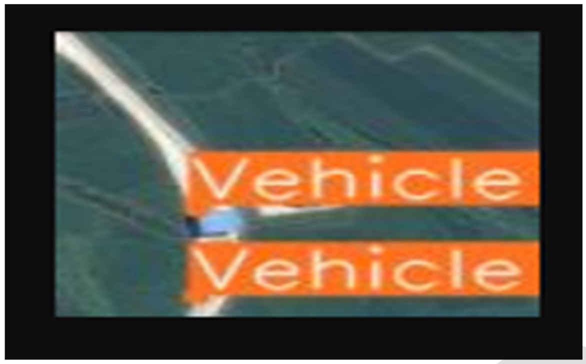

Fig 9 Predict result

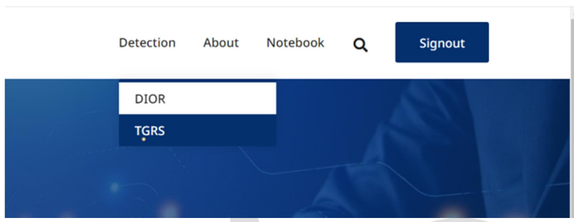

Fig 10 TGRS dataset detection

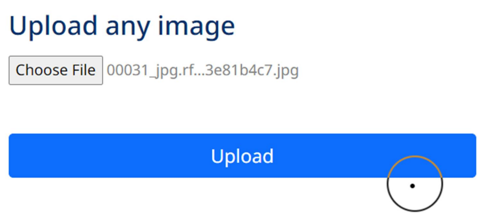

Fig 11 Upload another input image

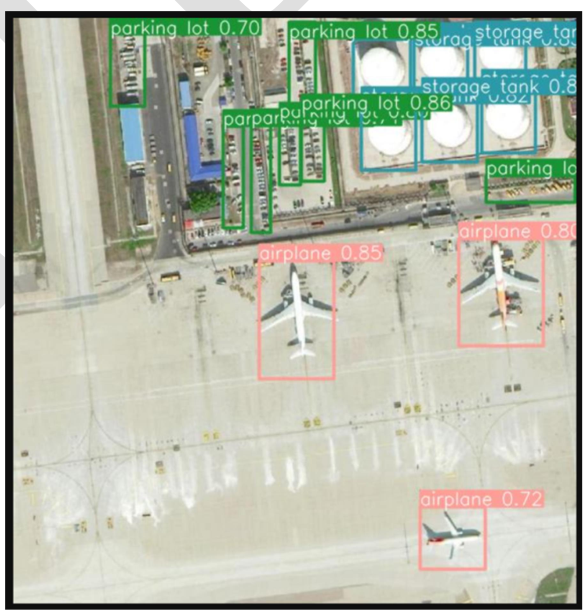

Fig 12 Final outcome for given input

5. CONCLUSION

Overall, the RAST-YOLO system, which incorporates a Swin Transformer backbone, demonstrates significant progress in tackling the existing obstacles in remote sensing object recognition. The introduction of the RA mechanism allows for the efficient extraction of both overall background information and specific specifics about the target, hence reducing the influence of complicated backdrops. The C3D module strengthens the feature pyramid, hence boosting the accuracy of identifying multiscale and tiny objects. By effectively using both global and local information, the ACmix Plus Detector enhances the accuracy of category predictions and target localizations. We examined many cutting-edge models, such as YOLOv5s, YOLOv3, Faster R-CNN, RetinaNet, YOLOv5x6, and YOLOv8, on difficult datasets in our Colab implementation. Notably, YOLOv5x6 exhibited exceptional performance, obtaining an impressive mAP of 0.80% or higher. The result highlights the effectiveness of sophisticated models such as YOLOv5x6 in expanding the limits of remote sensing object recognition. The results not only demonstrate the effectiveness of the proposed RAST-YOLO framework but also emphasize the possibility of further enhancing accuracy and reliability by investigating and using state-of-the-art approaches in remote sensing image processing.

6. FUTURE SCOPE

The future potential is in enhancing the identification of objects in remote sensing via the exploration of innovative designs and the integration of developing technology. Future research might prioritize enhancing the interpretability of models, improving computing efficiency, and adjusting to changing environmental circumstances. Utilizing techniques such as self-supervised learning and attention processes may improve the performance of models. In addition, it will be crucial to focus on overcoming real-time deployment obstacles and expanding the framework's usefulness in other remote sensing fields, such as environmental monitoring and disaster response. These areas will be the major focus for future research and development.

REFERENCES

[1] H. Lee, H. K. Jung, S. H. Cho, Y. Kim, H. Rim, and S. K. Lee, ‘‘Realtime localization for underwater moving object using precalculated DC electric field template,’’ IEEE Trans. Geosci. Remote Sens., vol. 56, no. 10, pp. 5813–5823, Oct. 2018.

[2] I. Muhammad, K. Ying, M. Nithish, J. Xin, Z. Xinge, and C. C. Cheah, ‘‘Robot-assisted object detection for construction automation: Data and information-driven approach,’’ IEEE/ASME Trans. Mechatronics, vol. 26, no. 6, pp. 2845–2856, Dec. 2021.

[3] Ijteba Sultana, Dr. Mohd Abdul Bari ,Dr. Sanjay,” *Routing Performance Analysis of Infrastructure-less Wireless Networks with Intermediate Bottleneck Nodes*”, International Journal of Intelligent Systems and Applications in Engineering, ISSN no: 2147-6799 IJISAE,Vol 12 issue 3, 2024, Nov 2023

[4] Md. Zainlabuddin, "*Wearable sensor-based edge computing framework for cardiac arrhythmia detection and acute stroke prediction*”, Journal of Sensor, Volume2023.

[5] Md. Zainlabuddin, "*Security Enhancement in Data Propagation for Wireless Network*", Journal of Sensor, ISSN: 2237-0722 Vol. 11 No. 4 (2021).

[6] Dr MD Zainlabuddin, "*CLUSTER BASED MOBILITY MANAGEMENT ALGORITHMS FOR WIRELESS MESH NETWORKS*", Journal of Research Administration, ISSN:1539-1590 | E-ISSN:2573-7104 , Vol. 5 No. 2, (2023)

[7] Vaishnavi Lakadaram, " Content Management of Website Using Full Stack Technologies", Industrial Engineering Journal, ISSN: 0970-2555 Volume 15 Issue 11 October 2022

[8] Dr. Mohammed Abdul Bari,Arul Raj Natraj Rajgopal, Dr.P. Swetha ," *Analysing AWSDevOps CI/CD Serverless Pipeline Lambda Function's Throughput in Relation to Other Solution*", International Journal of Intelligent Systems and Applications in Engineering , JISAE, ISSN:2147-6799, Nov 2023, 12(4s), 519–526

[9] Ijteba Sultana, Mohd Abdul Bari and Sanjay," *Impact of Intermediate per Nodes on the QoS Provision in Wireless Infrastructure less Networks*", Journal of Physics: Conference Series, Conf. Ser. 1998 012029 , CONSILIO Aug 2021

[10] M.A.Bari, Sunjay Kalkal, Shahanawaj Ahamad," *A Comparative Study and Performance Analysis of Routing Algorithms*", in 3rd International Conference ICCIDM, Springer - 978- 981-10-3874-7_3 Dec (2016)

[11] Mohammed Rahmat Ali,: BIOMETRIC: AN e-AUTHENTICATION SYSTEM TRENDS AND FUTURE APLLICATION", International Journal of Scientific Research in Engineering (IJSRE), Volume1, Issue 7, July 2017

[12] Mohammed Rahmat Ali,: BYOD.... A systematic approach for analyzing and visualizing the type of data and information breaches with cyber security", NEUROQUANTOLOGY, Volume20, Issue 15, November 2022

[13] Mohammed Rahmat Ali, Computer Forensics -An Introduction of New Face to the Digital World, International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169-453 – 456, Volume: 5 Issue: 7

[14] Mohammed Rahmat Ali, Digital Forensics and Artificial Intelligence ...A Study, International Journal of Innovative Science and Research Technology, ISSN:2456-2165, Volume: 5 Issue:12.

[15] Mohammed Rahmat Ali, Usage of Technology in Small and Medium Scale Business, International Journal of Advanced Research in Science & Technology (IJARST), ISSN:2581-9429, Volume: 7 Issue:1, July 2020.

[16] Mohammed Rahmat Ali, Internet of Things (IOT) Basics - An Introduction to the New Digital World, International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169-32-36, Volume: 5 Issue: 10

[17] Mohammed Rahmat Ali, Internet of things (IOT) and information retrieval: an introduction, International Journal of Engineering and Innovative Technology (IJEIT), ISSN: 2277-3754, Volume: 7 Issue: 4, October 2017.

[18] Mohammed Rahmat Ali, How Internet of Things (IOT) Will Affect the Future - A Study, International Journal on Future Revolution in Computer Science & Communication Engineering, ISSN: 2454-424874 – 77, Volume: 3 Issue: 10, October 2017.

[19] Mohammed Rahmat Ali, ECO Friendly Advancements in computer Science Engineering and Technology, International Journal on Scientific Research in Engineering(IJSRE), Volume: 1 Issue: 1, January 2017

[20] Ijteba Sultana, Dr. Mohd Abdul Bari ,Dr. Sanjay, "*Routing Quality of Service for Multipath Manets, International Journal of Intelligent Systems and Applications in Engineering"*, JISAE, ISSN:2147-6799, 2024, 12(5s), 08–16;

[21] Mr. Pathan Ahmed Khan, Dr. M.A Bari,: Impact Of Emergence With Robotics At Educational Institution And Emerging Challenges", International Journal of Multidisciplinary Engineering in Current Research(IJMEC), ISSN: 2456-4265, Volume 6, Issue 12, December 2021,Page 43-46

[22] Shahanawaj Ahamad, Mohammed Abdul Bari, Big Data Processing Model for Smart City Design: A Systematic Review ", VOL 2021: ISSUE 08 IS SN : 0011-9342 ;Design Engineering (Toronto) Elsevier SCI Oct : 021

[23] Syed Shehriyar Ali, Mohammed Sarfaraz Shaikh, Syed Safi Uddin, Dr. Mohammed Abdul Bari, "Saas Product Comparison and Reviews Using Nlp", Journal of Engineering Science (JES), ISSN NO:0377-9254, Vol 13, Issue 05, MAY/2022

[24] Mohammed Abdul Bari, Shahanawaj Ahamad, Mohammed Rahmat Ali," Smartphone Security and Protection Practices", International Journal of Engineering and Applied Computer Science (IJEACS) ; ISBN: 9798799755577 Volume: 03, Issue: 01, December 2021 (International Journal,U K) Pages 1-6

[25] .A.Bari& Shahanawaj Ahamad, "Managing Knowledge in Development of Agile Software", in International Journal of Advanced Computer Science & Applications (IJACSA), ISSN: 2156-5570, Vol: 2, No: 4, pp: 72-76, New York, U.S.A., April 2011

[26] Imreena Ali (Ph.D), Naila Fathima, Prof. P.V.Sudha ,"Deep Learning for Large-Scale Traffic-Sign Detection and Recognition", Journal of Chemical Health Risks, ISSN:2251-6727/ JCHR (2023) 13(3), 1238-1253

[27] Imreena, Mohammed Ahmed Hussain, Mohammed Waseem Akram" An Automatic Advisor for Refactoring Software Clones Based on Machine Learning", Mathematical Statistician and Engineering ApplicationsVol. 72 No. 1 (2023)

[28] Mrs Imreena Ali Rubeena,Qudsiya Fatima Fatimunisa "Pay as You Decrypt Using FEPOD Scheme and Blockchain", Mathematical Statistician and Engineering Applications: https://doi.org/10.17762/msea.v72i1.2369 Vol. 72 No. 1 (2023)

[29] Imreena Ali , Vishnuvardhan, B.Sudhakar," Proficient Caching Intended For Virtual Machines In Cloud Computing", International Journal Of Reviews On Recent Electronics And Computer Science , ISSN 2321-5461,IJRRECS/October 2013/Volume-1/Issue-6/1481-1486

[30] Heena Yasmin, A Systematic Approach for Authentic and Integrity of Dissemination Data in Networks by Using Secure DiDrip, INTERNATIONAL JOURNAL OF PROFESSIONAL ENGINEERING STUDIES, Volume VI /Issue 5 / SEP 2016

[31] Heena Yasmin, Cyber-Attack Detection in a Network, Mathematical Statistician and Engineering Applications, ISSN:2094-0343, Vol.72 No.1(2023)

[32] Heena Yasmin, Emerging Continuous Integration Continuous Delivery (CI/CD) For Small Teams, Mathematical Statistician and Engineering Applications, ISSN:2094-0343, Vol.72 No.1(2023)