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TARGET RECOGINITION AND DETECTION USING DEEP LEARING TECHNIQUE

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ABSTRACT

Object detection is a fundamental computer vision function for identifying and locating things in images or videos. Unlike image classification, object detection not only classifies the items in an image but also locates them inside the picture by constructing a bounding box around each one. Defence objects include a wide range of key assets needed for military and security activities. Tanks, armoured personnel carriers (APCs), military trucks, planes, helicopters, naval boats, and unmanned ground vehicles (UGVs) are among the types of vehicles included. Detection of these vehicles is critical for tracking troop movements, analysing battlefield dynamics, and maintaining operational preparedness. The modern defence scenario demands improved surveillance and security measures to successfully counter growing threats. This work suggests using the You Only Look Once (YOLO) method for real-time identification of numerous defence items. The project's goal is to improve security by properly detecting a variety of items, including cars, individuals, equipment, and structures, with a single deep learning model. Methodologically, a broad dataset containing photos and videos of defence items in various locations is collected and preprocessed. The YOLO algorithm is then trained on this dataset, with parameters optimised for high accuracy and recall rates. Performance evaluation include thorough testing on various datasets to determine accuracy, speed, and resilience.

KEYWORDS: Target recognition, Detection, YOLO algorithm, Military applications, Flying objects, Vehicles, Sensor integration, Real-time processing, Threat detection, Situational awareness.

1. INTRODUCTION

Real-time object detection remains difficult due to differences in object spatial sizes and aspect ratios, inference speed, and noise. This is especially true for our use case, as flying objects can change their location, size, rotation, and trajectory fast. This emphasises the need of quick inference speed and comprehensive model assessment across low-variance classes, object sizes, rotations, backgrounds, and aspect ratios. Artificial intelligence researchers have focused heavily on computer vision in drones.

Drone intelligence will help to solve a variety of real-world issues. Object detection, tracking, and counting are important computer vision tasks for monitoring certain situations. However, elements like altitude, camera angle, occlusion, and motion blur make the process more difficult. Yolo has introduced a new object detecting algorithm. The feature extraction and object localization modules are merged to form a single monolithic entity. The heads of localization and categorization are also merged.

This single-stage approach allows for rapid inference time. This innovative method, together with other detectors based on Convolutional neural networks, has moved the idea of edge devices closer to reality. Detecting military vehicles and drones with YOLO (You Only Look Once) entails many important procedures. Initially, a large dataset of photos and videos of military vehicles and drones in diverse situations and conditions is compiled. Each image or frame is thoroughly labelled, with bounding boxes indicating the exact location of the vehicles and drones.

To assist model creation and assessment, the annotated dataset is partitioned into three sets: training, validation, and testing. Next, the YOLO technique is used to train a deep neural network to recognise and categorise military vehicles and drones in real time. During training, the model learns to recognise patterns and attributes typical of these items, fine-tuning its performance through iterative modifications based on feedback from the validation set.

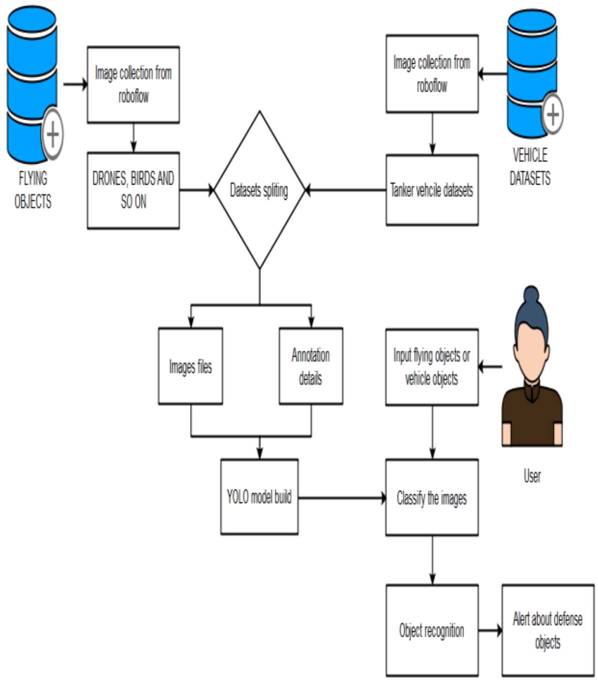

FIG 1.1 SYSTEM ARCHITECTURE

In this paper, we will look at the theoretical foundations of the YOLOv5 algorithm, its implementation in military applications, experimental results and validation methods, and prospective future research and development directions in this critical subject. We hope that our study will provide insights and answers that will assist influence the ongoing expansion of military reconnaissance capabilities and boost national security.

2. RELATED WORK

2.1 TITLE: DRONE DETECTION USING YOLOV5
AUTHOR:BURCHAN AYDIN, 2023
DESCRIPTION:

This research compares the performance of one of the most recent versions of YOLO, YOLOv5, to our previously suggested drone detection system, which uses YOLOv4. To provide an accurate comparison, we used the same dataset and computer settings (e.g., GPU). We initially fine-tuned the original YOLOv5 using our customised dataset, which consisted of two classes: birds and drones. To increase detection accuracy, we adjusted the hyperparameter values (e.g., learning rate, momentum, and decay). To accelerate the training, we applied transfer learning, incorporating the pre-trained weights supplied by the original YOLOv5. The weights were learned on MS COCO, a well-known and widely used dataset.

To address data scarcity and overfitting concerns, we employed data augmentation via the Roboflow API as well as data pretreatment approaches to train the model efficiently. To assess the model's performance, we computed evaluation metrics on a testing dataset. We employed precision, recall, F-1 score, and mAP, and the results were 0.918, 0.875, 0.896, and 0.904. The movies were captured at three different altitudes—20 ft., 40 ft., and 60 ft.—to test the detector's capacity to identify things at high altitude. In the future, we want to employ other variants of YOLO as well as larger datasets. In addition, various object detection techniques will be used to compare performance. To strengthen the model's capacity to identify between similar things, several drone-like items such as aeroplanes will be incorporated as classes in addition to birds.

2.2 TITLE: DRONE DETECTION AND TRACKING USING RF IDENTIFICATION SIGNALS
AUTHOR: DRISS AOULADHADJ, 2023
DESCRIPTION:

The research presents information about drone detection and tracking technologies, with a focus on the Mavic Air, Mavic 3, and Mavic 2 Pro drones. The study describes the detection range for these drones, with maximum observed distances of 1.3 km, 1.5 km, and 3.7 km, respectively. Factors such as the drone's transmission power and multipath propagation impact detecting capabilities, resulting in fluctuation in observed findings. The study finds that when drones travel away from the system, their position estimation inaccuracy increases. The relative inaccuracy in calculating speed and altitude rose with distance, but did not surpass 7% and 14%, respectively. The Haversine equation was used to estimate the remaining distance between the identified drone and the system, which produced encouraging results.

The technology was also evaluated in a hypothetical situation involving the security of a 200-meter radius. The remaining reaction times of several drones were calculated, giving significant information for applications aimed at intercepting unauthorised drones. This research study dives into drone detection and tracking using RF spectrum monitoring and proposes a method to decode drone identifying signals. To carry out detection and tracking duties, the suggested system combines both hardware components and software. A measurement experiment involving three drones was carried out to assess the system's efficacy in terms of range detection, calculating each drone's altitude and velocity, trajectory, and, lastly, remaining time to infiltrate a secure zone protected by the system.

2.3 TITLE: SAFESPACE MFNET: PRECISE AND EFFICIENT MULTIFEATURE DRONE DETECTION NETWORK
AUTHOR: MISHA UROOJ KHAN, 2023
DESCRIPTION:

This research introduces Safe Space Multi Feature Net (MFNet), an accurate and efficient multi-feature, multi-scale UAV detection network. We address the previously identified deficiencies by creating an open dataset and providing a real-time detection algorithm capable of accurately classifying birds vs. UAVs with short inference times by focusing on the most significant feature maps. In addition, the unique SafeSpace Multi feature Net (MFNet) architecture was suggested, which greatly increased UAV detection precision and mAP when compared to YOLOv5s. To effectively construct the suggested architecture and demonstrate its validity in severe weather situations, we obtained five datasets of birds and UAVs from the literature and verified their performance on three MFNet/MFNet FA variations.

The detection performance of all algorithms was extensively investigated and analysed under various environmental backdrops (i.e., weather conditions) and target scales. The proposed MFNet/MFNet-FA-small, MFNet/MFNet-FA-medium, and MFNet/MFNet-FA-large schemes effectively recognised and identified UAVs with higher UAV detection precision than YOLOv5s and current state-of-the-art schemes. Multiple UAV swarms are gaining popularity among domestic, commercial, and military users, owing to their ability to improve performance.

Nonetheless, the deployment of these swarms need sophisticated collision avoidance and detection technology, particularly in crowded skies. This highlights the critical significance of high-precision multi-target detection under demanding situations. We evaluate the performance of the proposed MFNet/MFNet-FA in the context of multi-target scenarios placed in difficult situations.

2.4 TITLE: NOVEL RIFLE NUMBER RECOGNITION BASED ON IMPROVED YOLO IN MILITARY ENVIRONMENT
AUTHOR: HYUN KWON, 2024
DESCRIPTION:

In this paper, we suggest a method for recognising gun numbers using deep neural networks when the amount of actual weapon picture data is limited. The suggested technique employs data fusion and transfer learning methods to increase the recognition rate of a certain dataset. Real firearm photos and existing digit images are combined as training data in the proposed technique, and the final layer is sent into the Yolov5 algorithm. This approach determines the rifle number-corresponding region and the number of rifles in it. In addition, a strategy for increasing the performance of the suggested method was developed by using other datasets in circumstances where the amount of real firearm data was inadequate. The contributions of this study are as follows.

In cases when genuine rifle data is scarce, we offer a rifle number identification approach that learns a real rifle dataset and another numerical dataset in a fusion format. In terms of the experimental setting, we took the original K-2 rifle dataset and combined it with other numerical datasets to conduct a performance comparison. The Yolo model is a deep learning algorithm that recognises objects by evaluating the full image at once. This approach can recognise the location of an object in a picture and classify it. The Yolo model is broken into two components: object location detection and object categorization. In the case of object location detection, a rectangular bounding box is used to calculate the length based on the coordinates of the detected item's four corners. The bounding box is a regression issue that identifies a suitable item position while minimising the difference between the correct and projected values.

2.5 TITLE: REAL-TIME VEHICLES DETECTION USING A TELLO DRONE WITH YOLOV5 ALGORITHM
AUTHOR: SHALAW M. ABDALLAH, 2024
DESCRIPTION:

Incorporating Unmanned Aerial Vehicles (UAVs) with AI systems has resulted in an important and academically significant method to vehicle identification. This paper describes a real-time vehicle recognition framework that uses the you only look once (YOLO) method to precisely identify automobiles using the DJI Tello drone's camera. The study is supported by a large collection of around 2000 photos that have been painstakingly annotated with the relevant vehicle angles. The framework's uniqueness is its complete training regimen, which covers all aspects of vehicles: vehicle-front, vehicle-rear, vehicle-above, and vehicle-sides.This comprehensive method seeks to produce a model capable of reliably detecting and monitoring cars from a variety of perspectives.

The YOLO method, which is augmented by Ultralytics HUB, provides the resilience and precision necessary for moving object identification. The model's capacity to effectively track objects attests to the algorithm's effectiveness. We used a comprehensive set of assessment metrics to analyse the framework's performance, which included mean average accuracy, precision, recall, and F1 scores.

This study not only demonstrates the usefulness of UAVs in the field of artificial intelligence, but it also illustrates the quality obtained in real-time vehicle identification. YOLOv5 distinguishes itself from its predecessors with numerous major benefits. These include a smaller model size, faster processing, higher accuracy, and seamless interaction with the renowned PyTorch open source machine learning framework. Furthermore, YOLOv5 adds 10 new varieties that were not available in previous editions, increasing its flexibility. The YOLOv5 method is useful in data science projects since it categorises publicly available datasets from Internet sources such as Roboflow.

3. METHODOLOGY

YOLO OBJECT DETECTION MODEL

You Only Look Once (YOLO) is an object detector that employs deep convolutional neural network characteristics to categorise objects in computer vision. YOLO uses just convolutional layers, resulting in a fully convolutional network (FCN). Up sampling layers and skip links are examples of convolutional layers. The feature charts are downsampled using convolutional layers with a stride of 2. This helps to prevent the loss of lower-level functionality. The size of the supplied image does not affect YOLO. To prevent various difficulties that appear only when the method is used, the input size must be kept constant. Because our photographs were chosen to be processed in batches (images in batches may be handled in parallel by the GPU, resulting in speed improvements), we must provide the height and width for all images.

Concatenating numerous images into a batch is crucial. The stride element is responsible for the network's down sampling of signals. For example, an input image of size 416 by 416 would produce an output of size 13 x 13. The stride of each layer in the network is equal to the ratio of the layer's output to its input picture. Typically, the information obtained by the convolutional layers are handed on to a classifier/regressor, allowing detection prediction (bounded box coordinates, class label, etc.). YOLO predicts using 1x1convolutions.

The size of the prediction map is exactly the function map's scale prior to inclusion in the convolution. This prediction map is understood as each cell estimating a certain number of bounding boxes.

The YOLO method separates the input image into a grid of cells, predicting the likelihood of an object's presence as well as the object's bounding box coordinates. It also predicted the object's class.

- A CNN is used to extract features from the input picture.
- Fully connected layers forecast class probabilities and bounding box coordinates after processing the features.
- A grid of cells predicts bounding boxes and class probabilities for the picture.
- The network generates bounding boxes and class probabilities for each cell.
- The bounding boxes are filtered using a non-max suppression approach to eliminate overlapping boxes and choose the highest probability box.
- The final output includes predicted bounding boxes and class labels for each picture item.

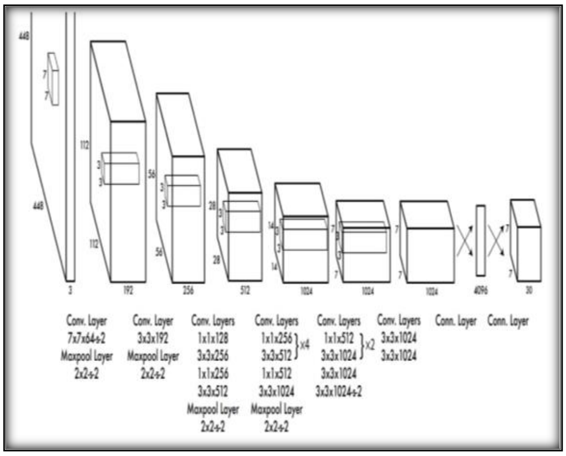

FIG 3.1 YOLO MODEL CONSTRUCTION

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4. DATASET PREPERATION

In this module, collect defense-related datasets. Defence datasets include flying objects and vehicles of many sorts. Images are taken from the Roboflow website. This module is in charge of obtaining a diverse collection of photos or movies featuring flying objects. It also performs preprocessing activities like scaling, normalisation, and augmentation to get the data ready for training.

Create a dataset of photos or videos that include drones. Ensure that the collection covers a diverse range of drone kinds, sizes, orientations, backdrops, and lighting conditions. Preprocess the data by shrinking, normalising, and enriching it to improve the model's generalisation capabilities.

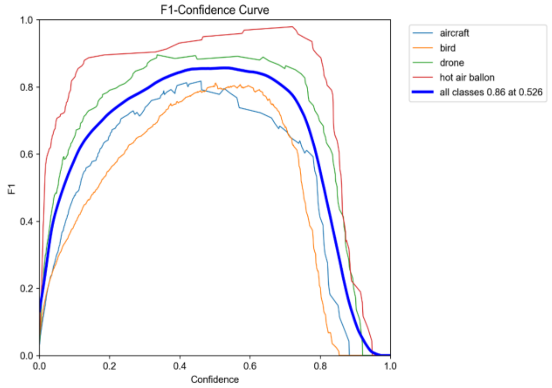

FIG 4.1 CONFIDENCE SCORE

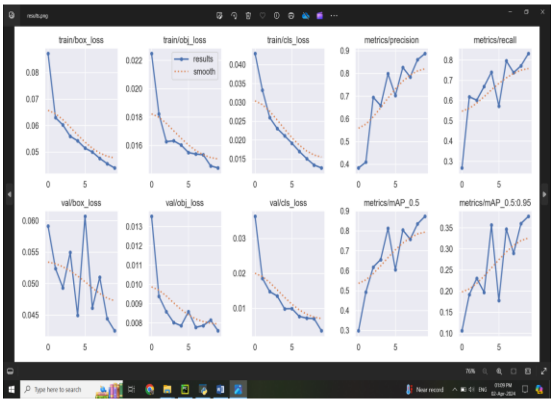

FIG 4.2 TRAINING AND VALIDATION LOSS

The YOLO (You Only Look Once) paradigm is a significant development in computer vision, particularly for object identification applications. YOLO transforms this technique by analysing the full image in one step while also predicting bounding boxes and class probabilities. This single-pass inference enables YOLO to attain incredible speed, making it suited for real-time applications.

YOLO's unified detection technique, which directly predicts bounding boxes and class probabilities for all objects in an image, results in a more streamlined and efficient procedure. Define the YOLO model architecture for drone detection. This entails setting the network architecture, changing factors like input size and anchor boxes, and maybe introducing particular features or tweaks to increase drone detection performance.

5. RESULT AND DISCUSSION

After running the YOLO model on the input photos, use post-processing techniques to filter and refine the discovered items. This might involve deleting duplicate detections, modifying confidence levels, or using non-maximum suppression to save the most important detections. Integrate the YOLO-based object detection system into the desired application. Evaluate the trained model's performance on a different validation dataset to determine its accuracy, precision, recall, and other important drone detection characteristics.

Analyse the model's strengths and flaws to discover opportunities for development. To identify drones, apply the trained YOLO model to new photos or videos in real time or batch mode. Process the input data, run the model to identify drone positions, and create bounding boxes and class labels for identified drones.

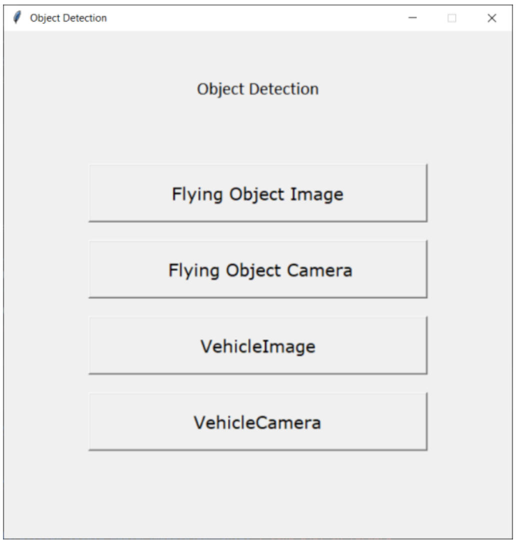

FIG 5.1 PREDICTION IMAGE

Label the item name using the YOLO recognition method. Make a notification concerning military objects. Incorporate the drone detection model into a bigger system or application for practical usage. This might include creating APIs for model access, connecting with drone surveillance systems or security cameras, and deploying the model in real-world contexts.

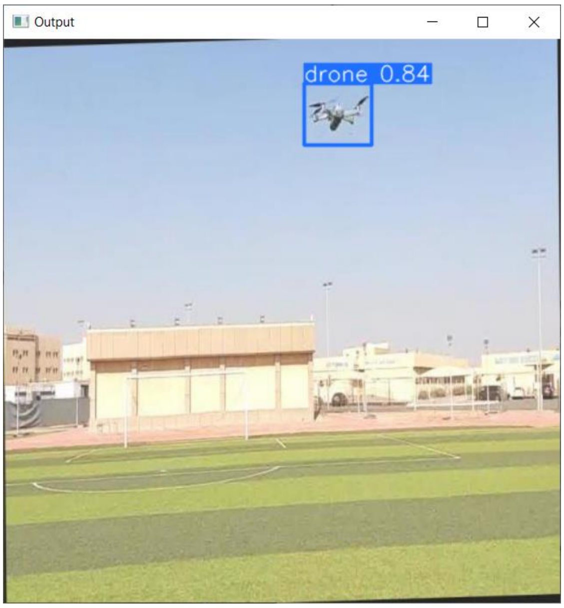

FIG 5.2 FLYING OBJECT DETECTION

FIG 5.3 VEHICLE DETECTION

Drone and flying object identification is essential in a variety of industries, including security, surveillance, and airspace control. The rise of drones for both commercial and recreational purposes has necessitated the development of dependable detection systems to assure safety and security. The user may choose any form of picture to input. Train the customised YOLO model with an annotated dataset of drone or vehicle photos. Set up the training procedure, which includes hyperparameters, loss functions, and optimisation algorithms. Monitor the training progress and make adjustments as needed to attain desired results.

6. CONCLUSION

To summarise, detecting defence objects is critical for defending military and security activities, assuring operational preparedness, and protecting men and assets. Security forces can successfully monitor battlefield dynamics, assess possible threats, and take countermeasures by correctly detecting diverse defence objects such as vehicles, persons, equipment, buildings, and explosive devices. Leveraging sophisticated technologies, such as deep learning algorithms like YOLO (You Only Look Once), has the potential to improve the efficiency and accuracy of defence object identification in real-time circumstances. As the landscape of security threats evolves, the development and implementation of effective detection systems becomes increasingly important for maintaining a proactive and adaptable defence posture. Security personnel may better anticipate and respond to new difficulties by constantly improving detection capabilities, therefore strengthening overall security and protecting against future attacks.

Further refining of the deep learning model to increase defence object categorization accuracy, including fine-tuning the network architecture and optimising training procedures to deal with complicated circumstances and item appearance fluctuations. Investigating the use of several sensor modalities, such as visual, infrared, and radar data, to improve detection effectiveness in difficult environmental situations such as limited visibility, poor weather, and concealment.

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