IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

AI For Wild Life Conservation Wild-Fire detection using YOLOv5 Model

Submitted By HEMANTHI NAIDU PAIDI

Under the Guidance of Dr. Sonali Kapoor, Faculty of Bachelor of Engineering in AI&ML,AIT-CSE,

Chandigarh University ,Mohali,Punjab

Abstract : This article discuss about the usage of artificial intelligence in the conserving wild life via detecting the wild fire occurrence using improved version of YOLO model.The YOLOv5 deep learning model for fire detection is investigated in this work. Rapid fire and smoke identification is made possible by the framework's efficient analysis of photos at a resolution of 416x416 pixels using a single neural network. We study how well YOLOv5 detects items that resemble fire in a variety of settings, such as indoor and outdoor spaces, different types of lighting, and even small-scale fires. The suggested approach's potential for real-time fire detection applications ,which also highlights its excellent balance of speed and accuracy.

***IndexTerms* - YOLO, YOLOv5.**

I.INTRODUCTION

The nature and wild life are seriously threatened by forest and urban fires. For safety and damage reduction, early and precise fire detection is essential. Because deep learning approaches can extract intricate information from picture input, convolutional neural networks (CNNs) in particular have become highly effective tools for fire detection [1]. In real-time fire detection applications, the YOLOv5 model has gained popularity due to its speed and accuracy balance [5, 6, 8]. Current studies investigate ways to enhance YOLOv5's performance in this area. Research suggests modifying the YOLOv5 architecture by adding ghost modules and mixed convolutions [4] or using YOLOv5s [6] as lightweight variants for situations when resources are limited.
Developing a variety of fire picture datasets can be made easier with the help of a public repository .The training data can be further enhanced by data augmentation approaches, which will improve the model's capacity to manage fluctuations in lighting, surroundings, and fire size [3, 9, 10]. To achieve reliable fire and smoke detection under a variety of environmental situations, combining YOLOv5 with additional methods like Local Binary Patterns (LBP) for feature extraction is being investigated [10]. are indicated in italic form, inside brackets, as seen in the example. While many table text styles are offered, other components, such pictures, tables, and multi-leveled equations, are not required. These elements must be created by the formatter, who must also incorporate the following appropriate criteria.

II. STUDY ON YOLO MODELS

"You Look Only Once" (YOLO) family of object detection algorithms has completely changed the industry , it is a well-liked real-time object detection technique. It analyses a full image at once using a convolutional neural network (CNN), forecasting bounding boxes and class probabilities for items it detects. Compared to other object recognition techniques, YOLO is extremely quick thanks to this one-shot procedure. Because real-time item recognition is critical in applications like security systems and self-driving automobiles, speed YOLO is very helpful.

YOLOv1: Paving the Way for Instantaneous Detection (2015) introduced a one-stage network design that performed object identification and classification on the entire image at once. Depicts remarkable speed in comparison to conventional techniques, which qualifies it for real-time applications. Accuracy was still difficult, though, especially with smaller items.

YOLOv4: Acknowledging Complexity to Improve Outcomes(2020) provided a modular design with multiple configurations to meet varying requirements for accuracy and speed, introduced novelties such as For improved object detection, the Spatial Attention Module (SAM) focuses on informative regions.

YOLOv5, which was created without the original authors' input, was designed with the following goals in mind: User-friendliness; a simplified framework for deployment and training. This model is designed to be deployed on a range of hardware systems. Balance between precision and Speed: Both real-time capabilities and high precision were given priority. Uses BottleneckCSP Blocks: Compact construction elements for effective feature extraction. Emphasis on PyTorch for its versatility and ease of use. We are going to research on YOLOv5 model for wild fire detection.

III.METHODOLOGY

One-stage object detection model YOLOv5 is renowned for its quickness and precision. An analysis of the code you submitted that relates to wildfire detection is as follows:

The number of classes the model identifies is set by the nc: {num_classes} parameter. It is probably set to nc: 1 for smoke detection (one class) in this instance.

Anchors: These specify the bounding box shapes that are pre-defined and used by the model to detect objects. They are essential for precisely locating smoke plumes in photos taken during wildfires.

Backbone: This is YOLOv5's central feature extraction network. It takes relevant details out of wildfire photos, such as edges, textures, and forms, to help detect smoke.

Head: This part predicts bounding boxes and confidence scores for detections using information gleaned from the backbone. The setup that has been presented seems to leverage features from multiple backbone levels to enhance smoke detection at different-scales(small,medium,large).

Detect: Using the confidence scores and anticipated bounding boxes as a guide, this layer makes the final detection. In this case, it uses features that have been retrieved at several scales (P3, P4, P5) to detect items, most likely smoke.

3.1 POPULATION AND SAMPLING

We have used a dataset of 737 images with smoke labels collected from a pubic repository, split into training (70%), validation (20%), and testing (10%) sets. This model is trained on a dataset containing only limited amount of pre processed images. While the specific content is not provided, it is focused on "smoke" as the feature for detection.

IV. RESULTS AND DISCUSSION

4.1.RESULTS

Fig. 4.1. This figure shows an input image(left) and output image(right) after detection .

4.2 .PERFORMANCE INDICATORS

In this research we have conducted implementation of YOLOv5 model on test dataset for achieving the best possible outcomes.The following are appropriate indicators to assess the neural network model's efficacy: precission, recall and F1.

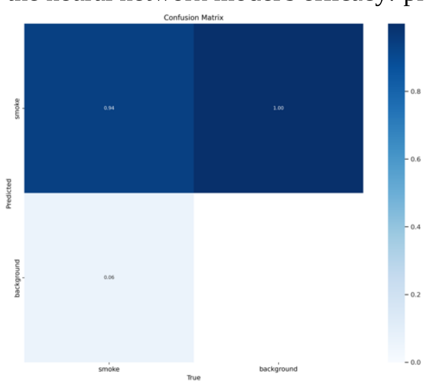

Fig.4.2.1This image depicts the confusion matrix of real and predicted values.

The F1-score offers a fair assessment of a performance of model by taking the harmonic mean of precision and recall. In skewed datasets, where wildfires may represent a minority class relative to the background.

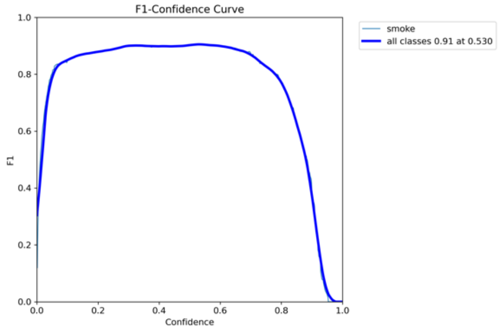

Fig. 4.2.2 This image depicts the model detects smoke items with an F1-score of 91% at a confidence level of 53%.

Plotting precision on the y-axis and recall on the x-axis is the PR curve. The trade-off between these measures is graphically represented as the model's categorization threshold is changed.

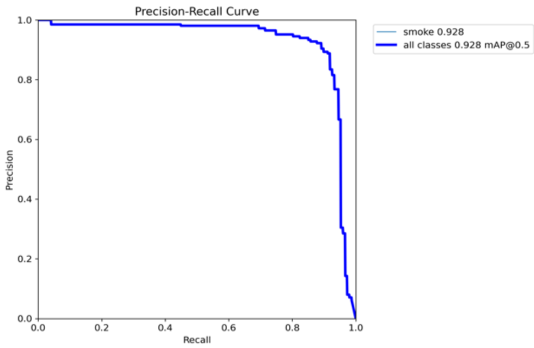

Fig. 4.2.3. Here, the overall object detection and smoke detection mAPs (mean average precision) of 0.928 show strong performance at the 0.5 IoU threshold.

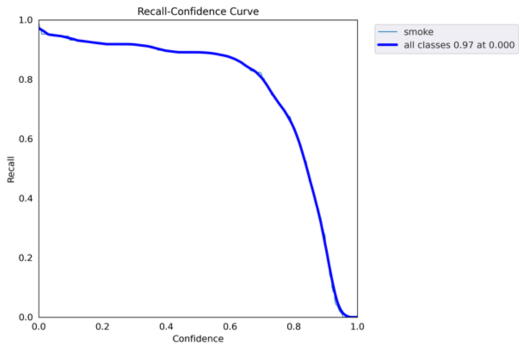

Fig. 4.2.4. This graph explains recall of 0.97 with a 0.00 confidence level indicates a high level of sensitivity.

4.3 DISCUSSION

Our research on using YOLOv5 to detect wildfires presents a very promising picture. The model performs exceptionally well across a number of important parameters. First off, the testing data shows that it rarely misses real cases of wildfire smoke, as evidenced by the high recall of 0.97. This corresponds to great sensitivity, which is essential for spotting wildfires early on. Second, a robust mAP (mean average precision) of 0.928 indicates good performance for all objects, especially smoke at the 0.5 IoU threshold. This shows that the model can accurately and efficiently identify smoke boundary boxes. Lastly, the model's good F1-score of 91% shows that, when accuracy and recall are taken into account, it can reliably identify smoke items with a 53% confidence threshold. Together, these findings demonstrate YOLOv5's enormous potential as a real-time wildfire detection.

4.4.CONCLUSION

Even though the current results are encouraging, more research is needed in a few areas. Crucially, information regarding the training data quantity, makeup, and source is absent. The capacity of the model to generalise to real-world scenarios and lower false positives is probably going to be enhanced by a larger and more varied dataset that includes a greater range of wildfire events and smoke characteristics. Furthermore, it is uncertain how to interpret the high recall of 0.97 at the 0.00 confidence level. Generally speaking, confidence levels indicate how certain the model is of its predictions. In this case, a value of 0.00 is rare and might be an anomaly or call for more investigation into the particulars of the implementation.

4.5. SCOPE FOR FUTHER REASERCH

With good recall, mAP, and F1-score, our investigation of YOLOv5 for wildfire detection yields encouraging results, suggesting its great potential as a real-time detection method. But there are restrictions. It is necessary to employ a larger and more diversified wildfire dataset because to the absence of information regarding the size and composition of the training data. Furthermore, more research is necessary to understand how the high recall's 0.00 confidence level should be interpreted. Subsequent investigations ought to concentrate on obtaining a more comprehensive wildfire dataset, utilising data augmentation methodologies, and maybe capitalising on transfer learning from previously trained models. For this important application, the model can be further refined by optimising hyperparameters. We can greatly increase YOLOv5's efficacy by taking care of these issues, which will ultimately lead to better wildfire response and mitigation tactics.

REFERENCES

[1] Enhancing Fire and Smoke Detection Using Deep Learning Techniques S Chitram, S Kumar, S Thenmalar - Engineering Proceedings, 2024 - mdpi.com.

[2] Forest Fire Detection using AI. PM Ginkal, K Kalaiselvi - Grenze International Journal of Engineering & Technology (GIJET), 2024, Vol 10, p2857 - search.ebscohost.com.

[3] FSDF: A high-performance fire detection framework H Zhao, J Jin, Y Liu, Y Guo, Y Shen - Expert Systems with Applications, 2024 – Elsevier.

[4] Fire Detection and Flame-Centre Localisation Algorithm Based on Combination of Attention-Enhanced Ghost Mode and Mixed Convolution J Liu, J Yin, Z Yang - Applied Sciences, 2024 - mdpi.com.

[5] YOLOFM: an improved fire and smoke object detection algorithm based on YOLOv5n X Geng, Y Su, X Cao, H Li, L Liu - Scientific Reports, 2024 - nature.com.

[6] An improved YOLOv5s fire detection model Z Dou, H Zhou, Z Liu, Y Hu, P Wang, J Zhang, Q Wang, Liangchao Chen, Xu Diao & Jinghai Li- Fire Technology, 2024 - Springer.

[7] Lightweight fire detection algorithm based on deep learning W Bi, B Li, B Lei - Proc. SPIE 13104, Advanced Fiber Laser Conference (AFL2023), 1310429 (18 March 2024); spiedigitallibrary.org.

[8] Intelligent UAV fire monitoring method based on improved YOLOv5 algorithm H Zhan, J Li, G Wei, C Han - Journal of Intelligent & Fuzzy Systems - content.iospress.com.

[9] An effective graph embedded YOLOv5 model for forest fire detection Hui Yuan, Zhumao Lu, Ruizhe Zhang, Jinsong Li, Shuai Wang, Jingjing Fan , 2024 - Wiley Online Library- https://doi.org/10.1111/coin.12640 .

[10] A hybrid LBP-CNN with YOLO-v5-based fire and smoke detection model in various environmental conditions for environmental sustainability in smart city S Dalal, UK Lilhore, M Radulescu, S Simaiya, Vivek Jaglan & Ashish Sharma, Environmental Science and Pollution Research, 2024 – Springer.