Crop Identification by using Real Time Object Detection

Sandhya Umrao
Noida Institute of Engineering & Technology
Greater Noida, India

Sanjay Kumar, Vivekta Singh
Greater Noida Institute of Technology
Greater Noida, India

Kanika Singhal
Indraprastha Engineering College
Ghaziabad, India

ABSTRACT
Computer vision techniques have been used in every field nowadays and find a wide range of application in agriculture field too due to their fast response and high accuracy. Several applications of computer vision are self-driving cars, the camera of the mobile phones and detection of faces. One of the most popular techniques in computer vision is real time object detection, it is not difficult in humans but for machines difference between main objects and other objects has to be trained. In this paper deep learning is used for detecting and identifying crops using YOLO (You Only Look Once) approach. For recognition and detection of crops, effective training needs to be carried out. The prime reason for using YOLO algorithm is that it looks the image completely by outlining the bounding regions of objects to be detected.

Keywords
Computer vision, Deep Learning, YOLO, Bounding regions

1. INTRODUCTION
The idea of this project emerges from the wish to know about any plant which can be seen around and to get information about the same in minimum time and more accuracy. And to present this idea Artificial Intelligence is used. Artificial Intelligence refers to those systems that think like humans i.e., Machine with mind. They think and act rationally like humans. In the field of AI, this study is defined as the study of "Intelligent Agents." Artificial Intelligence have been divided into subfields like Machine Learning, Neural Networks and Deep Learning [1], Computer vision.

In the recent years, object detection [7] [10] using computer vision has been actively studied by many researchers. Object detection is not the new term and can be done by various methods. Object detection [10] methods can be broadly classified into region based and regression-based methods. Several methods have been used to capture region like RCNN (Region based Convolution Neural Network) [12], CNN (Convolution Neural Network), Fast RCNN [14], Faster RCNN. YOLO (You Only Look Once) [8] [15] is used to compute regression-based methods and SSD (Single Shot Mutlibox Detector) [19].

Human workload has been reduced by introducing computer vision in agriculture. It initiates from automation [8] of basic activities of agriculture like seeding or watering and expands till complex and advance tasks like distinguishing weeds and crops and identification of plants and crops [4].

The project focuses on crop detection system. It is programmed to click images of the plants and crops in real time and then based on features and dimensions of the elements of the images the background substitution is performed [2]. Now the question arises, in agriculture why should these plants be appropriately distinguished and identified? In today's era the convenience is the best answer. To facilitates the understanding. To make sure that one will exactly get the reference point referred by the other one. After getting the reference point anyone can simply find the usage domain of a particular plant e.g., Medical, clothing etc. This categorization of the plants and crops promotes conservation, development, and improvement of the certain plants. It also facilitates the communication. This information is required by the government and agricultural managers for the area of cultivated crops for planning purposes and spatial distribution. On the basis of such information the government plan the export and import of the food products [8].

2. LITERATURE SURVEY
The table above represent the previous work done in the field of object detection using various algorithms such as CNN, R-CNN, YOLO [3][6], YOLOv1, YOLOv2, YOLOv3[11], YOLOv4 and how object detection has been used to solve various problems such as Agricultural and food product inspection, human detection [5], face recognition [9], vehicle logo recognition [12] pedestrian detection [13] and bicycle and many others. It also represents future researches which can be done in this field.

Lots of work has been already done in this area. Lots of methodologies have been compared to get the maximum benefit to get to know about object detection. To real time object detection different parameters are chosen like which kind of crops are taken and how that data is made noise free. Advantages and limitations of color and shape-based object detection is chosen in some paper. The factors on which learning rate depends are the size of both network and object. SVM provides very accurate and best results using SVM classifier with minimum computational time.

Table 1. Literature analysis

S. No	Author	Problem	Area of Application	Findings	Future Research
1.	Redmon Joseph S. Divvala, et. al.	Slow object detection	YOLO and Object Detection	Provide fast and efficient object detection technique	Real time object detection
2.	Liu Li Wanli Ouyang Xiaogang Wang, et. al.	A comprehensive survey of the recent achievements in generic object detection	Deep Learning and Object recognition	Description about main challenges faced by different object detection	Object detection under constrained conditions

S. No	Author	Problem	Area of Application	Findings	Future Research
		.		methods	
3.	Juan Wu1 Bo Peng1 Zhenxiang Huang1 and et. al.	Agricultural and food product inspection	Color based and shape-based features of detection	Advantages and limitations of color and shape-based object detection	Research on neural networks
4.	Dweepna Garg Parth Goel Sharnil Pandya Ganatra Amit Kotecha Ketan	Face detection using YOLO	Face Detection YOLO Neural network	The factors on which learning rate depends are the size of both network and object.	Further optimization of the model can be done for very small face detection and partial face detection.
5.	Oliver Javier Albiol Samuel Alberto Guillermo Morillas	Real time person detecting technique for the camera in motion	HBHS and SVM classification methods	Boosting techniques in human detection	Person detection in more dense area.
6.	ZuWhan Kim	Problems in background subtraction methods like occlusions, sudden illumination changes and , the presence of shadows in real time	Object level tracking and background subtraction	Tracking and detection of bicycle and pedestrian detection	To perform comparative studies on different applications with different sensor-based approaches and vision.
7.	S. Ramya M.Usharani N. Shwetha Rajkumar Y. Soundarya Varsha	Tracking of plantation crops and object detection by the use of SVM algorithm	Image processing and classification	Very accurate and best results using SVM classifier with minimum computational time	Calculation of amount of pests control to be used in crops.
8.	Kaur Amandeep Kaur Deepinder	YOLO based object detection from an image	K-mean clustering and YOLO	Found all objects in a single detection by using YOLO.	Time complexity and accuracy improvement to detect object in a image
9.	V.R. Vijay Kumar V. Murugan A. Nidhila	Recognition of vehicle logo by the use of RCNN	Deep Learning and RCNN	The seven various vehicle logos with various traffic sets of data can be recognized using RCNN.	Increasing accuracy, efficiency, specificity, sensitivity and precision value.
10.	Huieun Kim, Youngwan Lee Hakil Kim and et. al.	Object detection on road by the use of Deep Neural Network	Deep neural network and localization	Fine-tuned SSD on the road dataset by the use of data augmentation can improve the result	Research on the deep compression for reducing the memory of the model has to be accompanied.
11.	G Chandan Jain Ayush Jain Harsh Mohana	Efficient detection of object and maintaining the overall performa	Mobile net algorithm and SSD algorithm	Real time analysis of ecosystem can produce great results	In case of terrorist attacks, to detect guns and ammuni

S. No	Author	Problem	Area of Application	Findings	Future Research
		nce		by enabling order,utility and security for any of the enterprise.	tion to trigger alarm.
12.	Hyeon-Cheol Shin Lee Kwang-Il Lee Chang-Eun	For Deep Learning in Maritime Image, Data Augmentation Method of Object Detection	Deep Learning and Data Augmentation	Generating labelling which make it easy to generate annotations	In autonomous ships data fusion technology through image-based object detection
13.	Chen Xianqiao Liyan Yu Zhou Sansan	Research of the picture Main Objects Detection Algorithm Based on the Deep Learning	Selective Search and improved R-CNN	Picture main objects are related to the size of candidate region and the objects rarity.	More accurate methods to detect inaccurate image and no error alert
14.	Shaukat Hayat, She Kun and et. al.	Multi-class object recognition	CNN and L2-SVM classifier	Comparison of CNN with BOW approaches	Other applications of object detection and recognition.
15.	Liu1 Chengji Jiawei Liang1 Yufan Tao1 Yihang Chen1 Kai Li1	To train a robust model to improve the average precision (AP) of traffic signs detection in real scenes	YOLO and Image processing	Model which is trained with the degraded training sets has better generalizing ability and higher robustness.	Improving average precision of object detection

IMPLEMENTATION
The whole process is done in two phases respectively:

Training phase - The training is done using Darknet. Google Colab is used for efficient training. To train YOLO on darknet, import dataset on darknet Yolo format i.e., pre-processing the dataset. Minimum 2000 iteration are performed on each image. The dataset contains 50 labeled images showing different types of crops and plants. All images are quadratic but vary in size, resize them such that each image has the shape (299,299,3) for better accuracy and speed of detection. The tentative time required to train the network with above configuration was 7-8 hrs. So, the weights generated were used to perform detections analyzing the performance.

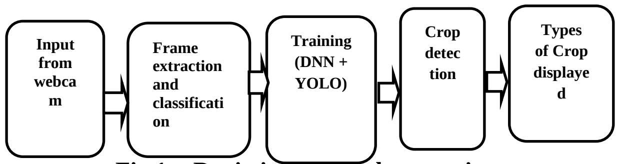

Fig 1: Depicting the implementation

Object Detection Phase (Testing phase) –In object detection phase , an image is captured from web cam using Open-CV and background subtraction is performed by subtracting is performed by subtraction from the current frame and the background frame then features are extracted using BCS and FCS and features are matched using hybrid model and object(crops) are identified and name of the object is displayed along with the description of the season in which they grow and the aces where they grow the most.

3. SOFTWARE REQUIREMENTS
- Library: Tensor flow, Open-CV
- Packages: NumPy, Pandas, Scikit-learn
- Language: Python 3.9.1
- IDE: Jupiter Notebook (Google Colab)
- Framework: Darknet
- API: Keras

4. WORKING OF YOLO
In the field of computer vision, YOLO is a real time object detection algorithm has become the main method of detecting the object. It is used to localize and identify objects up to 155 frames per second. It generates bounding boxes larger than the grid size of the image. Due to its speed and accuracy, YOLO has become an industry standard for object detection.

R-CNN and Fast R-CNN are the object detection algorithms which used selective search to find out the number of bounding boxes that the algorithm had to test. Faster R-CNN use a Region Proposal Network (RPN) to identify bounding boxes to test.

YOLO architectures were introduced in 2015 with huge improvement in speed making it real time. In terms of speeds R- CNN was 0.7 FPS. The matrices for R-CNN were 33.7mAP for accuracies and 14ms/image and for Fast R-

CNN were 66.0mAP for accuracies and 20ms/image and for Faster R- CNN were 73.2mAP for accuracies and 2ms/image while matrices for YOLO are 63.4mAP for accuracies and 22ms/image which is 45 frame per second which shows YOLO is much faster and accurate than another object detection algorithm. YOLO displays the objects detected with the confidence of .25 or higher.

YOLO's key advantage is its ability to perform object detection in real-time, making it suitable for applications where speed is crucial. Additionally, YOLO can detect multiple objects in a single pass, which sets it apart from some other object detection methods that require multiple passes through the network. Different versions of YOLO have been developed to improve accuracy and speed, making it a versatile choice for various computer vision tasks.

Working of YOLO is given below:

Input Image: YOLO takes a video frame or input image and resizes it to a fixed size (e.g., 416x416 pixels). This input is then passed through a convolutional neural network (CNN).

CNN Backbone: The CNN backbone is responsible for extracting features from the input image. YOLO typically uses a deep CNN architecture, such as Darknet or Tiny Darknet, which consists of convolutional layers, pooling layers, and other operations.

Grid Cell: YOLO divides the resized input image into a grid of cells. The responsibility of each cell is for predicting objects that are located within its boundaries. The size of this grid depends on the YOLO variant being used (e.g., YOLOv1, YOLOv2, YOLOv3, and YOLOv4).

5. SYSTEM ARCHITECTURE AND PERFORMANCE

The architecture consists of the three different layers forms. The first layer is residual layer which is formed when the activation is easily forwarded to the deeper layer in the neural network. In this residual set up the output of both the layers i.e., layer one and layer 2 are added. Second layer is named as detection layer which performs detection at distinct stages and scales. The size of grids is extended for detection. The third layer is up sampling layer by the green color blocks.

IOU = (Area of Intersection) / (Area of Union)

YOLO v3 uses a variant of Darknet, that has 53-layer network which is trained on Image net. 53 more layers are stacked onto it for the task of detection, giving us a fully convolutional underlying architecture of 106 layer for YOLO v3. In total YOLO v3 uses 9 anchor boxes.
The complete image into S x S grids by the YOLO.B boundary boxes will be predicted by each grid. When Object falls into the grid cell only then that cell is responsible for detecting that object. This process is implemented on all the cells at a time which provides it a faster processing speed. Green is the predicted boundary box.

For every bounding box, the network forecasts a confidence that every bounding box encloses an object, and the probability of this enclosed object being a particular class. Pr (Object) will be 1 if the object presents in a predicted boundary box, otherwise it would be 0. After training is done, testing for multiple images will be performed. Run the test dataset, it will detect the image and give the class name with confidence score.

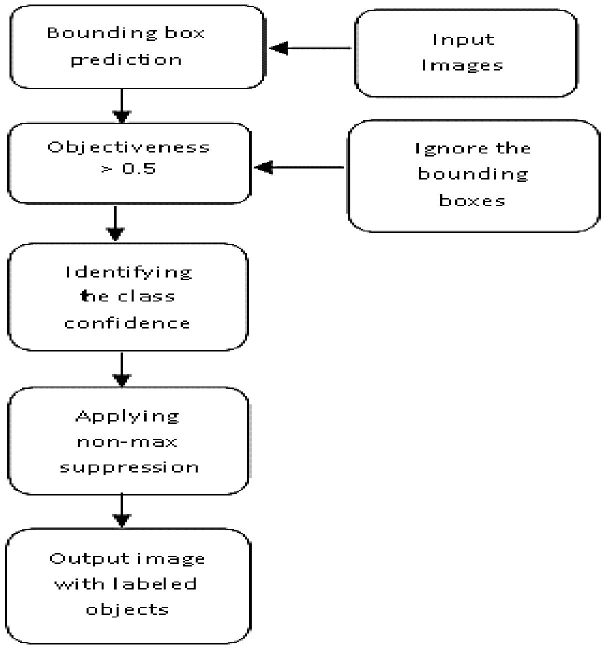

Fig 2: Working Model

Class Scores: Probability scores for different object classes (e.g., dog, car, person).

Non-Maximum Suppression: YOLO generates multiple bounding box predictions for each object. To remove duplicate or highly overlapping predictions, a technique called non-maximum suppression (NMS) is applied. NMS selects the most confident bounding box for each object, discarding the others.

Output: A list of bounding boxes is the final output of YOLO and each box is associated with an object confidence score and a class. In the input image These bounding boxes represent the detected objects.

Post-processing: The bounding box coordinates are transformed from relative coordinates to absolute coordinates in the original image. The class scores are threshold to remove low-confidence predictions. The remaining bounding boxes are then displayed or used for further processing, such as tracking or recognition.

i.e., layer one and layer 2 are added. Second layer is named as detection layer which performs detection at distinct stages and scales. The size of grids is extended for detection. The third layer is up-sampling layer that increases spatial resolution of the picture. So, here before scaling the picture is unsampled. The output of the previous layer and the present layer is concatenated with the help of concatenation operation.

Now with the help of addition operation the previous layer is added. In Fig 2, the residual layer is represented by pink color blocks, detection layer by the orange color blocks and the up-sampling layer by the green color blocks. blocks and the up-sampling layer by the green color blocks.

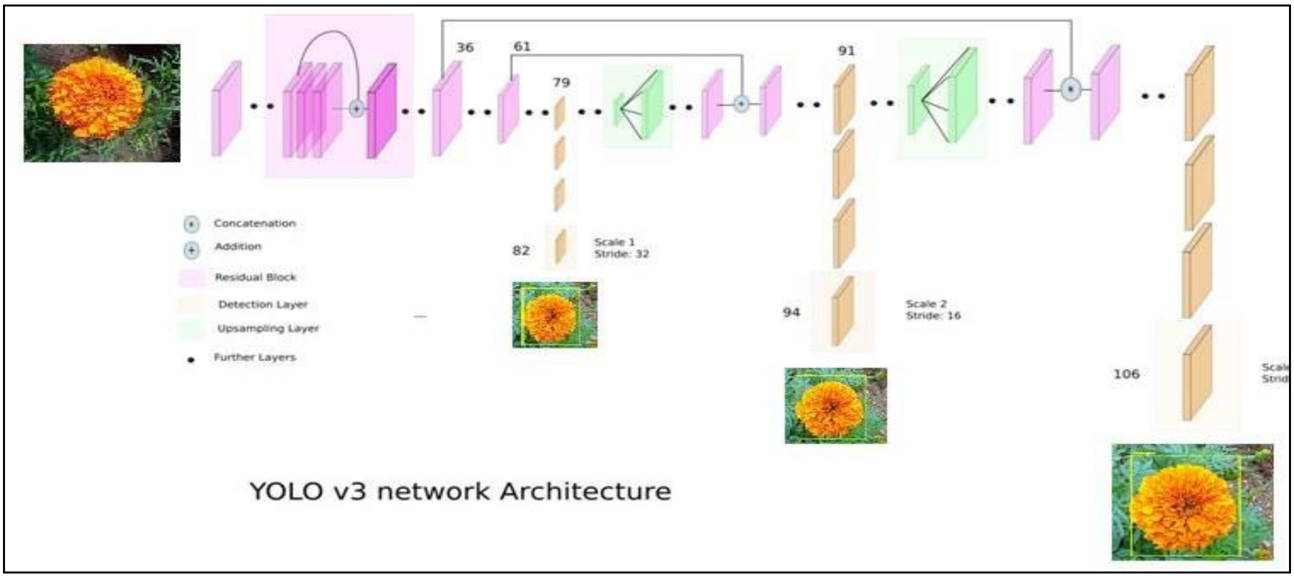

Fig 3. System Architecture

6. RESULT ANALYSIS

The model is trained to identify 12 different types of crops and plants. 70% of data set is used as training data and 30% is the testing data. Observations show that accuracy of the model remained almost constant. Following are the results obtained

Fig 4(a). Rice crop detection

Fig 4(b). Rice crop detection

In the above image the rice crop is identified with 92% accuracy and with it the information regarding the identified crop like the season in which the crop grows and main states where it is produced is displayed. In the above scenario all the similar crops are marked/identified with similar boundary with the description is presented.

7. CONCLUSION

In this paper, to detection of crop YOLO algorithm is used. Firstly, feed the model with S images then the model is trained to classify each image into various classes in real time. It can be worked upon full image. Main objective to use YOLO is because of its speed. It works faster in comparison to other object detection algorithms. The network helps better to generalize image. This model can be used in the field of agriculture to fight various plant diseases/pests, weed detection and to differentiate the types of fertilizers and pesticides used on them.

8. REFERENCES

[1] Amandeep Kaur and Deepinder Kaur. Yolo Deep Learning Model Based Algorithm for Object Detection, in JSCE International Journal of Computer Science and Engineering, doi:10.26438/ijcse/v8i1.174178,2020

[2] Zu Whan Kim. Real Time Object Tracking based on Dynamic Feature Grouping with Background Subtraction, California PATH, University of California at Berkeley, CA, USA,2018

[3] Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi. You Only Look Once: Unified, Real-Time Object Detection, IEEE,2015

[4] Mrs.M.Usharani,S.Ramya , N.Shwetha , Y.Soundarya , Varsha Rajkumar .Object Detection and Tracking Of Plantation Crops Using SVM Algorithm,International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 6, 2019

[5] Javier Oliver, Alberto Albiol, Samuel Morillas, and Guillermo Peris- Fajarn´es. A Real-Time Person Detection Method for Moving Cameras, IEEE,2016

[6] ChengjiLiu ,Yufan Tao ,Jiawei Liang ,Kai Li ,Yihang Chen .Object Detection based on YOLO network,IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC 2018).

[7] Zhong-Qiu Zhao, Member, IEEE, Peng Zheng, Shou-tao Xu, XindongWu.Object Detection with Deep Learning: A Review, arXiv:1807.05511v2 [cs.CV] 16 Apr 2019, IEEE

[8] Juan Wu, Bo Peng, Zhenxiang Huang, and JietaoXie,Research on Computer Vision-Based Object Detection and Classification, IEEE Transactions on Automation Science and Engineering 8, 292–302 2015

[9] Sharnil Pandey, Ketan Kotecha. A Deep Learning approach for Face detection using YOLO, IEEE Punecon,2018

[10] Li Liu1, Wanli Ouyang, Xiaogang Wang, Paul Fieguth, Jie Chen, Xinwang Liu, Matti Pietikäinen. Deep Learning for Generic Object Detection: A Survey,International Journal of Computer Vision, 2020

[11] Omkar Masurekar, Omkar Jadhav, Prateek Kulkarni, Shubham Patil. Real Time Object Detection Using YOLOv3, International Research Journal of Engineering and Technology (IRJET),2020

[12] V. Murugan, V.R. Vijaykumar, and A. Nidhila. Vehicle Logo Recognition using RCNN for Intelligent Transportation Systems, IEEE Student Conference on Research and Development (SCOReD), 2015

[13] Huieun Kim, Youngwan Lee, ByeounghakYim, Eunsoo Park, HakilKim. On-road object detection using Deep Neural Network,IEEE International Conference on Consumer Electronics-Asia ,2016

[14] Shaukat Hayat, She Kun, ZuoTengtao, Yue Yu, Tianyi Tu, YantongDu. A Deep Learning Framework Using Convolutional Neural Network for Multi-class Object Recognition,3rd IEEE International Conference on Image, Vision and Computing,2018

[15] Chengji Liu1, Yufan Tao1, Jiawei Liang1, Kai Li1, Yihang Chen.Object Detection Based on YOLO Network,IEEE 4th Information Technology and Mechatronics Engineering Conference,2018.

[16] Hyeon-Cheol Shin, Kwang-Il Lee, Chang-Eun Lee Data Augmentation Method of Object Detection for Deep Learning in Maritime Image 2020 IEEE International Conference on Big Data and Smart Computing (BigComp)

[17] Liyan Yu, Xianqiao Chen, Sansan Zhou Research of Image Main Objects Detection Algorithm Based on Deep Learning, 2018 3rd IEEE International Conference on Image, Vision and Computing

[18] Dweepna Garg, Parth Goel, Sharnil Pandya, Amit Ganatra, Ketan Kotecha A Deep Learning Approach for Face Detection using YOLO

[19] Chandan G, Ayush Jain, Hash Jain, Mohana Real Time Object Detection and Tracking Using Deep Learning and OpenCV Proceedings of the International Conference on Inventive Research in Computing Applications (ICIRC 2018).

[20] Nigam, A., Jain, D., Talan, M. S., Singh, S. K., & Umrao, S. (2023, May). A Comparative Analysis of ML Algorithms to Improve Crop Productivity Prediction. In 2023 International Conference on Disruptive Technologies (ICDT) (pp. 154-160). IEEE.