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Machine Learning Based Image Recognition System for Automotive and Supply Chain Industry

Shreehari H S, Kammarachedu Nandini, Annavajjala Niketh Sandilya

Assistant Professer Dept of Electronics and Communication,

SJC Institute of Technology Chickballapur,Karnataka,India

Abstract: Computer vision makes extensive use of object detection. and crucial for variety of applications, by identifying and locating objects in images and videos. It's a crucial technology for many applications, like self-driving cars and facial recognition. In general when objects are exposed to light then object detection can be done by using simple weights algorithm like Mobile Weight algorithm (MW) of object detection and identification and Common Objects In Context (COCO) data set. In MW algorithm the binary Images this used for comparison can't accept larger variation of objects and it have faults in algorithm so we utilized You Only Live Once Algorithm (YOLO).It is used most frequency in variety of application by charity of image or video is required so updated Algorithm need to be used for increasing the efficiency of system so that object detection and identification in even in front view and top view of images or in video. Finally, Using the Machine learning approach we are trying to improve the accuracy of the classification tasks. More or less we are expecting 0.88 weighted average precision, 0.74 weighted average recall, 0.80 weighted average f1-score, and 90.51 percent accuracyby the proposed Machine Learning and computer vision methods.

Keywords: Computer Vision Method, Image processing, Coco data set, Mobile Weight algorithm, Classification and detection, You Only Live Once algorithm.

I. INTRODUCTION

Real-time object identification is essential for evaluating possible landing locations and guaranteeing a safe descent in emergency landing scenarios involving flying objects, such as drones or aircraft. With the use of this technology, appropriate landing sites can be found and assessed in relation to a variety of parameters, including topography, obstructions, and ambient conditions. Computer vision techniques are employed by object detection algorithms to examine images or video streams and identify particular items or features within them. Large datasets are used to train these algorithms to identify patterns and traits connected to various things. The algorithm would have to be able to recognize wide spaces devoid of obstacles like buildings, trees, or power lines that could be dangerous during the landing procedure in the event of an emergency landing. The capacity of real-time object recognition to instantly send the flight control system feedback is a crucial feature that enables prompt decision-making and landing approach modifications. This capacity can be especially important in dynamic or quickly changing scenarios, when having access to current, precise information is critical to guaranteeing the safety of the flying object as well as any nearby people or property.

As technology advances, we might expect more developments in object detection algorithms that will enable them to operate more accurately and efficiently in a range of situations. Additionally, the inclusion of other sensor technologies, such as radar or LiDAR, to real-time object detection systems may prove beneficial. These technologies can offer context and extra data that can facilitate safer and more effective decision-making in emergency situations.

II. DATA PRE-PROCESSING

We will incorporate simulation methods to highlight important problems with graphic markers to make suspected illness diagnoses more persuasive.

A. Dataset

A popular benchmark dataset for computer vision tasks including object detection, segmentation, and captioning is the Common Objects in Context (COCO) dataset. It has a sizable library of photos, all of which have labels for the objects in the photos as well as bounding boxes and segmentations marked on them. Because of its recognized diversity and complexity, the COCO dataset is an invaluable tool for testing and training object detection systems. A broad spectrum of object categories are covered by the COCO dataset, including typical everyday objects like people, animals, cars,

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home goods, and more. Precise segmentations or bounding boxes are used to annotate these categories, showing the position and size of each object within the picture.

B. Data Augmentation

Predefined assessment measures are included with the COCO dataset to help evaluate the effectiveness of object detection algorithms. The accuracy and resilience of identification algorithms across various object categories and difficulty levels are measured by metrics like Average Precision (AP) and Mean Average Precision (MAP). We have several choices for image augmentation to select values from various sizes such as horizontal flip, rotation range, shear range zooming, etc. During the training process, every other alternative has the potential to depict images in a variety of ways and to provide essential characteristics, thereby maximizing the utility of the model.

Fig. 1. Images from Dataset

III. METHODOLOGY

To capture video footage, the first step in the process is to set up an ESP32 with a camera attached to an Arduino. A memory card holds the recorded data, which can be retrieved and processed later. After the data is acquired, a flying device, like a balloon or a drone, is used to move the entire system to an elevated location. After being retrieved, the data is processed with the OpenCV2 module to extract pertinent features. After that, a machine learning model is created using these attributes and a linearrecursion algorithm. The dataset that is used to train the model includes feature sets for multiple classes, including people, automobiles, trucks, motor vehicles, buildings, mountains, and rivers. Then, bounding boxes are created using the features that were extracted and labelled appropriately to help identify particular objects in the videostream. The processed video is shown in the final output together with bounding boxes and labels, which successfully identify and classify objects of interest.

A. Feature Extraction Phase

To achieve an appropriate Machine Learning model in both the view of image. As image is the combination of data which can be even represented in formof matrixes and pre-processing of image will be taken and That image can be converted into another plane format in order to detect like as foreground and background classification that classified foreground make objects to getdetected. In order to create a model we use YOLO Algorithm. As we the data which is Common object in context which we can call as original input image. For simplification purposes the processing image is taken as I.Now we create a Convolutional Neural Network (CNN).

Input Image= I – Original input image
Pre-processing which helps in extracting features in imagewhich can be explained by below equation
I(preprocessed) = PreProcess(I) – Pre-processingfunction
Set of grid cells, where each g(i) represents a grid cell.
G = {g1,g2,…,gn}
Anchor Boxes are created which sets the value of
B = {b1,b2,…,bm}
changing the amount of dilation, such as di = 1, 2, 3,..., N.Convolution layer with a dilatation rate of 1 is identical to the typical convolution. But when the rate of dilation is more then 1, it improves the convolution layer performancewhile processing data at a maximum magnification and achieves fine picture details. The section of image in which the filter generates a function even without modifying the filter magnitude is known as receptive field, which is basically a constant range entry, i.e. if there’s any dilation,then every input will lose (di 1) pixels. The dilation rate of1 is a normal convolution, if 2 becomes the value of dilationrate and aspects of the input picture data is two dimensionalthen each input data will skip a pixel for such dilation rate.When the kernel size is specified, the consequence of di upon rf supports the explanation of correlation between thedilation rate di and receptive field rf .If the kernel size is ks,which has been dilated

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by the dilation rate di then the representation of receptive filed is shown in the Equation no. 1,
rf = di(k1) + 1 (1)
If the output is O, where i× i input with dilation factor, di, padding pd & the stride is st respectively then the Equationno. 2 refers the size of output O.

O = i + 2pdrf st + 1 (2)

Significant features in the observation area are reported atvarious scales by utilizing two receptive fields of different size. In the current introduced model, each first two CBr=iconv block consist of two convolution layers and activation layers and last three CBr=iconv block consist of four convolution layer and activation layer and also each of them contains various filter (3 × 3) with stride and dilationrate with 1 and di, respectively. Convolution layer can be defined with filters Fs R1⇻n, the equation is given below,Fs = fj⇻j 1 fj⇻j 2 ...fj⇻j n=x (3)
here, j × j is filter size. For layer l,if dilation rate is di and mf x mf is denoted as input feature map then the proposed convolution network will generates Y mf ⇻mf l feature maps from the inputs. Which can be calculated by the equation given below:

Y o⇻o l = Y mf ⇻mf l1, di=k ⇻ lf + lb (4)
here, lb is the bias of the layer, and lf is filter. Just after the convolution layer, the generated features are used by the added activation function in the initial phases to create a new feature map as output. Towards the context of the activation unit, a was picked since this nonlinear layer andthe rectification layer can be merged into CNN. ReLU hasa range of benefits, and most notably, it can easily spread gradients. Consequently, the probability of gradient disappearance can be reduced if the preliminary mass calculates the fundamental features of CNN. Note that the activation function executes component-by-element operation upon this input feature diagram, as the output appears to be the similar size of the input. The developed scheme does have a block of CBr = iconv, supported by a layer of max-Pooling, which is designed in incremental form five times in tandem. An effective approach for downscaling the strained images is maxpooling, it demands maximum rate for every layer, as most of the features produced are overlooked in each layer by using a 2 x 2 filtersize with 2 level, which dramatically increases the performance of the next step of computation The maxpooling layer used in our study was 2x2 with stride 2 since, overlapped maxpooling windows won't enhance dramatically over the windows that has not been overlapped. The last convolution layer, with kernel size j xj, a total of 512 filters is used. The layer has dilation rate 1,which is followed by the ReLU activation function unit forcreating low-level features. The parallel branches of the convolution layer that produce the features are concatenated. The purpose of this concatenation operation is that every other branch generates features that have specific features from different layers, thereby concatenating the last level collateral branch features in the model to analyze the relationship of dilated convolution blocks so that the ultimate convolution layer can recognize superior classification features. Next, in the flattened layer,the model revealed to transforms the feature maps. For completing the classification task, a one-dimensional feature vector has been generated from the feature's maps. The last phase is the method of classification, which during the next segment will be illustrated briefly. For the classification task a one-dimensional feature vector has been generated from the feature's maps. Feature extraction

F = CNN(I preprocessed) – Convolutional neuralnetwork function to refine predicted bounding boxes
Bounding box regression – Bounding box regression function to refine predicted bounding boxes.
B(regressed) = Regress(F) – Bounding box regressionfunction to refine predicted bounding boxes
Non-Maximum suppression – Non-maximum suppressionfunction to remove redundant bounding boxes.
B(filtered) = NMS(B(regressed))
Object Classification-Classification function to assign classlabels to bounding boxes.
O = Classify(F)

B. Classification Phase Via two neural layers

In order to achieve this classification process, theoutput produced by flattened level were fed by a two-layerMLP (also known as a completely connected (FC) layer) during that stage.

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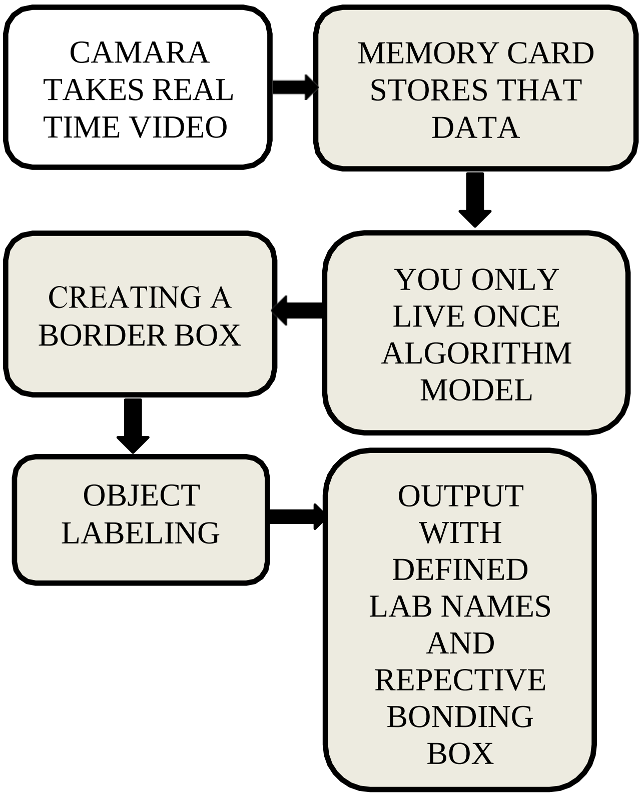
IV. FLOW CHART OF MODEL



In this system we are creating a system which have capacityto detect the object and label by YOLO model which helpsin modifying this system.

V. ADVANTAGES

Enhanced Security and Safety: advanced driver assistance systems (ADAS) in the auto industry, such as lane departure warning, identification of objects, and pedestrian detection, can be applied by machine learning- based image recognition, which will improve overall vehicle.

Efficient Inventory Management: Using image recognition technology, supply chain managers may automatically identify and track inventory items, minimizestock outs, and improve logistical processes.

Quality Control and Defect Detection: These technologies guarantee the maintenance of high standards by precisely identifying flaws or anomalies in automobile parts or products throughout the supply chain.

Streamlined Processes: Automation of tasks such as vehicle inspection, package sorting, and barcode scanning through image recognition systems leads to faster processing times and reduced manual labor costs.

Reduced Errors and Waste: Utilizing image recognition systems for automated product inspection and sorting minimizes human mistake and waste, leading to greater resource utilization and cost savings.

Compliance and Traceability: Businesses may provide end-to-end product traceability and guarantee regulatory compliance by precisely tracking and recording product movements across the supply chain.

V. APPLICATIONS

Inventory Management: Image recognition systems can be used to automate inventory management processes in warehouses and distribution centers. By analyzing images of incoming and outgoing shipments, these systems can accurately track inventory levels, identify products, and optimize storage space.

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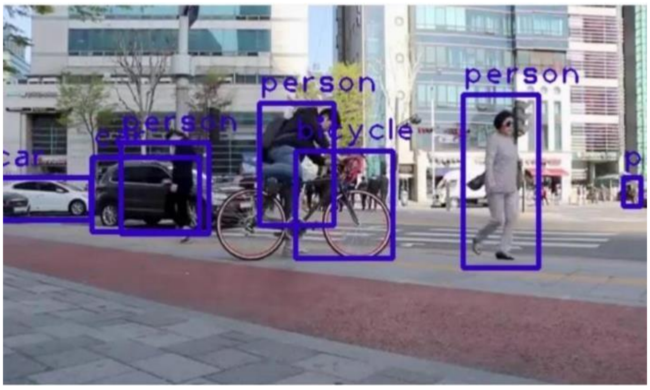
Vehicle Inspection and Maintenance: Images of cars can be analyzed by machine learning algorithms to find indications of damage, wear and tear, or mechanical problems. This makes proactive maintenance scheduling possible and lowers the possibility of unplanned malfunctions, which increases the dependability and safetyof vehicles.

Packaging Inspection: Machine learning algorithms can analyze images of packaged goods to ensure that they meet quality standards and comply with regulatory requirements. This includes verifying the accuracy of labeling, detecting packaging defects, and identifying counterfeit products.

Predictive Maintenance for Fleet Management: By analyzing images captured from vehicle-mounted cameras, machine learning algorithms can predict maintenance needs for fleet vehicles based on factors such as wear patterns, fluid leaks, and component degradation. This helps fleet managers optimize maintenance schedules, reduce downtime, and extend the lifespan of vehicles.

VII. RESULT

Method that uses a Convolution Neural Network to detect and Identify and label object. Image recognition and a deep learning algorithm are used in the diagnosis process. The noise and picture resolution were removed from the imageshot of objects that was taken. Using different image augmentation methods, the image count may also be improved. Finally, the Transfer Learning approach is used to improve the image recognition accuracy even further. The weighted average Precision of our CNN model is 0.88, the weighted average recall is 0.74, and the weighted f1- score was 0.80. The accuracy of the transfer learning method using the Reset model was 90.51 percent.



VIII .CONCLUSION

This paper presents a powerful model for detecting and classifying of common objects that are present in Common Object with combination of some Internet of thing artificialintelligence, and deep learning techniques to deliver accurate and reliable results, For different applications andoperation as there can be reliably strong for all kinds of Applications. The results are then uploaded to the cloud orother storage using WIFI modules.

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