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Development of Object Recognition Model Using Machine Learning Algorithms on MobileNet V2

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ABSTRACT

The proposed model is focused on achieving high accuracy and real-time performance in object detection using a deep learning-based approach. The two types of state-of-the-art methods for object detection were discussed: one-stage methods prioritizing inference speed, such as YOLO, SSD, and RetinaNet, and two-stage methods prioritizing detection accuracy, such as Faster R-CNN, Mask R-CNN, and Cascade R-CNN. The Faster R-CNN and SSD have better accuracy, while YOLO performs better when speed is given preference over accuracy. The proposed model uses a deep learning-based approach that combines SSD and MobileNet to efficiently implement detection and tracking. The SSD eliminates the feature resampling stage and combines all calculated results as a single component, while MobileNetV2 is a lightweight network model that uses depth-wise separable convolution to perform efficient object detection without compromising on performance. The model aims to elaborate on the accuracy of the SSD object detection method and the importance of the pre-trained deep learning model MobileNetV2. The experiments were conducted on the COCO dataset to recognize objects, and the model was also tested on real-time images for object recognition. The resulting system is fast and accurate, making it suitable for applications that require object detection.

Keywords –**RetinaNet, Object recognition, object detection, convolution network, MobileNetV2.**

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I. INTRODUCTION

Object recognition is indeed a challenging task in computer vision, as it requires identifying objects in images and videos, even when they appear under different conditions and with variations in shape, size, and appearance. To address these challenges, researchers have developed various strategies based on machine learning

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and deep learning algorithms. Support Vector Machines (SVM) is one of the popular ML-based approaches for object recognition, which uses a discriminative classifier to separate objects into different categories. Convolutional Neural Networks (CNNs) and Region-Based CNNs (R-CNNs) are deep learning techniques that have shown significant advancements in object recognition tasks. CNNs use multiple layers of convolutional operations to extract features from the images, while R-CNNs combine object proposals and feature extraction to achieve better object recognition. Object recognition has numerous practical applications, such as biometrics, defence, robotics, visual surveillance, and driver assistance. For instance, driver assistance systems use object recognition techniques for lane detection and obstacle identification. Visual surveillance systems rely on object recognition algorithms for pedestrian detection, vehicle recognition, and warning frameworks for object identification.

Despite the significant progress made in object recognition, there are still challenges that need to be addressed, such as changes in lighting conditions, partial occlusion, and deformations. Researchers are continually working to develop more robust and efficient object recognition techniques that can perform well in real-world scenarios. Object recognition is indeed a crucial research area in computer vision with applications in various domains such as navigation, surveillance, automation, biometrics, surgery, and education. The goal of object recognition is to correctly identify the objects present in a scene and recover their poses, which is the position and orientation of the objects. Object recognition has gained significant attention in recent years and has become a well-established technique in computer vision for identifying objects in images or videos.

Object recognition in videos involves recognizing both static objects such as landscapes and moving objects such as people, animals, and other entities in videos. For humans, detecting objects is usually an effortless task, even when the object is partially obstructed from view or undergoes deformations due to translation, rotation, or other variations. However, object recognition remains a challenging task for computers, and researchers have proposed various methods to address this challenge. Some of the commonly used object recognition methods include corner detection, scale-invariant feature transform, stochastic models, histogram of oriented gradients (HoG) with support vector machines (SVM), hidden Markov models (HMM), and others.

However, the performance of these systems has not been adequate, and there is still room for improvement in object recognition techniques. Researchers are continuously working to develop more robust and efficient object recognition systems that can work well in real-world scenarios with high variability in object appearances and environmental conditions. Many object recognition methods are known today, for instance, you only look once (YOLO). Single Shot Detector (SSD), homomorphic filtering, and Hear-like features. Convolutional Neural Networks (CNNs) have led to technological improvements in object recognition because of their success. The performance of these methods for detecting targets with deep learning is becoming increasingly streamlined, precise, and rapid. The user receives the result of the detection process in the form of a visual bounding box or label enclosing the name of the object.

A. Contribution of the paper

- To highlight our contribution to the existing literature, we next summarize some of the key points of our proposed object detection technique SSD algorithm. The SSD algorithm uses depth-wise separable convolution and spatial separable convolutions in their convolutional layers. The depth-wise separable convolution performs operations such that it maps each number of input channel with its corresponding number of output channel separately. Spatial separable convolution is the same as depth-wise convolution along the x- and y-axis.
- This architecture reduces the number of operations to execute the algorithm in fast speed through ways used by depth-wise separable convolution to reduce the number of channels with the help of width multiplier and those used by spatial separable convolution to reduce the feature maps of spatial dimensions by applying resolution multiplier.
- The proposed approach enables us to produce real-time object detection by using optimal values of aspect ratio and SSD algorithm uses many default boxes, which results in more accurate detection of objects.

B. Problem Definition

It seems that the focus of the proposed work is to implement and compare different machine learning methods for object recognition in the domain of driver assistance systems. The previous work in object recognition has been extensive, but with the advances in machine learning, there is an opportunity to evaluate the performance of recent methods on publicly available datasets. Deep learning methods have been implemented, but there is no comparison with other deep learning methods, which suggests the need for a comparative analysis. By analyzing the performance of different machine learning methods, the proposed work aims to identify the most suitable method for object recognition in the domain of driver assistance systems. The main objective of the proposed model is to develop an object recognition system using machine learning techniques that can overcome challenges such as illumination and viewpoint variations. Additionally, the proposed model aims to implement and compare existing object recognition techniques with the new proposed approach to determine its effectiveness and performance. Overall, the objective of the proposed model is to contribute to the development of more accurate and reliable object recognition systems.

C. Open issues and Challenges

Humans can easily recognize various objects in an image, even if they appear in different scales, viewpoints, or distortions. However, developing an object recognition system that can perform this task accurately is a significant challenge. Object recognition poses several challenges, some of which include:

- Variety of viewpoints: Objects in real-life scenarios can appear in different views, making it challenging for computer vision systems to recognize them accurately.
- Illumination variation: Objects can appear differently under different lighting conditions, making it difficult for computer vision systems to detect them accurately.
- Occlusion: Objects can be partially or completely obstructed by other objects or the environment, making it challenging for computer vision systems to recognize them.
- Scale variation: Objects of the same class can have different sizes, and their appearance can change when viewed from different distances or angles.
- Single object recognition: Even when dealing with a single object, there can be challenges such as viewpoint variation, illumination, and scale issues.

Addressing these challenges requires the development of robust and efficient object recognition algorithms that can handle variations in object appearance, lighting conditions, and environmental factors. Researchers are constantly working to develop new techniques and algorithms to improve the accuracy and reliability of object recognition systems.

II. LITERATURE SURVEY

There have been momentous advancements in object recognition. Quite possibly the most difficult and essential issue in object identification is finding a particular object from the various objects present in a scene. Prior conventional recognition strategies were utilized for identifying the objects with the presentation of CNNs. Afterward, deep learning-based strategies were utilized for feature extraction, and that prompted exceptional breakthroughs in this field. C.B. Murthy et al. [1] presented a definite overview on ongoing headways and accomplishments in object identification utilizing different deep learning methods. Extensive discussions on some significant applications in object detection including pedestrian detection, crowd recognition, and real-time object identification on GPU-based frameworks have been introduced.

R. Girshick et al. [2] proposed a straightforward and adaptable recognition algorithm that linked in two key points: first, high-capacity CNNs be applied to region proposals to confine and fragment objects, and second the performance was enhanced by using domain-specific fine-tuning for insufficient labeled training data. The algorithm R-CNN is due to a conjunction of region proposals and CNNs. The R-CNN outperforms the similar architecture Over Feat detector by a huge margin on the 200-class ILSVRC2013 dataset. K. He et al. [3] furnished the network with a spatial pyramid pooling technique to produce a rigid-length portrayal regardless of picture size/scale. CNN-based image classification approaches were improved by SPP-net. On the ImageNet 2012 dataset, they exhibit that SPP-net enhanced the accuracy of different CNN on the ImageNet 2012 dataset. The exactness of an assortment of CNN structures notwithstanding their various plans. In SPP-net, the feature maps from the whole image are calculated just a single time, and afterward pooled features are used to produce fixed-length portrayals for detector training. In handling test pictures, this strategy was quicker than the R-CNN technique. Fast R-CNN is proposed by R. Girshick et al. [4] for object location. It utilized a few developments to enhance the speed of training and testing as well as improving the detection accuracy as compared to past work. It trained the VGG16 network faster than R-CNN accomplished a greater mAP on PASCAL VOC 2012 and was also faster and more accurate than SPPnet.

Ren et al. [5] presented Faster RCNN having an RPN that shared convolutional features with the recognition network, subsequently empowering region proposals. An RPN [6] is a completely convolutional network that anticipates object ness scores and objects bound at every location. It was trained end to end to produce better region proposals, which were utilized by Fast R-CNN for identification. They combined RPN and Fast R-CNN into a solitary network by using the convolutional features utilizing the ‘attention’ mechanism, the RPN segment advises this network where to look. W. Zhao et al. [7] proposed an object-based deep learning strategy to precisely characterize the high-resolution imagery without escalated human contribution. This technique was based on a conjunction of a deep feature learning methodology and an object-based classification for the translation of high-resolution images. High-level features are investigated on five distinct layers of structure. Besides, to further develop the characterization precision, the object-based classification technique likewise had been incorporated with the deep learning procedure to enhance the classification accuracy. Rothe et al. [8] proposed an approach for age assessment using a solitary face image without the utilization of landmarks of the face. They handled the two tasks with CNNs which are pre-trained for image classification using ImageNet. They represented the age assessment as a classification issue succeeded by a SoftMax expected value rectification. The deep networks from huge data, expected value formulation, and strong alignment of face for age regression. Mou et al. [9] presented a Conv-Deconv network for hyper spectral images to perform unsupervised spectral-spatial feature learning. During the trial, it was tracked that this network was difficult to improve. To resolve this issue, this network design was refined by joining un-pooling operation and residual learning that can utilize retained indexes of max pooling. The results on two broadly

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utilized hyper-spectral data, Pavia University, and Indian Pines, exhibit emulative execution acquired by this approach contrasted with other contemplated techniques. Redmon et al., [10] presented YOLO9000, a real-time recognition framework that can identify more than 9000 article classifications. The improved model, Yolov2, outperformed the other techniques like Faster RCNN with ResNet and SSD in terms of speed. At long last a technique to mutually train on object recognition and classification. Utilizing this strategy, they prepared YOLO9000 all the while on the COCO detection dataset and the ImageNet characterization dataset. They validated their methodology on the ImageNet detection task. W. Liu et al., [11] introduced a strategy for recognizing objects using a solitary deep network, named SSD. It discretized the yield bounding boxes space to a bunch of boxes over various scales and aspect ratios at every location of the feature map [12]. It joined anticipations from numerous feature maps with different resolutions to normally handle objects of different scales.

III. PROPOSED MODEL

The proposed approach for object detection using SSD involves using a convolutional neural network for deep learning to detect objects in real-time from images. SSD uses multiple layers to achieve significant results in detection, and it was introduced in January 2016, setting new records on datasets like Pascal VOC and COCO. The major issue with previous methods was the drop in precision, which SSD improves by using multi-scale feature maps and default boxes. To detect small objects with higher resolutions, feature maps are used. The training set for the improved SSD algorithm relies on three main components: selecting the size of the box, matching the boxes, and the loss function. The proposed system model can be understood through the diagram given in figure 1. Object detection is the process that identifies or locates objects in an image while image classification is the process that assigns labels (classes) to images based on their content. When using deep learning-based object detection, the following algorithms are the most important:

- Faster RCNN
- MobileNet V2
- Single Shot Detector (SSD)

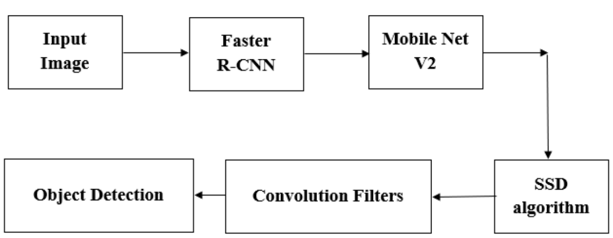

Fig 1: The proposed system model.

Here, the Single Shot Detector framework combined with the MobileNet architecture as our deep learning-based object detector is used. MobileNet is a lightweight and fast object detector model that was developed by Google. It was trained on the ImageNet dataset and can run on real-time and resource-constrained devices such as smartphones and other embedded systems.

Faster RCNN: Region Proposal Network for generating regions and detecting objects uses two methods of fast RCNN. The first method proposes regions and uses the proposed regions respectively. In fast RCNN, has used 16 architectures in convolution layers to achieve detection and classification accuracy on datasets. Figure 2 demonstrates the architecture of Faster RCNN. There is a limitation in Faster R-CNN that it has a complex training process and slow processing speed.

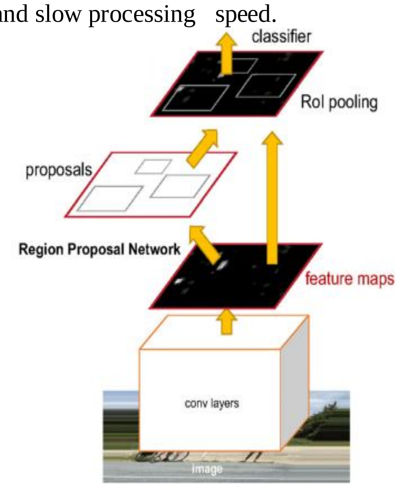

Fig 2: Architecture of F-RCNN [10]

MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices. It is based on an inverted residual structure where the residual connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depth wise convolutions to filter features as a source of non-linearity. The architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers as shown in figure 3.

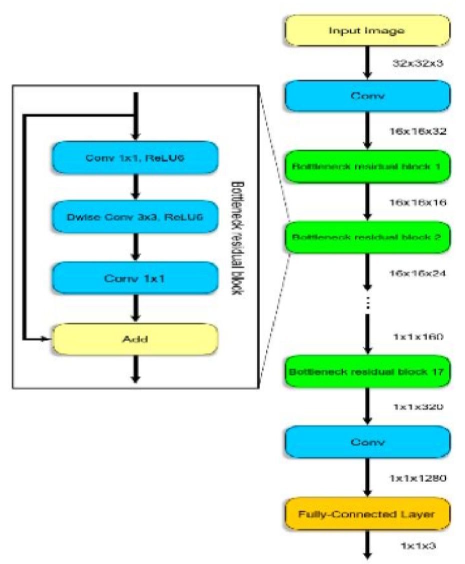

Fig 3: Architecture of Mobile Net V2 [11]

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Single-Shot Detector (SSD): The backbone model in SSD is typically a pre-trained image classification network like ResNet or VGG, which has been trained on a large-scale dataset such as ImageNet. By removing the final classification layer, we get a feature extractor that can extract high-level semantic features from the input image. These features are then used by the SSD head to predict the location and class of objects in the input image.

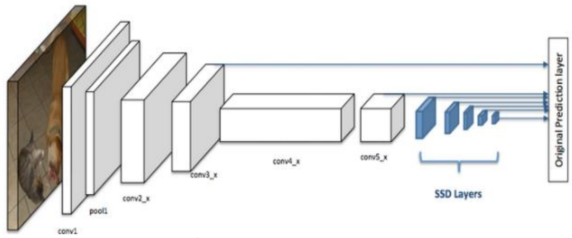

Fig 4: Architecture of a convolutional neural network with an SSD detector

The SSD head consists of one or more convolutional layers that are responsible for generating a set of default bounding boxes at different scales and aspect ratios, and then refining them to better fit the objects in the input image. Finally, the predicted bounding boxes are matched with the ground truth boxes using a matching strategy to compute the loss and update the network parameters during training. The first few layers (white boxes) are the backbone, the last few layers (blue boxes) represent the SSD head as shown in figure 4.

- Single shot: This refers to the fact that the network performs both object localization and classification in one forward pass.
- Default size of boxes: The size of the boxes is based on the minimum value of convolutional layers and the maximum values of the change in intensity.
- Feature maps: The first algorithm produces feature maps F(m) which are used to detect objects in the image.
- Truth boxes: After finding the size of the boxes, the next phase matches the boxes with the corresponding truth boxes in the training data.
- Loss function: The loss function is a way to evaluate how well the model is performing. The goal is to minimize the loss function, which is a combination of both the localization and classification loss functions.

When a color image is fed into the input layer, SSD does the following.

- Step 1: Image is passed through large number of convolutional layers extracting features maps at different points.
- Step 2: Every location in each of those feature maps uses a 4x4 filter to judge a tiny low Default Box.
- Step 3: Predict the bounding box offset for each box.
- Step 4: Predict the class probabilities for each box.
- Step 5: Based on IOU, the truth boxes are matched with the predicted boxes.
- Step 6: Instead of exploiting all the negative examples, the result exploits the best assured loss for every default box.
- Step 7: Further we apply SSD algorithm with convolution filters finally, the object will be detected.

IV. RESULT ANALYSIS AND DISCUSSIONS

The proposed model focuses on real-time object detection using Python and PyCharm. The use of open-source libraries for construction and training of the object detection model is also a cost-effective approach. It's good to note that the study took into consideration the dataset used and their limitations. The use of depth-wise separable convolution and spatial separable convolutions to improve the speed and accuracy of object detection is also an innovative approach. Finally, the use of COCO2 object detection datasets and real-time datasets for experimentation is a good way to validate the proposed model's performance.

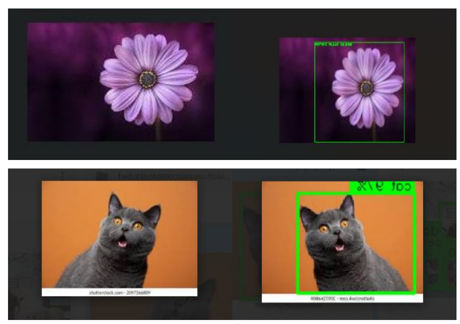
Fig 5: Outputs of dataset images

It is observed that, the model performs better accuracy for the images of COCO dataset and real time images. The bounding box of cat image in the dataset shows 97% of detection and real time images having person and bag detected as shown in Figure 5 and 6 respectively.


Fig 6: Fig 5: Results of real time images

Object detection is a computer vision task where models are trained to locate and classify objects within an image by predicting bounding boxes around them. IOU is a measure of how much two bounding boxes overlap. It's

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calculated as the ratio of the area of intersection between the predicted and ground truth bounding boxes to the area of their union.

- True Positive (TP): A predicted bounding box correctly matches a ground truth bounding box with a high IOU.
- False Negative (FN): A ground truth bounding box doesn't have a matching predicted bounding box (missed detection).
- False Positive (FP): A predicted bounding box doesn't have a matching ground truth bounding box (false detection).
- Precision: The ratio of true positive predictions to the total predicted positives (true positives + false positives). Precision indicates how accurate the positive predictions are.
- Recall: The ratio of true positive predictions to the total actual positives (true positives + false negatives). Recall indicates how well the model captures all the positive instances.
- The F1 score is a metric that combines precision and recall into a single value. It's the harmonic mean of precision and recall and provides a balanced measure of a model's performance and is given in equation 1.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (1)$$

Table 1: Comparison of different models

Methods	**Description**	**Result (%)**
R-FCN [4]	The test time of R-FCN is much faster than that of R-CNN. R-FCN has a competitive mAP but lower than that of Faster R-CNN.	88
Mask R-CNN [13]	The location of the objects is more precise, when making a segmentation of the objects in the images. Its execution time is greater than that used by the Faster-RCNN method, therefore, it cannot be implemented in applications that require real time.	94
FRCNN +MobileNet V2 + SSD Proposed Model	The RPN method allows object detection to be almost real-time, approximately 0.12 seconds per image. The use of a single network, makes the location of the objects faster than the Fast-RCNN and Faster RCNN methods.	97

The model is compared with the existing different model and achieved better accuracy in detection of the object.

V. CONCLUSION AND SCOPE OF THE WORK

Object detection and recognition are important tasks in computer vision and have many applications in various fields such as robotics, autonomous vehicles, and security systems. Using the SSD with MobileNetV2 detection tracking method is a great approach as it allows for real-time object detection and is accurate even for smaller objects. Also, improving the global and local features of the system can further enhance its efficiency and accuracy. Overall, this model has the potential to be very beneficial in developing autonomous systems that can recognize and interact with the world around them.

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