Research Article

Revolutionizing Home-Office Call Centers: Object Recognition for Performance and Data Security

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Abstract

Modern call centers operate within complex ecosystems where digitalization, automation, and surveillance technologies intersect. These advancements enable multi-channel communication, personalized services, and proactive customer support. Moving beyond traditional phone-based models, modern call centers leverage digital tools to enhance operational efficiency and customer experience. One of the key technologies driving this transformation is image processing techniques. These technologies automate tasks, minimizing human intervention and optimizing workflow. With the rise of home-office work setups, physical workspaces have become less common, and the boundaries between work and personal life have blurred. This situation causes employees to feel less supervised, leading to inefficient use of work hours and potential data breaches. This project aims to protect home-office employees' performance and data security using image processing technology, specifically object recognition and detection methods. The goal is to prevent issues such as virtual idleness, unauthorized data recording, and behaviors against workplace culture without violating employee privacy. By detecting objects such as phones, pens, paper, cameras, tablets, and cameras, behaviors that don't align with company culture will be prevented, and data privacy violations will be avoided. The proposed system demonstrates high performance, with object recognition algorithms achieving approximately 90% accuracy.

Keywords: Banking operations; object detection; artificial intelligence; remote working

1. Introduction

Object detection is crucial in computer vision, enabling machines to recognize and locate objects within digital images and videos. Significant advancements have been seen in recent years, primarily driven by deep learning techniques. This article explores the fundamental principles of object detection, key algorithms, and the evolution of methods over time. We also examine the field's challenges, including scalability, real-time processing, and accuracy issues. Finally, we discuss the wide range of object detection applications, including autonomous vehicles, security surveillance, healthcare, and robotics.

The call center industry has dramatically shifted with the increasing adoption of remote or home office agents. The growing demand for flexibility, cost-effectiveness, and a broader talent pool has driven this change. In particular, the banking sector, which handles sensitive financial information, faces significant challenges in maintaining security and surveillance while allowing agents to work remotely.

Financial institutions place a high emphasis on security, especially in customer interactions related to account details and transactions. The challenge is to ensure that remote agents can offer the same level of service and protection as their in-office counterparts. Combining advanced technology, training programs, and strict security measures helps banks maintain customer trust and safety.

In this study, an artificial intelligence model is used to develop an image processing system for remote supervision of agents in a company's customer service department. Its primary purpose is to analyze the behavior of the employees in the work environment, detect objects such as phones, cigarettes, glasses, etc., in front of the camera, and evaluate work discipline. However, it shows that expanding the data sets and using them in more dense environments can improve model accuracy and generalizability [1]. For this reason, since sufficient data sources were unavailable within the scope of the project, data collected over the Internet were used to train the model. In this process, data sets such as Roboflow, Kaggle, COCO, and ImageNet were utilized, and the project purpose also applied data augmentation methods.

1.1. Object Detection in Video Processing

Object detection studies can typically be divided into two primary focus areas: improving image processing techniques and developing deep learning (DL) algorithms for either one-stage or two-stage detection frameworks. Deep learning is based on artificial neural networks and computational systems that mimic the functions of the human brain [2]. In the case of deep learning-based algorithms, a data set is required. Image processing approaches, as presented in works like [3, 4, 5, 6, 7, 8], involve enhancing the quality of images to optimize object detection. In contrast, DL-based methods, such as those discussed in [9, 10, 11, 12, 13, 14, 15, 16, 17, 18], aim to boost the performance of deep learning architectures, including models like YOLO, Single Shot Detection (SSD), Faster R-CNN, RetinaNet, CoupleNet CNN, SqueezeNet, VGG, ResNet, and DenseNet.

Regarding the detection algorithms, there are two main approaches: one-stage and two-stage detection. The one-stage approach processes the entire image simultaneously, analyzing all pixels in a single pass to detect objects. Conversely, the two-stage approach involves initial generating region proposals—essentially identifying potential object locations—followed by a second stage where object detection is performed within those proposed regions. Both approaches offer distinct advantages, with the one-stage method being faster and more efficient, while the two-stage method generally provides better accuracy. YOLO is known for its speed and effectiveness among the one-stage methods, often outperforming other techniques like SSD, as shown in [19]. Thus, YOLO is a highly efficient when detection speed is a key priority. Thus, YOLO is highly efficient when detection speed is a key priority.

Redmon et al. [20] proposed a method demonstrating YOLO's effectiveness for object detection. Unlike previous approaches using classifiers, YOLO frames object detection as a regression problem, predicting bounding boxes and class probabilities directly from images. The entire detection pipeline can be optimized end-to-end as a single network. YOLO processes images in real-time at 45 frames per second, with Fast YOLO achieving 155 frames per second and outperforming other real-time detectors. YOLO also showed superior performance compared to models like R-CNN in their experiments.

A study for object detection compares YOLO (You Only Look Once) and Haar function-based cascade classifier implemented with the OpenCV library. YOLO is a deep learning-based method for real-time object detection, offering high accuracy and fast processing. The Haar method is a traditional approach that provides fast feature identification. Experiments show that YOLO performs well on large datasets and works efficiently with GPU support. Tests between different versions of YOLO (YOLOv4, YOLOv5, YOLOv7) showed that YOLOv7 is the most suitable version for real-time applications with low latency and high accuracy[21].

2. Materials and Methods

Object detection is applied to many areas, such as work safety and fighter jets. Personal Protective Equipment (PPE) is vital for worker safety, but inconsistent use challenges site management. To improve PPE detection, the MARA-YOLO model, based on YOLOv8-s, incorporates a modified MobileOne-S0 backbone, Attentional Space-to-Depth Block (AS-Block), and R-C2F and RASFF modules for better feature fusion and multi-scale handling. Tested on a custom dataset of 2750 images across nine categories, MARA-YOLO shows a 6.7% improvement in AP50, a 10.2% increase in AP75, and achieves 74.7% mAP, outperforming other lightweight models by 4.95% [22].

In another study, we compared the performance of YOLOv7 and YOLOv8 algorithms in detecting fighter jets. YOLOv8 outperformed YOLOv7 (0.902 mAP) with 0.940 mAP. Increasing the learning capacity of the models and optimizing the processes improved the overall performance. YOLOv8 accelerated the NMS process by predicting object centers. The results show that YOLOv8 performs better in detecting fighter jets [23].

Computer vision tasks are classified as follows.

Object classification specifies any number of class objects in an image, and label assignment of each object is done in an image [24].

Object localization identifies the location of objects in an image or video by enclosing each object within a bounding box [24].

Object detection combines object localization and classification to recognize and locate objects in videos or images [25].

Object recognition is a process that gives an input image to the model. First, it finds the objects, and then, label assignment is done to each class object, which gives the likelihood of a recognized object in the class [26].

2.1. Benefits of Home Office Agents in Call Centers

Despite the challenges, there are several benefits to using home office agents in the banking sector:

- **Cost Savings**: Call centers can reduce overhead costs by outsourcing customer service operations to home-based agents. There is less need for physical office space and equipment.
- **Scalability**: Remote call centers can quickly scale operations to meet demand during peak periods, such as financial crises or promotional events.
- **Flexibility**: Remote work increases employee satisfaction and retention and opens up a broader talent pool, as banks can hire agents from different geographic locations.

- **Business Continuity**: Home office agents provide continuity during unforeseen events such as natural disasters or pandemics, allowing banks to continue their operations without disruption.

2.2. Proposed System

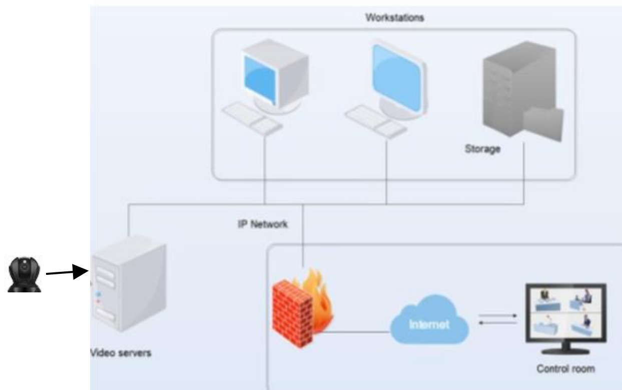

Figure 1: Proposed system infrastructure

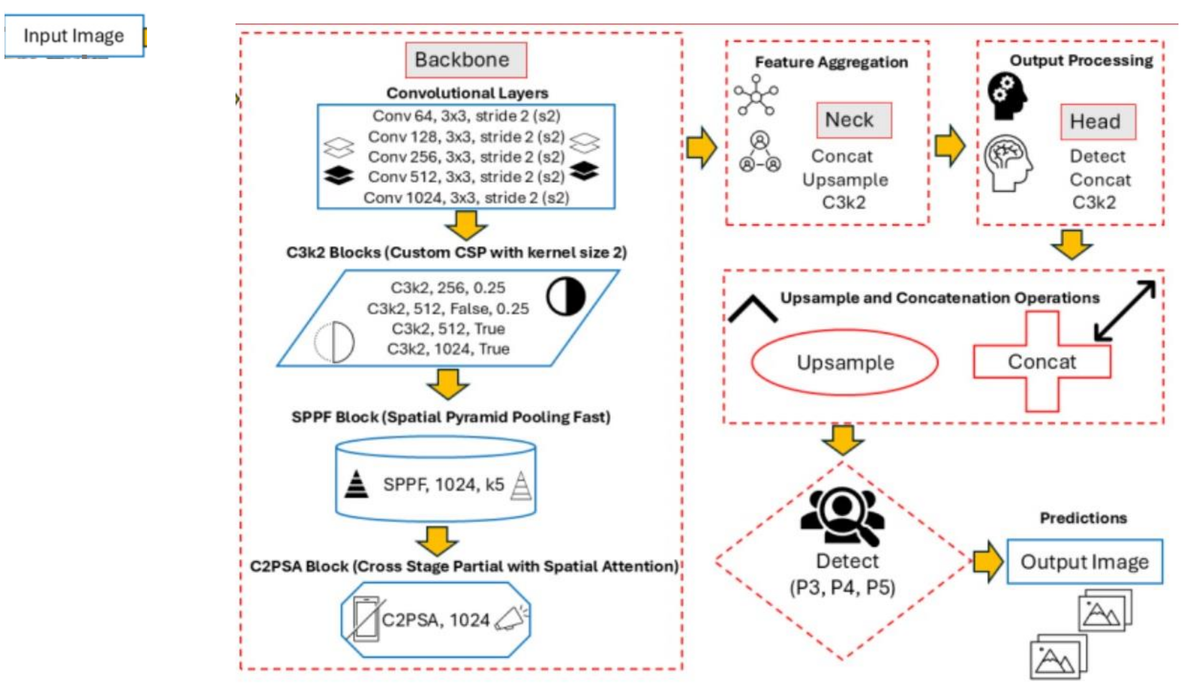

Figure 2: Yolo v11 architecture

3. Results

This study uses video frames to describe the banking operation of the CMC call center in Turkey. Four thousand images, 2000 CMC data sets, and 2000 COCO data sets are used. The results obtained from the experiments with these data sets are as follows. An equal number of data sets were used for all objects, including cigarettes, phones, glasses, tablets, and pens. A data augmentation method called Random Brightness Adjustment is applied, and the obtained results are given in Table 1.

Table 1: Yolo results according to Coco and CMC Datasets

Model	Data set	Random brightness adjusment	mAP (%)	Recall	Precision	F1-score	Accuracy	Difference
YOLOv8	COCO	Not appplied	71	0,75	0,68	0,71	0,85	0,03
YOLOv8	COCO	Applied	72,5	0,78	0,7	0,74	0,88	
YOLOv9	COCO	Not appplied	72,5	0,76	0,69	0,72	0,86	0,03
YOLOv9	COCO	Applied	74	0,79	0,71	0,75	0,89	
YOLOv10	COCO	Not appplied	72,2	0,76	0,69	0,72	0,86	0,03
YOLOv10	COCO	Applied	74	0,8	0,72	0,76	0,89	
YOLOv11	COCO	Not appplied	73	0,78	0,71	0,74	0,87	0,03
YOLOv11	COCO	Applied	75	0,81	0,73	0,77	0,9	
YOLOv8	CMC	Not appplied	70	0,74	0,67	0,7	0,84	0,03
YOLOv8	CMC	Applied	71,5	0,77	0,69	0,73	0,87	
YOLOv9	CMC	Not appplied	71,5	0,75	0,68	0,71	0,85	0,03
YOLOv9	CMC	Applied	73	0,78	0,7	0,74	0,88	
YOLOv10	CMC	Not appplied	71,2	0,75	0,68	0,71	0,85	0,03
YOLOv10	CMC	Applied	73	0,79	0,71	0,75	0,88	
YOLOv11	CMC	Not appplied	72	0,77	0,7	0,73	0,86	0,03
YOLOv11	CMC	Applied	74	0,8	0,72	0,76	0,89	0,03

4. Discussion and Conclusion

Object recognition systems have the potential to significantly enhance remote call center operations by improving employee performance monitoring, ensuring security, and providing emotional support. However, adopting such technology raises several challenges, particularly around privacy, ethics, and data accuracy. Organizations must carefully navigate these issues by developing transparent, fair, and respectful policies prioritizing employee well-being to ensure the successful implementation of object recognition systems. Future AI and computer vision advancements may further optimize object recognition technology, making remote call centers more efficient and supportive work environments.

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