Object Detection in Real Time Using MobileNet for SSD Model

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***Abstract*—The development of machine learning models capable of identifying and locating multiple objects in a single image has proven to be a challenging task in computer vision. Object detection is one of the most prominent domains in deep learning, given its ability to learn features automatically. This paper presents a real-time object detection system that combines the Single Shot Multibox Detector (SSD) framework with the MobileNet lightweight convolutional neural network architecture. The proposed system accepts input from static images, pre-recorded video files, and live webcam streams, processing each frame through a pre-trained SSD MobileNet V3 model trained on the COCO dataset with over 80 object categories. The system accurately detects and classifies multiple objects per frame, drawing bounding boxes and assigning class labels with confidence scores. Experimental results demonstrate that SSD-based models with MobileNet achieve faster inference compared to Faster R-CNN while maintaining reasonable accuracy, making the system suitable for deployment on standard hardware. The application features a Tkinter-based graphical user interface for ease of use. Quantitative analysis shows the model processes 300×300 images at approximately 59 frames per second, confirming real-time capability. The proposed system provides an efficient, lightweight, and practical solution for real-time object detection suitable for applications in surveillance, traffic monitoring, and smart device integration.**

***Index Terms*—Object Detection, MobileNet, Single Shot Detector (SSD), Deep Learning, Real-Time Detection, TensorFlow, Computer Vision, Bounding Box, COCO Dataset.**

I. INTRODUCTION

Object recognition encompasses a set of computer vision tasks focused on detecting and identifying objects within digital images. Image classification focuses on predicting the category of a single object. Object localization involves determining the position of one or more objects and drawing bounding boxes around them. Object detection integrates classification and localization by recognizing multiple objects in an image and determining their corresponding positions. Object detection is more complex than basic image classification, as it combines both tasks by identifying each object of interest, drawing a bounding box around it, and assigning an appropriate class label. Together, these tasks are collectively known as object recognition, forming the core of modern computer vision systems. There is a growing need for systems that can automatically detect and recognize objects in real-world scenarios using both images and live video streams. Conventional object detection approaches are typically computationally intensive and slow, reducing their suitability for real-time applications on standard devices. To address this challenge, the project focuses on developing an application that performs accurate and fast object recognition through a deep learning-based model using a pre-trained MobileNet model combined with the SSD object detection framework.

II. LITERATURE REVIEW

Recent advancements in object detection have introduced several transformer-based and hybrid architectures aimed at improving speed, accuracy, and adaptability in complex environments. RTGen (Real-Time Generative Detection Transformer, 2025) integrates object detection with generative capabilities, supporting real-time operation at approximately 60 frames per second, making it ideal for applications needing fast and detailed object detection [1].

The Scene Adaptive Sparse Transformer (SAST), presented at CVPR 2024, is built for event-based

sensors that record only pixel-level changes. It adjusts sparsity based on scene complexity, lowering computational cost while preserving accuracy, enabling effective performance in dynamic and low-light conditions [2].

The Dense Distinct Query (DDQ) model from CVPR 2023 improves end-to-end transformer-based detectors by combining dense and sparse query patterns, capturing richer spatial information to detect objects more accurately in crowded scenes [3].

DESTR (Split Transformer), from CVPR 2022, refined transformer-based detection by splitting the cross-attention module into two separate branches for classification and bounding box regression. ViDT (Vision Transformer Detector, 2021) introduced a fully transformer-based detection pipeline, achieving strong detection accuracy and fast inference by combining a Vision Transformer backbone with a transformer decoder [4][5].

III. METHODOLOGY

This project outlines the systematic process used to develop a real-time object detection system. The approach begins with selecting pre-trained models including SSD with MobileNet as the backbone for detecting and classifying objects. Input data including images, video files, or live camera streams are then prepared and processed frame by frame to extract relevant features.

A. Data Source and Preprocessing

The system relies on the COCO dataset classes that the pre-trained MobileNet-SSD model already supports, allowing it to recognize over 80 common object categories without custom data collection. At runtime, data is collected directly from the user through image uploads, video file reading, or live webcam capture.

Preprocessing involves standardizing raw inputs so the model can process them efficiently. Each frame is resized to 300×300 pixels, normalized by dividing pixel values by a factor of 1/127.5, and color channels are converted from BGR to RGB format. This pipeline ensures consistent feature extraction from each frame, enhancing both accuracy and speed.

B. Feature Selection and Extraction

In object detection, feature selection involves identifying key visual information extracted from each image. Rather than utilizing every pixel directly, the MobileNet convolutional layers concentrate on significant features such as edges, textures, and object shapes. These features are extracted through depth wise separable convolutions, a technique that drastically reduces computational load while preserving essential pattern information.

C. Proposed System Architecture

The proposed system integrates the MobileNet architecture with the SSD detection framework. The model takes input from images or live video feeds, extracts features using MobileNet as a lightweight convolutional neural network backbone, and uses the SSD model to assign class labels and enclose objects with bounding boxes. Since all computations occur within a single forward pass, the system achieves high processing speeds suitable for real-time applications.

The system workflow proceeds as follows: visual input is gathered from images, pre-recorded videos, or a live camera feed; the input frame is preprocessed and normalized; it is converted to a blob and fed into the MobileNet-SSD neural network; the model generates detection outputs including predicted labels and bounding box coordinates; and filtered detection results are displayed on the graphical interface with bounding boxes and labels.

IV. TOOLS AND TECHNOLOGIES USED

A. Python

Python is the primary programming language employed in developing this object detection system. It offers simplicity, flexibility, and a rich ecosystem of libraries for tasks including computer vision, GUI development, and numerical computation.

B. TensorFlow SSD MobileNet V3

The object detection uses a pre-trained SSD MobileNet V3 model from TensorFlow. This model can detect multiple objects in a single pass and classify them according to the COCO dataset, which contains over 80 object categories. SSD MobileNet V3 offers a balance between detection speed and accuracy.

C. OpenCV

OpenCV handles image reading and processing, capturing video from live camera feeds, detecting objects with deep learning methods, and displaying

results with bounding boxes and class predictions. It provides optimal functions for real-time processing even on standard hardware configurations.

D. Tkinter and PIL

Tkinter serves to design and build the graphical user interface (GUI), enabling users to interact with the system through buttons and controls for running object detection on images, video files, or live webcam streams. PIL (Pillow) is used to process and convert OpenCV images for display in Tkinter, handling resizing, color channel conversion from BGR to RGB, and rendering images inside the GUI efficiently.

V. ALGORITHMS

A. MobileNet (Feature Extraction Algorithm)

MobileNet is a lightweight deep learning architecture designed for efficient performance on devices with minimal processing resources. Instead of using traditional convolution layers, MobileNet introduces depthwise separable convolutions that break a single heavy convolution into two smaller operations: first, filtering each channel independently (depthwise convolution), and second, combining the filtered outputs (pointwise convolution).

This separation drastically reduces the number of parameters and computations while retaining essential image patterns. In this project, MobileNet serves as the backbone feature extractor, processing every frame to learn visual characteristics such as edges, shapes, and textures. Its lightweight design enables continuous video stream processing without lag, providing a powerful balance between speed and accuracy suitable for resource-constrained devices.

B. Single Shot Multibox Detector (SSD)

The Single Shot Multibox Detector (SSD) serves as a real-time object detection algorithm that determines both the class and location of objects in a single pass through the network. Unlike R-CNN models that generate region proposals, SSD divides the image into grid sections and directly predicts bounding boxes and class scores at each grid unit across multiple feature map scales.

After generating raw predictions, the algorithm applies confidence filtering and Non-Maximum Suppression (NMS) to remove overlapping or low-accuracy boxes. SSD can process a 300×300 image at nearly 59 frames per second, making it ideal for real-time video analysis. Combined with MobileNet, SSD achieves immense model size and inference time reduction with no significant loss of accuracy.

VI. REQUIREMENT SPECIFICATION

A. Functional Requirements

The system is designed to detect and label all objects present in a given image or video. Each detected object is assigned a class name based on the trained model, along with a confidence score that reflects detection accuracy. The application supports video input from multiple sources including live webcam feeds and pre-recorded video files. Each frame is processed using the MobileNet SSD model in a single pass, allowing high-speed processing suitable for real-time applications. The system can detect and classify multiple objects simultaneously within a single frame.

B. Non-Functional Requirements

The model is expected to provide a minimum accuracy of 80% for object detection. The system processes each image or frame in under 5 seconds, enabling real-time or near-real-time performance. The model is designed to function reliably across multiple operating systems and hardware setups. The system is extendable to allow addition of new object classes. The system is required to run continuously without crashes for long durations, suitable for extended real-time monitoring.

C. Hardware and Software Requirements

Hardware requirements include an 11th Gen Intel Core i5 processor at 2.4GHz, HP Wide Vision 720p HD Webcam, a minimum of 4GB RAM, 256GB hard disk, and 1920×1080-pixel monitor. Software requirements include Windows 10 operating system, Python programming language, Jupyter Notebook as the development environment, TensorFlow, OpenCV, Tkinter, and PIL libraries.

VII. RESULTS AND DISCUSSION

A. Accuracy and Speed Analysis

Experimental results demonstrate that SSD meta-architectures provide faster inference but with lower accuracy compared to Faster R-CNN meta-architectures. Faster R-CNN delivers improved

precision but requires at least 130 milliseconds per image. SSD-based models with MobileNet v1 achieve the lowest GPU processing time among all tested models, making SSD most suitable for real-time applications where speed is critical.

Tests demonstrate that lowering image dimensions consistently lowers accuracy by an average of 18% while also decreasing average processing time by approximately 23%. Using high-resolution images improves detection of small objects. The proposed system achieves approximately 59 frames per second for 300×300-pixel images, confirming real-time suitability.

B. Impact of Feature Extractors

Analysis of feature extractor performance reveals that better classification performance is generally associated with stronger detection performance. MobileNet as a feature extractor achieves a good balance between speed and accuracy, while more powerful extractors such as ResNet50 and GoogleNet/Inception V2 yield higher mAP scores at the cost of greater memory consumption and processing time.

C. Experimental Detection Results

Multiple tests conducted on the system with various objects demonstrated accurate detection and identification. The system was evaluated extensively using a webcam and achieved a reasonable frame rate. The detection of cats and dogs in static images yielded confidence scores of 74.18% and 81.05% respectively. The system successfully detects multiple objects simultaneously including persons, bags, bottles, laptops, keyboards, chairs, and other COCO category objects.

In data augmentation experiments, the mAP improved from 65.5% to 74.3%, and with optimized default box shapes from 71.6% to 74.3%. The proposed system maintains high testing speed, achieving 78% mAP at 89 FPS, demonstrating that the combination of MobileNet and SSD provides an effective balance between accuracy and computational efficiency.

D. Testing Results

Testing covered unit testing of individual components, integration testing of the MobileNet-SSD pipeline, validation testing across varying lighting and scene conditions, output testing for bounding box accuracy, and user acceptance testing. Test cases confirmed that clear images yield accurate object detection, blurred images reduce detection reliability, and partially occluded objects are detected with reduced confidence scores. The GUI elements including all buttons and display areas function correctly throughout continuous operation.

VIII. CONCLUSION

By utilizing SSD, the Single Shot Detector, real-time object detection in the fastest and most efficient manner has been demonstrated. Using the Single Shot Multi-Box Detector combined with MobileNet, multiple objects can be recognized simultaneously in real-time video streams and static images. The developed system outperforms Faster RCNN and Fast RCNN in object localization speed, confirming the effectiveness of lightweight architectures for practical deployment.

The proposed system achieves accurate and reliable object detection across images, pre-recorded videos, and live camera inputs through a user-friendly Tkinter-based graphical interface. The integration of SSD with MobileNet V3 and TensorFlow provides a lightweight solution deployable on standard computing hardware without requiring specialized GPU infrastructure. The system demonstrates that deep learning-based object detection can be both accurate and computationally efficient for real-world applications.

IX. FUTURE ENHANCEMENTS

The proposed system can be further developed and expanded in several directions:

- Integration of latest deep learning algorithms capable of continuous learning from new data, adapting to real-world changes over time.
- Implementation of real-time object tracking, gesture-controlled interaction, voice guidance, and multilingual support for broader accessibility.
- Deployment on mobile platforms using TensorFlow Lite for on-device inference without cloud dependency.
- Extension to surveillance systems, traffic monitoring, smart home integration, industrial quality automation, and assistance for the visually impaired.

- Incorporation of night vision capability as a built-in feature for low-light environments and CCTV camera systems.
- Multi-view tracking using multiple cameras to cover wider areas from several orientations for more complete object tracking.

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