**OBJECT DETECTION THROUGH LIVE WEBCAM**

**Submitted in partial fulfillment for the award of**

**MASTER OF COMPUTER APPLICATIONS DEGREE**

****

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**Certificate**

**Mini Project Report–2023**

This is to certify that the Project titled “**OBJECT DETECTION THROUGH LIVE WEBCAM**” is a bonafide record of independent work done by **ANANDITA KUMARI (2200110140019)** under my supervision during **SUMMER BREAK**, submitted to the Department of Computer Applications, **UNITED INSTITUTE OF MANAGEMENT, NAINI, PRAYAGRAJ** in partial fulfillment for the award of the degree of **MASTER IN COMPUTER APPLICATION from Dr. A.P.J. Abdul Kalam Technical University ( APJAKTU), LUCKNOW**.

The project is original work of the student and has not been submitted anywhere else in any manner.

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I am very grateful to my project guide **Dr. Awaneesh Gupta** for giving his valuable time and constructive guidance in preparing the Synopsis/Project.

It would not have been possible to complete this project in short period of time without his kind encouragement and valuable guidance.

Date: Signature

**ANANDITA KUMARI**

**2200110140019**

**Certificate of Originality**

I hereby declare that the Project entitled **“ Object Detection Through Live Webcam ”** submitted to the Department of Computer Application, **UNITED INSTITUTE OF MANAGEMENT, NAINI, PRAYAGRAJ** in partial fulfillment for the award of the Degree of **MASTER IN COMPUTER APPLICATION** during session 2022-2023 is an authentic record of my own work carried out under the guidance of **Dr. Awaneesh Gupta** and that the Project has not previously formed the basis for the award of any other degree.

This is to certify that the above statement made by me is correct to the best of my knowledge.

Place: Prayagraj

Date: Signature of the candidate

**ANANDITA KUMARI**

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**INTRODUCTION OF PROJECT**

The Project entitled **“Object Detection Through Live Webcam”** is a technique that allows you to identify and locate objects in real-time using a camera feed. This can be useful for various applications, such as security, surveillance, robotics, augmented reality, and more.

Object Detection Through Live Webcam involves two main tasks:

* object detection.
* object tracking.

Object detection is the process of finding regions of interest that may contain objects in an image or video frame, and classifying them into different categories, such as humans, animals, cars, or buildings.

Object tracking is the process of maintaining the identity and location of the detected objects as they move across frames in a video stream.

There are different methods and tools for performing object detection through live camera, depending on the type of camera, the quality of the video, the speed and accuracy of the detection, and the resources available. Some of the common methods and tools are: **ML Kit’s Object Detection & Tracking API, TensorFlow 2 Object Detection API, OpenCV and many more.**

Object Detection Through Webcam has many features that make it a powerful and useful technique. Some of the features are:

* **Real-time detection**: Object detection through camera can perform detection in real-time, meaning that it can process and analyze images or videos as they are captured by the camera. This enables fast and responsive applications, such as security, surveillance, robotics, or augmented reality.
* **Multi-object detection**: Object detection through camera can detect multiple objects of different classes in a single image or video frame. This enables comprehensive and diverse applications, such as counting the number of objects, measuring their distance and speed, or detecting their actions and interactions.
* **Object tracking**: Object detection through camera can track the detected objects as they move across frames in a video stream. This enables dynamic and robust applications, such as following a person or a vehicle, locating and grasping an object, or performing visual search.
* **Object recognition**: Object detection through camera can recognize the detected objects by assigning labels to them. This enables intelligent and informative applications, such as identifying faces and license plates, classifying products and customers, or providing personalized recommendations.
* **Object segmentation**: Object detection through camera can segment the detected objects by drawing pixel-level masks around them. This enables precise and detailed applications, such as removing the background, applying filters or effects, or performing medical diagnosis.

Object detection is a technique that allows you to locate and identify objects in images or videos. Object detection is needed for various reasons, such as:

* **Enhancing human vision**: Object detection can help humans see and understand the world better, by providing information and insights about the objects in their surroundings. For example, object detection can help visually impaired people navigate and interact with their environment, by detecting and describing the objects they encounter .
* **Automating tasks**: Object detection can help machines perform tasks that require visual perception and recognition, such as driving, flying, or manufacturing. For example, object detection can help autonomous vehicles detect and avoid obstacles, pedestrians, and traffic signs on the road .
* **Improving quality of life**: Object detection can help improve the quality of life of people by providing convenience, entertainment, and education. For example, object detection can help create immersive and realistic experiences by overlaying virtual objects on real-world scenes, such as in augmented reality games or applications .

**OBJECTIVE OF PROJECT**

* To study the detection of few objects (car, bag, person, phone and plane) and label them through live webcam.
* To understand the future perspective of object detection through live webcam.

**SYSTEM ANALYSIS**

1. **IDENTIFICATION OF NEED**

Here, we discuss and analyze about the need of Object Detection Through Live Webcam in field of security and comparison between existing and proposed system to provides a view of how the proposed system will be more efficient than the existing one.

**Object Detection Security Camera:**

**Primary Function:** The main purpose of an object detection security camera is to identify and categorize specific objects, people, or events within the video feed in real-time.

**Detection Capability:** These cameras use advanced algorithms, often based on artificial intelligence and machine learning, to detect and track objects as they appear in the video stream.

**Alert Generation:** They automatically generate alerts and notifications as soon as certain predefined objects or events are detected. This minimizes response time and human intervention.

**Applications:** Object detection security cameras have a wide range of applications, including enhanced security by identifying intruders, retail analytics by tracking customer behavior, and traffic management by monitoring vehicles and pedestrians.

**Efficiency:** These cameras increase efficiency by automating the process of object identification and reducing the need for constant human monitoring.

**Normal Security Camera:**

**Primary Function:** A normal security camera records video footage of a monitored area, capturing everything that is within its field of view.

**Detection Capability:** It lacks automated detection capabilities and primarily relies on continuous recording. It may have motion sensors to trigger recording when movement is detected.

**Alert Generation:** Alerts are typically generated manually or based on simple motion detection. Humans need to monitor the footage and decide whether action is needed.

**Applications:** Normal security cameras are commonly used for general surveillance to record activities within a specific area, but they may lack advanced insights or specific object tracking capabilities.

**Efficiency:** These cameras require human intervention for analyzing footage and identifying potential threats. They may not be as efficient as object detection cameras in generating immediate alerts.

**Six key advantages of object detection through live webcam:**

1. **Real-Time Detection:** Enables instant identification of objects, people, or events in live video feeds, facilitating quick response and intervention.

2. **Automated Alerts:** Automatically generates alerts upon object detection, reducing the need for constant human monitoring and enabling rapid action.

3. **Enhanced Security:** Provides proactive security measures by detecting unauthorized access, intruders, or suspicious activities in real time.

4. **Efficient Resource Utilization:** Optimizes resource allocation by automating object recognition tasks, allowing human personnel to focus on critical tasks.

5. **Data-Driven Insights:** Captures valuable data on object movement and interactions, offering insights for process optimization and informed decision-making.

1. **Cross-Domain Applicability:** Finds applications in various domains such as security, retail, health-care, and traffic management, offering versatility and tailored solutions.
2. **PRELIMINARY INVESTIGATION**

Object detection through a live webcam involves using advanced computer vision algorithms to identify and categorize specific objects, people, or events in real-time video streams captured by a webcam.

This technology offers several advantages, including real-time insights by swiftly recognizing objects as they appear, automated alerts that reduce the need for continuous human monitoring, enhanced security measures through prompt threat detection, and data-driven insights obtained from captured object movement patterns and behaviors.

These benefits make object detection through live webcams valuable for applications in security, retail analytics, traffic management, and various other domains.

**Problem Statement:**

The problem occurred in normal security camera:

1. **Limited Insight:** Conventional security cameras lack the ability to provide real-time insights, leading to delayed response and potential oversight of critical events.

2. **Manual Monitoring:** Human-dependent monitoring of recorded footage is time-consuming and prone to errors, reducing the efficiency of threat detection and prevention.

3. **Inaccurate Alerts:** Traditional cameras often trigger false alarms due to simple motion detection, causing alert fatigue and diverting resources away from genuine threats.

4. **Passive Surveillance:** Without object recognition capabilities, normal security cameras cannot proactively identify specific objects or events, hindering their effectiveness in proactive security measures.

**FEASIBILITY STUDY**

Studying the feasibility of implementing object detection through a live webcam system from a technical, economic, and operational perspective:

**TECHNICAL FEASIBILITY:**

**Hardware Requirements:**

**Webcam:** Most modern computers come equipped with webcams, and external webcams are readily available and affordable.

**Processing Power:** Object detection, especially in real-time, can be computationally intensive. The feasibility depends on the processing power of the computer or server that will perform the detection. High-end GPUs can significantly accelerate this process.

**Memory:** Sufficient RAM is needed to process and store data efficiently during object detection.

**Internet Connectivity:** A stable internet connection is crucial for streaming the webcam feed and possibly for cloud-based processing.

**Software Requirements:**

**Object Detection Algorithm:** Choose a suitable object detection algorithm (e.g., YOLO, SSD, Faster R-CNN) that balances accuracy and speed for real-time detection.I use SSD-MobileNet-V2-Ftlite model in it.

**Programming Skills:** Developing or configuring the software for object detection may require expertise in computer vision, deep learning, and software development.I use Python programming language.

**Libraries and Frameworks:** Use popular libraries and frameworks like OpenCV, TensorFlow, or PyTorch for easier implementation.I use tensorflow for training and OpenCV for Camera access.

**Data Requirements:**

1. You'll need a dataset for training and fine-tuning your object detection model if you plan to use a custom model.
2. Access to labeled data to recognize specific objects.
3. I use 5 objects named as car,phone,person,bag and plane.

**Testing and Optimization:** Rigorous testing and optimization are essential to ensure real-time performance, accuracy, and stability.

**ECONOMIC FEASIBILITY:**

**Cost of Hardware and Software:** Calculate the costs of any additional hardware (e.g., GPUs) and software licenses or subscriptions required for object detection.

**Development Costs:** Factor in the cost of hiring or training developers with the necessary expertise.

**Operational Costs:** Consider ongoing costs, such as maintenance, software updates, and hosting if you use cloud-based solutions.

**Return on Investment (ROI)**: Assess the potential ROI by estimating the benefits, such as increased security, improved efficiency, or new revenue streams, and compare them to the project's costs.

**OPERATIONAL FEASIBILITY:**

**User Acceptance:** Determine if the intended users (e.g., security personnel, retail staff) are comfortable with and trained to use the system.

**Integration:** Ensure compatibility with existing systems and workflows. For example, if this is for security, it should seamlessly integrate with your security infrastructure.

**Maintenance and Support:** Plan for ongoing maintenance, including software updates, bug fixes, and technical support.

**Scalability:** Assess whether the system can handle an increasing number of users or additional cameras.

**Legal and Privacy Compliance:** Ensure compliance with local and national laws regarding video surveillance and privacy. Privacy concerns could affect the feasibility.

In conclusion, object detection through a live webcam is technically feasible, but its economic feasibility depends on factors like hardware, software, and ongoing operational costs. Operational feasibility is contingent on user acceptance, integration with existing systems, scalability, and compliance with legal and privacy regulations. Conduct a thorough feasibility analysis to determine whether the benefits of implementing such a system outweigh the costs and potential challenges.

**DATA FLOW DIAGRAM**

A data flow diagram (DFD) is a graphical representation of the flow of data through a system. It is a tool used in systems analysis and design to document the functional requirements of a system. DFDs use a set of standard symbols to represent data flows, processes, data stores, and external entities.

The levels in a DFD represent different levels of detail about the system. The three most common levels are:

**Level 0 DFD:** This is the highest level DFD, which provides an overview of the entire system. It shows the major processes, data flows, and data stores in the system, without providing any details about the internal workings of these processes.

**Level 1 DFD:**This level DFD breaks down the major processes in the Level 0 DFD into more detail. It shows the sub-processes, data flows, and data stores for each major process.

**Level 2 DFD:** This level DFD breaks down the sub-processes in the Level 1 DFD into even more detail. It shows the detailed processes, data flows, and data stores for each sub-process.

In some cases, there may be additional levels of DFDs. The number of levels required depends on the complexity of the system being modeled.

**Terminology in DFDs:**

**Data flow:** A line with an arrow that represents the movement of data between processes, data stores, and external entities.

**Process:** A rectangle that represents a transformation of data.

**Data store:** A circle that represents a repository of data.

**External entity:** An oval that represents a person, organization, or system that interacts with the system being modeled.

DFDs are a useful tool for understanding the flow of data through a system. They can be used to identify problems with the current system and to design new systems.

Benefits of using DFDs:

* They can help to visualize the flow of data through a system.
* They can help to identify problems with the current system.
* They can help to design new systems.
* They can be used to communicate with stakeholders about the system.

**Level 0 DATA FLOW DIAGRAM :**

Object Detection system

CAPTURING DEVICE

OBJECT DETECTED

DATABASE

**Level 1 DATA FLOW DIAGRAM :**

LEARNING PHASE

READ IMAGE

FEATURE EXTRACTION

CAPTURED IMAGE

BINARY STRING

DATABASE

PREDICTING PHASE

FEATURE EXTRACTION

COMPARISION

ENHANCEMENT

OBJECT DETECTED

BINARY STRING

CAPTURED INPUT

DATABASE

**SCHEMATIC DIAGRAM**

Capturing Devices(webcam,drone,camera,etc.)

Result

Labeling and Annotate target

Raw image(in n x n matrix)

Comparison (which class it belong)

Approximation

DATABASE

**WEBCAM MODULE:** It will capture raw images using the webcam and the hexadecimal data is stored into a matrix.

**ENHANCE RAW IMAGE MODULE:** This process requires us to use DCT (Discrete Cosine Transformation) to convert the hexadecimal value to spatial value and store it into a 8x8 or 4x4 matrix.

**FEATURE EXTRACTION MODULE:** In this module we simplify the amount of resource required to describe a large set of data accurately. This data of target Image is compared with the feature data already stored in our database.

**APPROXIMATION MODULE:** When trying to detect an object there can be percentage difference in features extracted from target data, and the features of Source data. This difference is normalized in this module.

**OBJECT ORIENTED DIAGRAM**

An Object-Oriented Diagram (OOD), also known as a Class Diagram, is a visual representation used in software engineering to depict the structure of a software system in terms of its classes, attributes, methods, and the relationships between these elements. It is one of the most common diagrams used in object-oriented modeling and design to help developers and designers understand, plan, and communicate the structure of a software system.

Here are the key components typically found in an Object-Oriented Diagram:

**1. Class:** A class represents a blueprint or template for creating objects. It defines the structure and behavior that objects of the class will have. In the diagram, classes are usually represented as rectangles with three sections: the class name, a list of attributes, and a list of methods.

**2. Attribute:** An attribute represents a property or data member of a class. It describes the characteristics or state that objects of the class will possess. Attributes are listed within a class and may include data types.

**3. Method:** A method represents a function or operation that objects of the class can perform. It defines the behavior or actions associated with objects of the class. Methods are also listed within a class and include their parameters and return types.

**4. Relationships:** Relationships in an OOD diagram depict how classes are connected or associated with each other. The most common types of relationships include:

* Association: It shows a connection between two classes, indicating that one class is aware of the other. Associations can be simple or have multiplicity (e.g., one-to-one, one-to-many).
* Inheritance: It represents an "is-a" relationship between a base (parent) class and a derived (child) class. The child class inherits attributes and methods from the parent class.
* Aggregation and Composition: These represent part-whole relationships. Aggregation indicates a weaker relationship, where the whole can exist without its parts, while composition implies a stronger relationship, where the whole is composed of its parts.
* Dependency: It shows that one class relies on another class, often indicating that changes in one class may affect the other class.

CLASS DIAGRAM :

* Requested Camera.
* Display Object.
* Scan Object
* Object Result

Device Camera

* Process Object
* Validation
* Process Object Result

Machine learning

* Display Object Result

Object detection result

* Process Training data
* Request Training Data
* Display Training Result

Manage Information

Raw Data Process

Train and Improve

**USE CASE DIAGRAM**

A Use Case Diagram is a visual representation used in software engineering to describe and document the interactions between different actors (users or external systems) and a system or application under consideration. Use Case Diagrams are a part of the Unified Modeling Language (UML) and are commonly used during the early stages of software development to capture and define the functional requirements of a system.

Key elements of a Use Case Diagram include:

**1. Use Case:** A use case represents a specific functionality or a discrete unit of work that a system can perform. Use cases describe the interactions between an actor (user) and the system to achieve a particular goal. Each use case is typically represented by an oval shape and is labeled with a meaningful name.

**2. Actor:** An actor is an external entity that interacts with the system. Actors can be human users, other systems, or even hardware devices. Actors are represented as stick figures or blocks on the diagram, and they connect to use cases to show their involvement in specific actions or functionality.

**3. Association**: Lines connecting actors and use cases represent associations. An association line indicates that an actor interacts with a particular use case. The arrow on the line typically points from the actor to the use case to show the direction of the interaction.

**4. System Boundary:** The system boundary, often represented as a box, encloses all the use cases of the system. It defines the scope of the system under consideration.

USE CASE DIAGRAM :

Object Scan

Object Detection result

Object Detection

**ACTIVITY DIAGRAM**

An activity diagram is a type of UML (Unified Modeling Language) diagram used in software engineering to visualize the flow of activities or processes within a system, business process, or use case. Activity diagrams are particularly useful for modeling the workflow and behavior of a specific functionality or process, showing the sequence of actions, decision points, and transitions between different states or activities.

Here are some key components and concepts associated with activity diagrams:

**1. Activity:** An activity represents a specific task or action within the system or process being modeled. Activities are usually depicted as rounded rectangles and are labeled with a brief description of the action.

**2. Initial Node:** An initial node (depicted as a small filled circle) represents the starting point of the activity diagram. It indicates where the process begins.

**3. Final Node:** A final node (usually depicted as a circle with a border) represents the endpoint of the activity diagram, signifying the completion of the process.

**4. Action or Task:** Actions or tasks represent individual steps or operations within the process. They are typically depicted as rectangles with rounded corners and are labeled with a description of the task.

**5. Decision Node:** A decision node (diamond-shaped) represents a point in the process where a decision must be made. Depending on the outcome of the decision, the process may follow different paths or branches.

**6. Control Flow:** Control flow arrows (solid lines with arrowheads) connect the various elements of the diagram, indicating the order in which activities are performed. They show the flow of control from one activity to the next.

**7. Fork and Join Nodes:**  Fork nodes (solid black bars) are used to split the flow of control into multiple parallel paths, allowing activities to be executed concurrently. Join nodes (solid black bars with a small "x") bring these parallel paths back together.

**8. Swimlanes:** Swim-lanes are used to group activities based on the responsible entity or role. They help clarify who or what is responsible for each task in the process. Swimlanes are often depicted as vertical or horizontal partitions.

**9. Object Nodes:**  Object nodes represent the input or output of activities and can be used to show the data or objects passed between activities.

Activity diagrams are versatile and can be used in various domains, including software design, business process modeling, and system analysis. They provide a visual and structured way to represent complex workflows and make it easier to understand and communicate the logic and behavior of a process or system. Activity diagrams are particularly useful for documenting use cases, business processes, and the control flow within software applications.

ACTIVITY DIAGRAM :

1. Object Scan :

Running System

Point Object at the Camera

Object Scan

The object scan process, where the first object detection system will be run then the user directs the object to the camera. Then the object scan process will run.

1. Object Detection :

Detect whether the object has been captured by the camera

Processing the object detected by the camera

Successfully recognized

No

Yes

Object Recognized

?

The object detection process, the first process detects whether the object was successfully captured by the camera there are 2 conditions in this process, which is whether the system can recognize the object or not, if not, the system will return to the initial step, which is detecting the object to be captured by the camera.

1. Object Detection Result :

Object Detection Results

Object Name And Object Accuracy

Object Detection Results

Object Name And Object Accuracy

The process of object detection results, where after the system obtains the results, the system will display or provide the name of the object and the percentage of object accuracy.

1. Managing Object Information :

Configure Training Data

Train Training Data-set

Processing training Data-set

Success

**PHASE BASED WORK BREAKDOWN STRUCTURE**

A phase-based Work Breakdown Structure (WBS) is a project management tool that organizes project tasks and activities based on the different phases or stages of a project's life-cycle. Each phase represents a distinct set of activities and objectives that must be completed to move the project forward. The WBS helps project managers and teams break down complex projects into manageable and logical components, making it easier to plan, execute, and monitor the project's progress.

Here's how a phase-based WBS typically works:

**1. Project Phases:** A project is divided into several phases, which are typically sequential but can sometimes overlap or run in parallel. The phases are defined based on the nature of the project and may include stages like initiation, planning, execution, monitoring and control, and closure.

**2. Sub-Phases:** Each phase is further broken down into sub-phases or major deliverable. These sub-phases represent the key milestones or outcomes that need to be achieved within each phase. Sub-phases are essentially the highest level of tasks in the WBS for that phase.

**3. Tasks and Activities:** Under each sub-phase, you have a hierarchy of tasks and activities. These are the specific actions and work items that need to be completed to achieve the sub-phase's deliverable. Tasks and activities are typically the lowest level of detail in the WBS.

**4. Hierarchy:** The WBS is organized hierarchically, with phases at the top, followed by sub-phases, and then tasks and activities. This hierarchical structure helps in decomposing the project into manageable components and provides a clear view of how each task relates to the overall project objectives.

**5. Dependencies:** The WBS can also illustrate dependencies between tasks and activities. Some tasks may need to be completed before others can begin, and these dependencies are often indicated in the WBS to help project managers identify critical paths and potential bottlenecks.

**6. Resource Allocation:** By organizing tasks and activities by phases, project managers can allocate resources more effectively. Resources can be assigned to specific phases, ensuring that the right personnel, equipment, and materials are available when needed.

**7. Progress Tracking:** The phase-based WBS simplifies progress tracking and reporting. Project managers can monitor the completion of sub-phases and their associated tasks to gauge how well the project is progressing through its various phases.

**8. Risk Management:** It also aids in risk management by highlighting potential risks and issues associated with each phase. This allows project managers to focus on addressing risks at the appropriate stage of the project.

In summary, a phase-based WBS is a project management tool that organizes project work into phases, sub-phases, and tasks, providing a structured approach to project planning, execution, and monitoring. It is especially useful for complex projects with multiple phases, each requiring its own set of tasks and activities.

**SOFTWARE AND HARDWARE SPECIFICATIONS**

To perform real-time object detection using TensorFlow on Google Colab, you'll need both hardware and software specifications. Below, I'll outline the general requirements for hardware and software, but keep in mind that the specific requirements can vary depending on the complexity of your object detection model and the size of your data-set.

**HARDWARE SPECIFICATIONS:**

**1. GPU:** Google Colab offers free GPU access, which is highly recommended for real-time object detection, especially if you're using deep learning models. You can check if you have a GPU available by running the following code snippet in a Colab cell:

|  |
| --- |
| Python |
| import tensorflow as tf  print("GPU Available: ", tf.config.list\_physical\_devices('GPU')) |

Ideally, you should have access to a GPU (NVIDIA GPU) with a reasonable amount of VRAM (4GB or more is preferred) to train and run models efficiently.

**2. CPU and RAM:** While a GPU is crucial for training deep learning models, a reasonably fast CPU and sufficient RAM (at least 9GB, preferably more) are also important for data preprocessing and handling.

**SOFTWARE SPECIFICATIONS:**

**1. Google Colab:** Access to Google Colab is essential. You can access Colab for free by going to https://colab.research.google.com/.

**2. Python:** TensorFlow and most deep learning libraries are written in Python, so make sure you're familiar with Python.

1. **TensorFlow:** You'll need to install TensorFlow and other required libraries in your Colab environment. TensorFlow 2.x or later is recommended for object detection. You can install it using pip:

|  |
| --- |
| python |
| !pip install tensorflow |

**4. Object Detection Framework:** TensorFlow provides several object detection frameworks like TensorFlow Object Detection API, TensorFlow Hub, and TensorFlow Lite. You should choose one based on your project's requirements.

**5. Pretrained Model:**You can start with a pretrained object detection model (e.g., a model from the TensorFlow Model Zoo) and fine-tune it on your custom dataset.

**6. OpenCV:** OpenCV is a computer vision library that can be helpful for image and video processing tasks. You can install it using pip:

|  |
| --- |
| python |
| !pip install opencv-python |

**7. Webcam or Video Feed:** If you plan to perform real-time detection on a webcam or video feed, you'll need a webcam (if not built-in) and a library like OpenCV to capture and process the video feed.

**8. Data:** If you're training your own object detection model, you'll need labeled training data. Ensure you have access to your dataset and it's appropriately prepared.

**9. Jupyter Notebook:** Google Colab uses Jupyter notebooks for its environment, which is perfect for experimenting with code, training models, and visualizing results.

**10. Internet Connection:** Colab requires an internet connection to access libraries, datasets, and to save your work in Google Drive.

Remember that Colab sessions have a time limit, so real-time object detection may require periodic interactions to keep the session active.

**PREREQUIRE CONCEPT**

**MACHINE LEARNING**

Machine learning is a sub-field of artificial intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn and make predictions or decisions from data without being explicitly programmed. In machine learning, computers are trained to recognize patterns, make sense of data, and improve their performance over time through experience.

**1. Automated Learning:** Machine learning is a subset of artificial intelligence that enables computers to learn from data and improve their performance on tasks without being explicitly programmed.

**2. Data-Driven:** It relies on data to identify patterns, relationships, and insights, making it suitable for various applications, including prediction, classification, and recommendation systems.

**3. Algorithms:** Machine learning algorithms, such as decision trees, neural networks, and support vector machines, process data and adjust their parameters to make predictions or decisions.

**4. Supervised and Unsupervised Learning:** Common types of machine learning include supervised learning, where models learn from labeled data, and unsupervised learning, where models discover hidden patterns in unlabeled data.

**5. Applications:** Machine learning is used in diverse fields, from healthcare and finance to natural language processing and computer vision, and it continues to drive innovations and automation in various industries.

**NEURAL NETWORK**

A neural network is a computational model inspired by the structure and functioning of the human brain. It is a fundamental component of deep learning, a subfield of machine learning. Neural networks are used for various tasks in artificial intelligence, including image and speech recognition, natural language processing, and more.

At its core, a neural network is composed of interconnected nodes called neurons or artificial neurons. These neurons are organized into layers:

**1. Input Layer:** This layer receives the raw data or features as input. Each neuron in this layer represents a specific feature of the input data.

**2. Hidden Layers:** Between the input and output layers, there can be one or more hidden layers. These layers process the input data through a series of mathematical operations. Each neuron in a hidden layer takes inputs from the previous layer, performs a weighted sum, applies an activation function, and passes the result to the next layer.

**3. Output Layer:** The final layer produces the network's output. The number of neurons in this layer depends on the specific task. For example, in a binary classification problem, there may be one neuron that produces a probability score, while in a multi-class classification problem, there may be multiple neurons, each representing a different class.

Neurons are connected by weighted connections, which determine the strength of the connection between neurons. During training, these weights are adjusted to optimize the network's performance on a given task. This optimization process typically involves using a loss function to measure the network's error and an optimization algorithm like gradient descent to update the weights.

Activation functions, such as the sigmoid, ReLU (Rectified Linear Unit), and tanh, introduce non-linearity into the neural network, enabling it to model complex relationships in the data.

Deep neural networks, often referred to as deep learning models, have multiple hidden layers, making them capable of learning hierarchical and intricate patterns in data. Convolutional Neural Networks (CNNs) are commonly used for image-related tasks.

**TENSORFLOW OBJECT DETECTION API**

The TensorFlow Object Detection API is a powerful tool provided by Google's TensorFlow framework for building and training models to perform object detection tasks. Object detection is a computer vision task that involves identifying and locating objects of interest within an image or video.

The TensorFlow Object Detection API offers a pre-defined set of deep learning models, including Single Shot MultiBox Detector (SSD), Faster R-CNN, and others, which are pre-trained on large datasets like COCO (Common Objects in Context) for various object detection tasks.

Key features and components of the TensorFlow Object Detection API include:

1. **Pre-trained Models:** The API provides pre-trained models with weights and architectures that can be fine-tuned on custom datasets for specific object detection tasks.

**2. Customization:** Users can adapt and fine-tune these pre-trained models to work with their specific datasets and target objects, making it suitable for a wide range of applications.

**3. Training Pipeline:** The API offers a training pipeline that streamlines the process of training object detection models, including data preprocessing, model configuration, and optimization.

**4. Inference:** After training, the models can be used for inference to detect objects in new images or videos. This is valuable for applications like object tracking, surveillance, autonomous vehicles, and more.

**5. Evaluation:** The API includes evaluation tools to assess the performance of your custom object detection models on validation datasets.

**6. Model Zoo:** TensorFlow's Model Zoo provides a repository of pre-trained models and associated configuration files, making it easy to access and use a variety of models for different object detection tasks.

The TensorFlow Object Detection API has been widely adopted in computer vision research and applications, including autonomous driving, retail, healthcare, and many others, where accurate object detection is crucial. It simplifies the development and deployment of object detection systems by providing pre-built tools and models that can be adapted and extended to meet specific needs.

**SSD-MobileNet-V2-FPNLite-320 model**

"SSD-MobileNet-V2-FPNLite-320" refers to a specific object detection model architecture that combines the SSD (Single Shot MultiBox Detector) framework with the MobileNet-V2 backbone network and FPNLite (Feature Pyramid Network Lite) for feature extraction. The "320" in the name typically indicates the input image size.

Here's what each part of the name represents:

**1. SSD (Single Shot MultiBox Detector):** SSD is a popular object detection algorithm that performs both object localization (detecting the object's bounding box) and object classification (identifying the object's category) in a single pass through the neural network. It's known for its real-time and efficient performance.

**2. MobileNet-V2:** MobileNet-V2 is a lightweight convolutional neural network architecture optimized for mobile and embedded devices. It balances model size and accuracy, making it suitable for real-time applications on resource-constrained hardware.

**3. FPNLite (Feature Pyramid Network Lite):** Feature Pyramid Networks (FPNs) are used for multi-scale feature extraction, which helps the model detect objects of various sizes. FPNLite is likely a variant optimized for efficiency.

**4. 320:** The number "320" typically represents the expected input image size in pixels. In this case, it suggests that the model is designed to work with input images of size 320x320 pixels.

This specific model architecture would be used for object detection tasks where real-time or resource-efficient performance is desired, such as in mobile applications, robotics, or embedded systems, where the hardware may have limitations compared to high-end GPUs.

**GITHUB CLONING**

Cloning in GitHub involves making a copy of a remote repository onto your local machine:

**1. Repository Copy:** Cloning creates a local copy of a GitHub repository, including all its files, commit history, and branches.

**2. URL Required:** You need the repository's URL to clone it. This URL can be obtained from the GitHub repository's page.

**3. Git Command:** You use the Git command `git clone` followed by the repository URL to initiate the cloning process.

**4. Local Copy:** Once cloned, you can work on the code locally, make changes, and commit them. Changes can be pushed back to the remote repository when needed.

**5. Collaboration:** Cloning is essential for collaborating on projects, as it allows multiple developers to work on the same codebase, contribute changes, and maintain version control using Git.

**PACKAGES AND COMMANDS**

**Re :** "re" is a Python module for working with regular expressions, enabling pattern matching and text manipulation tasks.

It provides functions and classes to search, match, and manipulate strings based on user-defined patterns, making it a powerful tool for text processing and validation.

**Pyymal :** `PyYAML` is a Python library for parsing and working with YAML (YAML Ain't Markup Language) data, allowing you to read, write, and manipulate YAML-formatted configuration files and data structures in Python applications.

**Protoc :** `protoc` is a command-line tool used to compile Protocol Buffers (protobuf) schema definitions into language-specific code that can be used to serialize and deserialize structured data. It's commonly used in various programming languages for efficient data interchange and serialization.

**Shutil :** `shutil` is a Python module that provides a high-level interface for file operations, including copying, moving, and deleting files and directories. It simplifies tasks related to file and directory manipulation, making it easier to work with file systems in Python scripts and applications.

**Wget :** `wget` is a command-line utility for downloading files from the internet. It allows users to specify a URL, and it retrieves the file located at that URL, saving it to the local file system. `wget` is commonly used in Unix-based systems and is helpful for automating file downloads or fetching content from web servers.

Batch-size : Batch size, in the context of machine learning and deep learning:

**1. Training Efficiency:** It represents the number of data samples that are processed by a model in one forward and backward pass during a single training iteration.

**2. Impact on Training:** A larger batch size can speed up training but requires more memory. Smaller batches may be noisier but can help the model generalize better.

**3. Hyperparameter:** Batch size is a hyperparameter that needs to be tuned based on the specific dataset and hardware constraints to optimize model training.

**Pipeline model :** A pipeline model, in the context of machine learning:

**1. Sequential Processing:** It's a machine learning workflow where data is processed sequentially through a series of stages or transformers, often including data preprocessing, feature engineering, and model training.

**2. Automation:** Pipeline models automate the flow of data and operations, ensuring consistent and reproducible results, making them useful for data preparation and model deployment.

**3. Scikit-Learn:** Popular libraries like Scikit-Learn in Python offer tools to create and use pipeline models, streamlining the machine learning development process.

**os :** Provides functions for interacting with the operating system, such as file and directory operations.

**cv2 :** (OpenCV): Open Source Computer Vision Library used for image and video processing tasks.

**numpy (as `np`) :** A fundamental library for numerical computations, widely used for array manipulation in machine learning.

**Sys :** Provides access to Python interpreter variables and functions, used for system-specific operations.

**Glob :** Used for file pattern matching and retrieval of file paths.

**Random :** Provides functions for generating random numbers and making random selections.

**importlib.util :** Used for programmatically importing modules and packages.

**tensorflow.lite.python.interpreter (from TensorFlow Lite):** Specifically for using TensorFlow Lite's interpreter to work with optimized machine learning models on resource-constrained devices.

**matplotlib and `matplotlib.pyplot` (as `plt`) :** Used for data visualization, including creating plots and charts.

**TENSORBOARD**

TensorBoard is a web-based visualization tool provided by TensorFlow for tracking and visualizing various aspects of the training process and model performance in machine learning projects, including metrics, loss, graphs, and histograms. It aids in monitoring and optimizing deep learning models.

**CLASSIFICATION LOSS**

Classification loss, in the context of machine learning and deep learning, is a measure that quantifies the error or discrepancy between the predicted class labels and the true (ground truth) class labels in a classification problem. It is used during the training of classification models, such as neural networks, to guide the model's learning process by penalizing incorrect predictions.

**LEARNING RATE**

Learning rate, in the context of machine learning and deep learning, is a hyperparameter that determines the step size at which a model's parameters (such as weights and biases) are updated during the training process. It plays a crucial role in controlling the convergence and stability of the training algorithm.

**LOCALIZATION LOSS**

Localization loss, in the context of object detection and localization tasks within machine learning, is a component of the overall loss function that quantifies the error in predicting the precise location or coordinates of bounding boxes that enclose objects in an image or scene.

**REGULAIZTION LOSS**

Regularization loss, in the context of machine learning and deep learning, is a term that represents an additional component added to the overall loss function during training. It is used to prevent overfitting and encourage models to generalize better to unseen data.

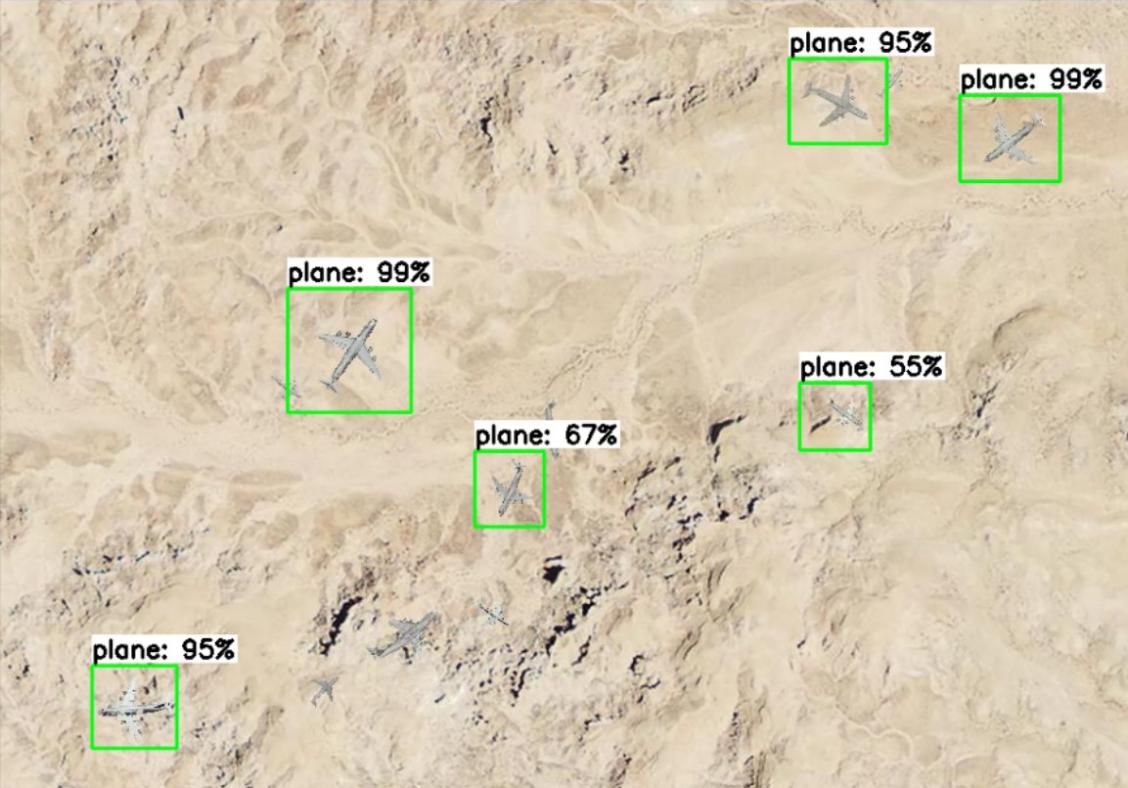
**TOTAL LOSS**

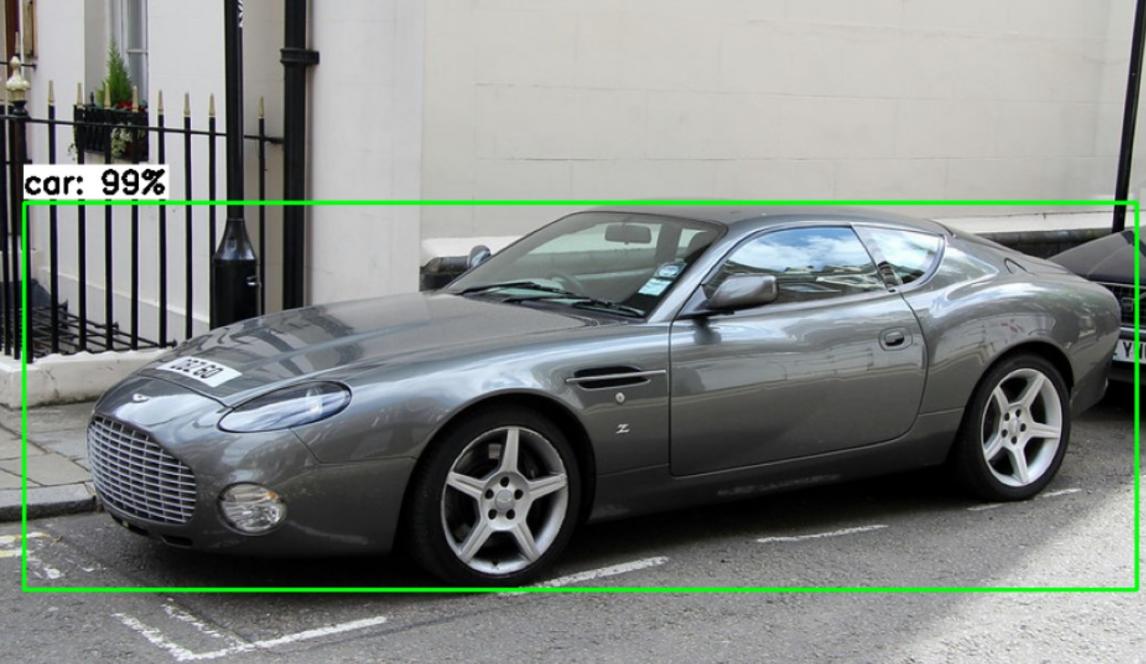
The total loss, in the context of machine learning and deep learning, refers to the overall objective function that a model aims to minimize during the training process. It is a combination of different types of loss terms, each serving a specific purpose. The total loss guides the optimization of model parameters (weights and biases) to make predictions that are as accurate as possible.

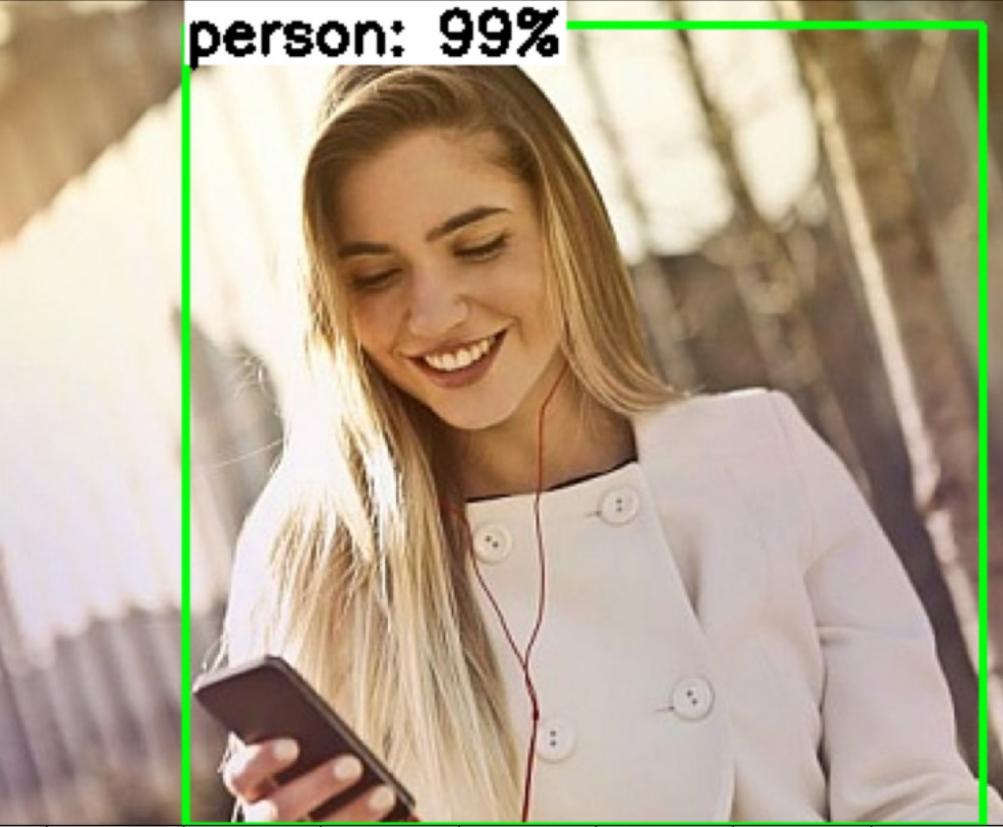
**SYSTEM DESIGN - SCREEN SHOTS**

The inference test images consist of 5 classes :

 ****

****

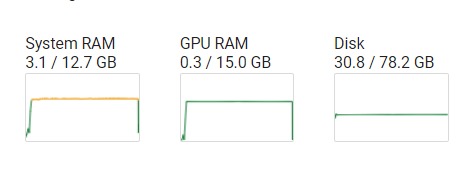
****

****

**OUTPUT SCREEN SHOT THROGH WEBCAM**



**GPU, SYSTEM RAM AND DISK USAGE SCRREN SHOT DURING TRAINING**



**CODING**

# Gather and Label Training Images

‘’’

Before we start training, we need to gather and label those images.

Collect and put images and .xml(contain annotation ) in one folder and compress it.

Upload it to Drive(same as google colab account) or directly upload it in home(or content) page.

‘’’

# Install TensorFlow Object Detection Dependencies

# Clone the tensorflow models repository from GitHub

!pip uninstall Cython -y # Temporary fix for "No module named 'object\_detection'" error

!git clone --depth 1 https://github.com/tensorflow/models

# Copy setup files into models/research folder

%%bash

cd models/research/

protoc object\_detection/protos/\*.proto --python\_out=.

#cp object\_detection/packages/tf2/setup.py .

# Modify setup.py file to install the tf-models-official repository targeted at TF v2.8.0

import re

with open('/content/models/research/object\_detection/packages/tf2/setup.py') as f:

    s = f.read()

with open('/content/models/research/setup.py', 'w') as f:

    # Set fine\_tune\_checkpoint path

    s = re.sub('tf-models-official>=2.5.1',

               'tf-models-official==2.8.0', s)

    f.write(s)

# Install the Object Detection API

# Need to do a temporary fix with PyYAML because Colab isn't able to install PyYAML v5.4.1

!pip install pyyaml==5.3

!pip install /content/models/research/

# Need to downgrade to TF v2.8.0 due to Colab compatibility bug with TF v2.10 (as of 10/03/22)

!pip install tensorflow==2.8.0

# Run Model Bulider Test file, just to verify everything's working properly

!python /content/models/research/object\_detection/builders

/model\_builder\_tf2\_test.py

# Upload Image Dataset and Prepare Training Data

# Upload Images

**#Copy from Google Drive**

from google.colab import drive

drive.mount('/content/gdrive')

!cp /content/gdrive/MyDrive/path/to/images.zip /content

## Split images into train, validation, and test folders

!mkdir /content/images

!unzip -q /content/gdrive/MyDrive/images.zip -d /content/images

!mkdir /content/images/train; mkdir /content/images/validation; mkdir /content/images/test

!wget https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/util\_scripts/train\_val\_test\_split.py

!python train\_val\_test\_split.py

## Create Labelmap and TFRecords

### This creates a a "labelmap.txt" file with a list of classes the object detection model will detect.

%%bash

cat <<EOF >> /content/labelmap.txt

person

car

plane

bag

phone

EOF

# Download data conversion scripts

!wget https://raw.githubusercontent.com/ANANDITA24/Mini-Project/main/create\_csv.py

! wget https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/util\_scripts/create\_tfrecord.py

!python3 create\_csv.py

# Create CSV data files and TFRecord files

!python3 create\_tfrecord.py --csv\_input=images/train\_labels.csv --labelmap=labelmap.txt --image\_dir=images/train --output\_path=train.tfrecord

!python3 create\_tfrecord.py --csv\_input=images/validation\_labels.csv --labelmap=labelmap.txt --image\_dir=images/validation --output\_path=val.tfrecord

train\_record\_fname = '/content/train.tfrecord'

val\_record\_fname = '/content/val.tfrecord'

label\_map\_pbtxt\_fname = '/content/labelmap.pbtxt'

# Set Up Training Configuration

# Change the chosen\_model variable to deploy different models available in the TF2 object detection zoo

chosen\_model = 'ssd-mobilenet-v2-fpnlite-320'

MODELS\_CONFIG = {

    'ssd-mobilenet-v2': {

        'model\_name': 'ssd\_mobilenet\_v2\_320x320\_coco17\_tpu-8',

        'base\_pipeline\_file': 'ssd\_mobilenet\_v2\_320x320\_coco17\_tpu-8.config',

        'pretrained\_checkpoint': 'ssd\_mobilenet\_v2\_320x320\_coco17\_tpu-8.tar.gz',

    },

    'efficientdet-d0': {

        'model\_name': 'efficientdet\_d0\_coco17\_tpu-32',

        'base\_pipeline\_file': 'ssd\_efficientdet\_d0\_512x512\_coco17\_tpu-8.config',

        'pretrained\_checkpoint': 'efficientdet\_d0\_coco17\_tpu-32.tar.gz',

    },

    'ssd-mobilenet-v2-fpnlite-320': {

        'model\_name': 'ssd\_mobilenet\_v2\_fpnlite\_320x320\_coco17\_tpu-8',

        'base\_pipeline\_file': 'ssd\_mobilenet\_v2\_fpnlite\_320x320\_coco17\_tpu-8.config',

        'pretrained\_checkpoint': 'ssd\_mobilenet\_v2\_fpnlite\_320x320\_coco17\_tpu-8.tar.gz',

    },

    # The centernet model isn't working as of 9/10/22

    #'centernet-mobilenet-v2': {

    #    'model\_name': 'centernet\_mobilenetv2fpn\_512x512\_coco17\_od',

    #    'base\_pipeline\_file': 'pipeline.config',

    #    'pretrained\_checkpoint': 'centernet\_mobilenetv2fpn\_512x512\_coco17\_od.tar.gz',

    #}

}

model\_name = MODELS\_CONFIG[chosen\_model]['model\_name']

pretrained\_checkpoint = MODELS\_CONFIG[chosen\_model]['pretrained\_checkpoint']

base\_pipeline\_file = MODELS\_CONFIG[chosen\_model]['base\_pipeline\_file']

# Create "mymodel" folder for holding pre-trained weights and configuration files

%mkdir /content/models/mymodel/

%cd /content/models/mymodel/

# Download pre-trained model weights

import tarfile

download\_tar = 'http://download.tensorflow.org/models/object\_detection/tf2/20200711/' + pretrained\_checkpoint

!wget {download\_tar}

tar = tarfile.open(pretrained\_checkpoint)

tar.extractall()

tar.close()

# Download training configuration file for model

download\_config = 'https://raw.githubusercontent.com/tensorflow/models/master/research/object\_detection/configs/tf2/' + base\_pipeline\_file

!wget {download\_config}

# Set training parameters for the model

num\_steps = 5000

if chosen\_model == 'efficientdet-d0':

  batch\_size = 4

else:

  batch\_size = 32

# Create custom configuration file by writing the dataset, model checkpoint, and training parameters into the base pipeline file

import re

%cd /content/models/mymodel

print('writing custom configuration file')

with open(pipeline\_fname) as f:

    s = f.read()

with open('pipeline\_file.config', 'w') as f:

    # Set fine\_tune\_checkpoint path

    s = re.sub('fine\_tune\_checkpoint: ".\*?"',

               'fine\_tune\_checkpoint: "{}"'.format(fine\_tune\_checkpoint), s)

    # Set tfrecord files for train and test datasets

    s = re.sub(

        '(input\_path: ".\*?)(PATH\_TO\_BE\_CONFIGURED/train)(.\*?")', 'input\_path: "{}"'.format(train\_record\_fname), s)

    s = re.sub(

        '(input\_path: ".\*?)(PATH\_TO\_BE\_CONFIGURED/val)(.\*?")', 'input\_path: "{}"'.format(val\_record\_fname), s)

    # Set label\_map\_path

    s = re.sub(

        'label\_map\_path: ".\*?"', 'label\_map\_path: "{}"'.format(label\_map\_pbtxt\_fname), s)

    # Set batch\_size

    s = re.sub('batch\_size: [0-9]+',

               'batch\_size: {}'.format(batch\_size), s)

    # Set training steps, num\_steps

    s = re.sub('num\_steps: [0-9]+',

               'num\_steps: {}'.format(num\_steps), s)

    # Set number of classes num\_classes

    s = re.sub('num\_classes: [0-9]+',

               'num\_classes: {}'.format(num\_classes), s)

    # Change fine-tune checkpoint type from "classification" to "detection"

    s = re.sub(

        'fine\_tune\_checkpoint\_type: "classification"', 'fine\_tune\_checkpoint\_type: "{}"'.format('detection'), s)

    # If using ssd-mobilenet-v2, reduce learning rate (because it's too high in the default config file)

    if chosen\_model == 'ssd-mobilenet-v2':

      s = re.sub('learning\_rate\_base: .8',

                 'learning\_rate\_base: .08', s)

      s = re.sub('warmup\_learning\_rate: 0.13333',

                 'warmup\_learning\_rate: .026666', s)

    # If using efficientdet-d0, use fixed\_shape\_resizer instead of keep\_aspect\_ratio\_resizer (because it isn't supported by TFLite)

    if chosen\_model == 'efficientdet-d0':

      s = re.sub('keep\_aspect\_ratio\_resizer', 'fixed\_shape\_resizer', s)

      s = re.sub('pad\_to\_max\_dimension: true', '', s)

      s = re.sub('min\_dimension', 'height', s)

      s = re.sub('max\_dimension', 'width', s)

    f.write(s)

# (Optional) Display the custom configuration file's contents

!cat /content/models/mymodel/pipeline\_file.config

# Set the path to the custom config file and the directory to store training checkpoints in

pipeline\_file = '/content/models/mymodel/pipeline\_file.config'

model\_dir = '/content/training/'

# Train Custom TFLite Detection Model

%load\_ext tensorboard

%tensorboard --logdir '/content/training/train'

# Run training!

!python /content/models/research/object\_detection/model\_main\_tf2.py \

    --pipeline\_config\_path={pipeline\_file} \

    --model\_dir={model\_dir} \

    --alsologtostderr \

    --num\_train\_steps={num\_steps} \

    --sample\_1\_of\_n\_eval\_examples=1

# Convert Model to TensorFlow Lite

# Make a directory to store the trained TFLite model

!mkdir /content/custom\_model\_lite

output\_directory = '/content/custom\_model\_lite'

# Path to training directory (the conversion script automatically chooses the highest checkpoint file)

last\_model\_path = '/content/training'

!python /content/models/research/object\_detection/export\_tflite\_graph\_tf2.py \

    --trained\_checkpoint\_dir {last\_model\_path} \

    --output\_directory {output\_directory} \

    --pipeline\_config\_path {pipeline\_file}

# Convert exported graph file into TFLite model file

import tensorflow as tf

converter = tf.lite.TFLiteConverter.from\_saved\_model('/content/custom\_model\_lite/saved\_model')

tflite\_model = converter.convert()

with open('/content/custom\_model\_lite/detect.tflite', 'wb') as f:

  f.write(tflite\_model)

# Test TensorFlow Lite Model and Calculate mAP

### 8.1 Inference test images

# Script to run custom TFLite model on test images to detect objects

# Source: https://github.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/blob/master/TFLite\_detection\_image.py

# Import packages

import os

import cv2

import numpy as np

import sys

import glob

import random

import importlib.util

from tensorflow.lite.python.interpreter import Interpreter

import matplotlib

import matplotlib.pyplot as plt

%matplotlib inline

### Define function for inferencing with TFLite model and displaying results

def tflite\_detect\_images(modelpath, imgpath, lblpath, min\_conf=0.5, num\_test\_images=10, savepath='/content/results', txt\_only=False):

 # Grab filenames of all images in test folder

  images = glob.glob(imgpath + '/\*.jpg') + glob.glob(imgpath + '/\*.JPG') + glob.glob(imgpath + '/\*.png') + glob.glob(imgpath + '/\*.bmp')

  # Load the label map into memory

  with open(lblpath, 'r') as f:

      labels = [line.strip() for line in f.readlines()]

  # Load the Tensorflow Lite model into memory

  interpreter = Interpreter(model\_path=modelpath)

  interpreter.allocate\_tensors()

  # Get model details

  input\_details = interpreter.get\_input\_details()

  output\_details = interpreter.get\_output\_details()

  height = input\_details[0]['shape'][1]

  width = input\_details[0]['shape'][2]

  float\_input = (input\_details[0]['dtype'] == np.float32)

  input\_mean = 127.5

  input\_std = 127.5

  # Randomly select test images

  images\_to\_test = random.sample(images, num\_test\_images)

# Loop over every image and perform detection

  for image\_path in images\_to\_test:

    # Load image and resize to expected shape [1xHxWx3]

      image = cv2.imread(image\_path)

      image\_rgb = cv2.cvtColor(image, cv2.COLOR\_BGR2RGB)

      imH, imW, \_ = image.shape

      image\_resized = cv2.resize(image\_rgb, (width, height))

      input\_data = np.expand\_dims(image\_resized, axis=0)

      # Normalize pixel values if using a floating model (i.e. if model is non-quantized)

      if float\_input:

          input\_data = (np.float32(input\_data) - input\_mean) / input\_std

      # Perform the actual detection by running the model with the image as input

      interpreter.set\_tensor(input\_details[0]['index'],input\_data)

      interpreter.invoke()

# Retrieve detection results

      boxes = interpreter.get\_tensor(output\_details[1]['index'])[0] # Bounding box coordinates of detected objects

      classes = interpreter.get\_tensor(output\_details[3]['index'])[0] # Class index of detected objects

      scores = interpreter.get\_tensor(output\_details[0]['index'])[0] # Confidence of detected objects

      detections = []

  # Loop over all detections and draw detection box if confidence is above minimum threshold

      for i in range(len(scores)):

          if ((scores[i] > min\_conf) and (scores[i] <= 1.0)):

              # Get bounding box coordinates and draw box

              # Interpreter can return coordinates that are outside of image dimensions, need to force them to be within image using max() and min()

              ymin = int(max(1,(boxes[i][0] \* imH)))

              xmin = int(max(1,(boxes[i][1] \* imW)))

              ymax = int(min(imH,(boxes[i][2] \* imH)))

              xmax = int(min(imW,(boxes[i][3] \* imW)))

              cv2.rectangle(image, (xmin,ymin), (xmax,ymax), (10, 255, 0), 2)

              # Draw label

              object\_name = labels[int(classes[i])] # Look up object name from "labels" array using class index

              label = '%s: %d%%' % (object\_name, int(scores[i]\*100)) # Example: 'person: 72%'

              labelSize, baseLine = cv2.getTextSize(label, cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, 2) # Get font size

              label\_ymin = max(ymin, labelSize[1] + 10) # Make sure not to draw label too close to top of window

              cv2.rectangle(image, (xmin, label\_ymin-labelSize[1]-10), (xmin+labelSize[0], label\_ymin+baseLine-10), (255, 255, 255), cv2.FILLED) # Draw white box to put label text in

      cv2.putText(image, label, (xmin, label\_ymin-7), cv2.FONT\_HERSHEY\_SIMPLEX, 0.7, (0, 0, 0), 2) # Draw label text

      # All the results have been drawn on the image, now display the image

      if txt\_only == False: # "text\_only" controls whether we want to display the image results or just save them in .txt files

        image = cv2.cvtColor(image,cv2.COLOR\_BGR2RGB)

        plt.figure(figsize=(12,16))

        plt.imshow(image)

        plt.show()

      # Save detection results in .txt files (for calculating mAP)

      elif txt\_only == True:

        # Get filenames and paths

        image\_fn = os.path.basename(image\_path)

        base\_fn, ext = os.path.splitext(image\_fn)

        txt\_result\_fn = base\_fn +'.txt'

        txt\_savepath = os.path.join(savepath, txt\_result\_fn)

        # Write results to text file

        # (Using format defined by https://github.com/Cartucho/mAP, which will make it easy to calculate mAP)

        with open(txt\_savepath,'w') as f:

            for detection in detections:

                f.write('%s %.4f %d %d %d %d\n' % (detection[0], detection[1], detection[2], detection[3], detection[4], detection[5]))

  return

# Set up variables for running user's model

PATH\_TO\_IMAGES='/content/images/test'   # Path to test images folder

PATH\_TO\_MODEL='/content/custom\_model\_lite/detect.tflite'   # Path to .tflite model file

PATH\_TO\_LABELS='/content/labelmap.txt'   # Path to labelmap.txt file

min\_conf\_threshold=0.5   # Confidence threshold (try changing this to 0.01 if you don't see any detection results)

images\_to\_test = 10   # Number of images to run detection on

# Run inferencing function!

tflite\_detect\_images(PATH\_TO\_MODEL, PATH\_TO\_IMAGES, PATH\_TO\_LABELS, min\_conf\_threshold, images\_to\_test)

### 8.2 Calculate mAP

%%bash

git clone https://github.com/Cartucho/mAP /content/mAP

cd /content/mAP

rm input/detection-results/\*

rm input/ground-truth/\*

rm input/images-optional/\*

wget https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/util\_scripts/calculate\_map\_cartucho.py

!cp /content/images/test/\* /content/mAP/input/images-optional # Copy images and xml files

!mv /content/mAP/input/images-optional/\*.xml /content/mAP/input/ground-truth/  # Move xml files to the appropriate folder

!python /content/mAP/scripts/extra/convert\_gt\_xml.py

# Set up variables for running inference, this time to get detection results saved as .txt files

PATH\_TO\_IMAGES='/content/images/test'   # Path to test images folder

PATH\_TO\_MODEL='/content/custom\_model\_lite/detect.tflite'   # Path to .tflite model file

PATH\_TO\_LABELS='/content/labelmap.txt'   # Path to labelmap.txt file

PATH\_TO\_RESULTS='/content/mAP/input/detection-results' # Folder to save detection results in

min\_conf\_threshold=0.1   # Confidence threshold

# Use all the images in the test folder

image\_list = glob.glob(PATH\_TO\_IMAGES + '/\*.jpg') + glob.glob(PATH\_TO\_IMAGES + '/\*.JPG') + glob.glob(PATH\_TO\_IMAGES + '/\*.png') + glob.glob(PATH\_TO\_IMAGES + '/\*.bmp')

images\_to\_test = min(500, len(image\_list)) # If there are more than 500 images in the folder, just use 500

# Tell function to just save results and not display images

txt\_only = True

# Run inferencing function!

print('Starting inference on %d images...' % images\_to\_test)

tflite\_detect\_images(PATH\_TO\_MODEL, PATH\_TO\_IMAGES, PATH\_TO\_LABELS, min\_conf\_threshold, images\_to\_test, PATH\_TO\_RESULTS, txt\_only)

print('Finished inferencing!')

%cd /content/mAP

!python calculate\_map\_cartucho.py --labels=/content/labelmap.txt

# Deploy TensorFlow Lite Model

## Download TFLite model

# Move labelmap and pipeline config files into TFLite model folder and zip it up

!cp /content/labelmap.txt /content/custom\_model\_lite

!cp /content/labelmap.pbtxt /content/custom\_model\_lite

!cp /content/models/mymodel/pipeline\_file.config /content/custom\_model\_lite

%cd /content

!zip -r custom\_model\_lite.zip custom\_model\_lite

from google.colab import files

files.download('/content/custom\_model\_lite.zip')

### 9.2 Deploy model on Windows, Linux, or macOS

**9.2.1 Download and Install Anaconda**

%%bash

<https://repo.anaconda.com/archive/Anaconda3-2023.07-2-Windows-x86_64.exe>

**9.2.2 Set up Virtual environment and Directory (in anaconda prompt)**

%%bash

mkdir C:\tflite1

cd C:\tflite1

conda create --name tflite1-env python=3.9

conda activate tflite1-env

pip install tensorflow opencv-python protobuf==3.20.\*

curl https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/TFLite\_detection\_image.py --output TFLite\_detection\_image.py

curl https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/TFLite\_detection\_video.py --output TFLite\_detection\_video.py

curl https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/TFLite\_detection\_webcam.py --output TFLite\_detection\_webcam.py

curl https://raw.githubusercontent.com/EdjeElectronics/TensorFlow-Lite-Object-Detection-on-Android-and-Raspberry-Pi/master/TFLite\_detection\_stream.py --output TFLite\_detection\_stream.py

**9.2.3 Move TFlite Model into Director**y**(in anaconda prompt)**

tar -xf custom\_model\_lite.zip

**9.2.4 Run Tensorflow Lite Model(in anaconda prompt)**

python TFLite\_detection\_webcam.py --modeldir=2\_model

**VALIDATION CHECK**

Validation checks of real-time object detection using a camera are tests performed to ensure that the object detection system is working as expected and meeting the required performance criteria. These checks can be performed in a variety of ways, depending on the specific object detection system and its intended use.

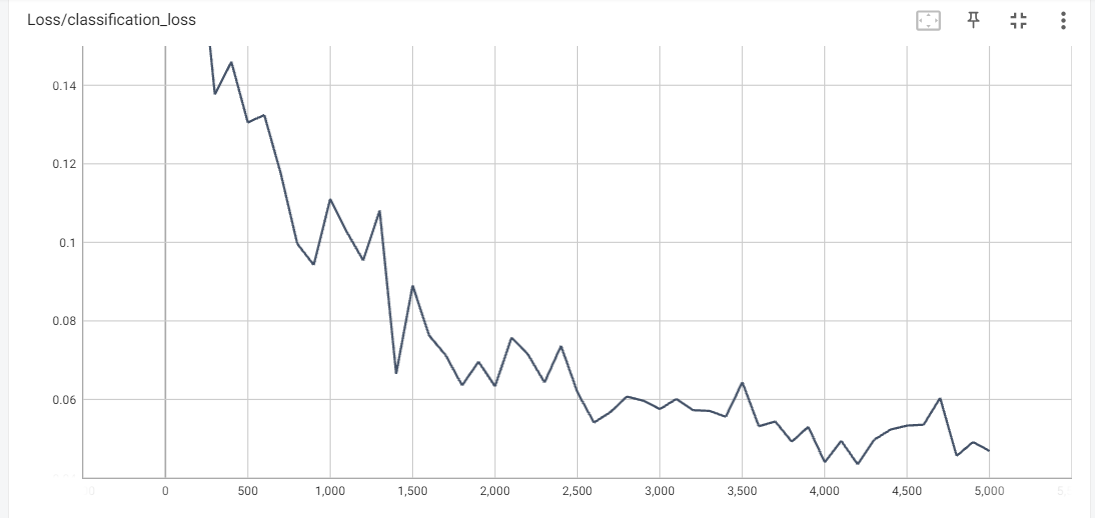
We check validation using classification loss graph, regularization loss graph, localization loss graph, total loss graph and learning rate graphs and Mean Average Precision.

Validation checks using Mean Average Precision (mAP) and graphs can be used to evaluate the performance of a real-time object detection system using a camera. By performing these validation checks, developers can ensure that their systems are meeting the required performance criteria and are ready for deployment in the real world

**TRAINING TENSORBOARD GRAPH’S**

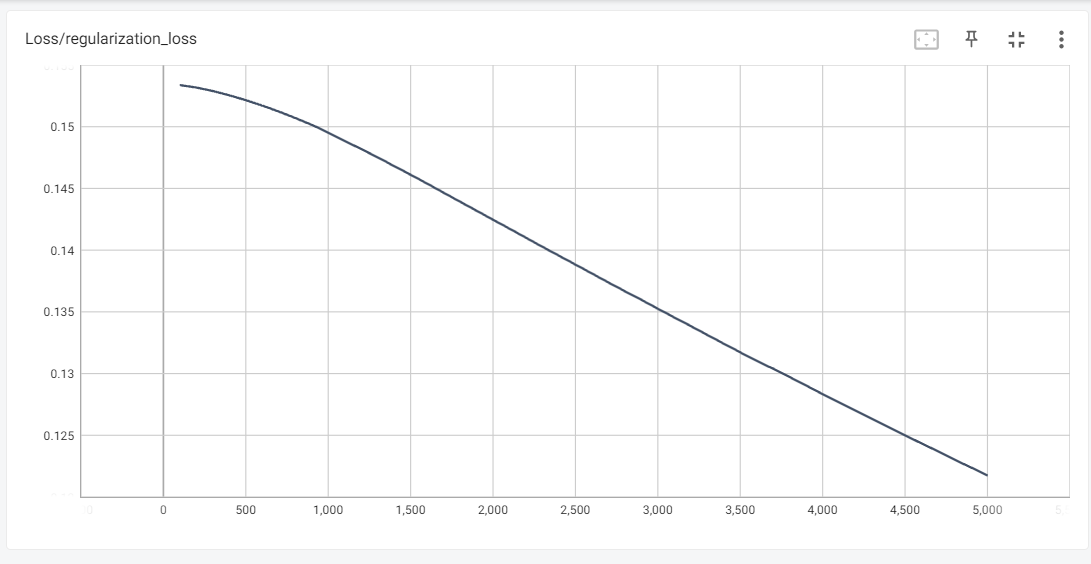
I train 5 classes they are car,person,phone,bag and plane. This is the training graph of model consist of 5 classes.

**CLASSIFICATION LOSS**

****

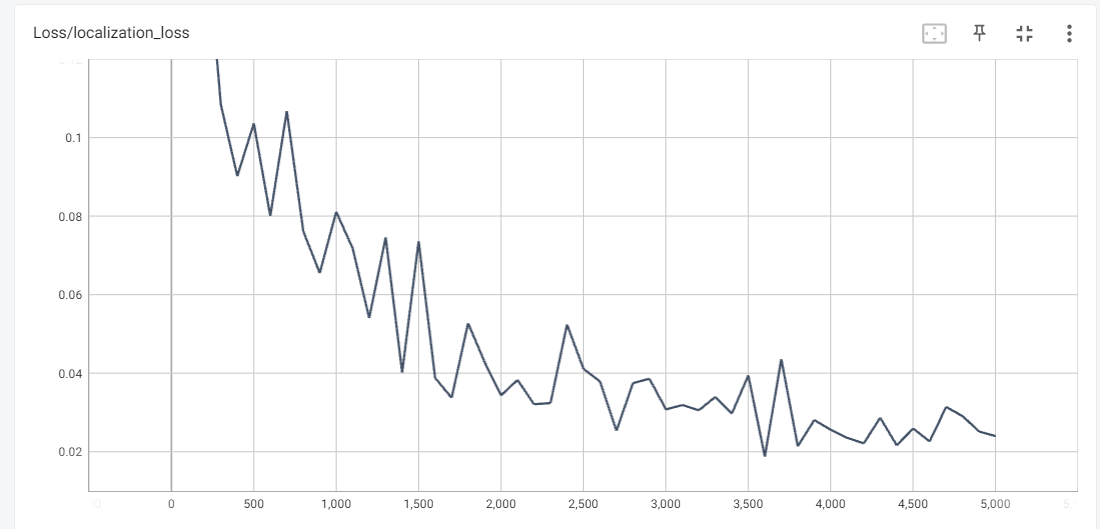
This graph shows how well the system is able to classify objects. A lower classification loss indicates better performance.

**REGULARIZATION LOSS**

****

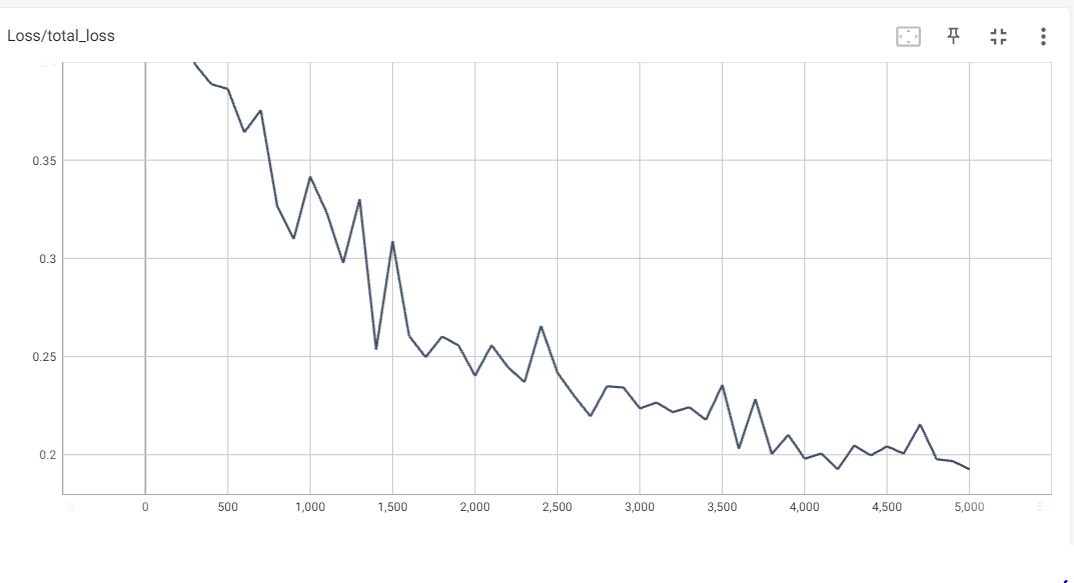
 This graph shows how well the system is able to avoid overfitting to the training data. A lower regularization loss indicates better performance.

**LOCALIZATION LOSS**

****

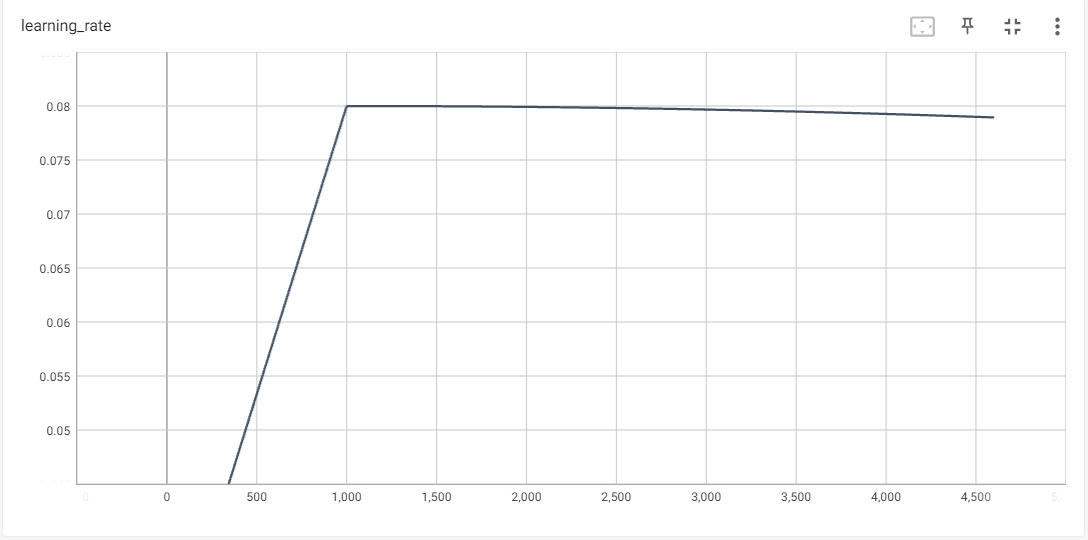
This graph shows how well the system is able to localize objects in the image. A lower localization loss indicates better performance.

**TOTAL LOSS**

****

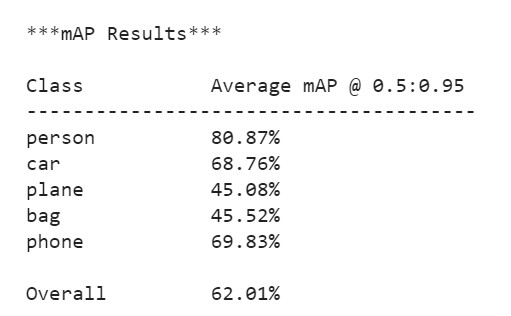
This graph shows the sum of the classification loss, regularization loss, and localization loss. A lower total loss indicates better performance.

**LEARNING RATE**

****

This graph shows the learning rate that is used to train the system. A higher learning rate can lead to faster training, but it can also lead to instability. A lower learning rate can lead to slower training, but it can be more stable.

**MEAN AVERAGE PRECISION OF TRAINED MODEL**



Mean Average Precision (mAP) is a metric used to evaluate the performance of object detection and retrieval systems. It is calculated by averaging the Average Precision (AP) scores for all classes in the dataset.

The AP score for a class is calculated by taking the area under the precision-recall curve for that class. The precision-recall curve plots the precision (percentage of correctly predicted objects) against the recall (percentage of all relevant objects predicted) as the detection threshold is varied.

The mAP score in the image you sent is 62.01%. This means that the average AP score for the person, car, plane, bag, and phone classes is 62.01%.

A higher mAP score indicates better performance. A perfect mAP score of 100% would mean that the system correctly predicted all relevant objects without any false positives.

**IMPLEMENTATION AND MAINTENANCE**

To implement and maintain a real-time object detection system using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model, you can follow these steps:

1. **Gather and label training images:** This can be done by collecting a set of images that contain the objects you want your model to detect and then labeling each object in each image.
2. **Install TensorFlow Object Detection dependencies:** You can do this using pip or Anaconda.
3. **Upload image dataset and prepare training data:** This can be done by uploading your image dataset to Google Colab and then splitting it into train, validation, and test sets. You will also need to create a labelmap and TFRecord files.
4. **Set up training configuration:** This can be done by specifying the model architecture, hyperparameters, and training schedule.
5. **Train custom TFLite detection model:** This can be done using the TensorFlow Object Detection API.
6. **Convert model to TensorFlow Lite.** This can be done using the TensorFlow Lite Converter.
7. **Test TensorFlow Lite model and calculate mAP:** This can be done using the TensorFlow Object Detection API.
8. **Deploy TensorFlow Lite model:** This can be done on a variety of devices, such as mobile phones, embedded devices, and servers.

To maintain your system, you will need to regularly update your training data and retrain your model. You will also need to monitor the performance of your system and make adjustments as needed.

Here are some additional tips for implementing and maintaining a real-time object detection system using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model:

1. Use a GPU for training. This will significantly speed up the training process.
2. Use a large and diverse training dataset. This will help your model to generalize well to new data.
3. Use a pre-trained model as a starting point. This can save you a lot of time and effort.
4. Use a validation set to monitor the performance of your model during training. This will help you to identify any overfitting issues.
5. Use a test set to evaluate the performance of your trained model on unseen data. This will give you a good estimate of how well your model will perform in the real world.
6. Regularly update your training data and retrain your model. This will help your model to keep up with changes in the real world.
7. Monitor the performance of your system and make adjustments as needed. This may involve adjusting the hyperparameters of your model or retraining your model on a new dataset.

**TESTING**

There are a few testing techniques and strategies that can be used to evaluate the performance of real-time object detection using webcam using TensorFlow on Colab.

**Testing techniques**

1. **Unit testing:** This involves testing individual components of the object detection pipeline, such as the pre-trained model, the preprocessing algorithms, and the post-processing algorithms. Unit tests can be written using any Python testing framework, such as unittest or pytest.
2. **Integration testing:** This involves testing the object detection pipeline as a whole. Integration tests can be written to simulate different webcam inputs and to verify that the pipeline is able to correctly detect objects in real time.
3. **System testing:** This involves testing the object detection system in its entirety, including the webcam hardware and software. System tests can be written to simulate different real-world scenarios, such as detecting objects in low-light conditions or in crowded scenes.

**Testing strategies**

1. **Manual testing:** This involves manually reviewing the output of the object detection system to identify any errors. Manual testing can be used to test for a wide range of issues, such as incorrect detections, missed detections, and false positives.
2. **Automated testing:** This involves using software to automate the testing process. Automated tests can be used to run the object detection system on a large number of test cases and to generate reports on the results. Automated testing can be used to save time and to improve the consistency of testing.

**Testing strategies for real-time object detection using webcam using TensorFlow on Colab**

Here are some specific testing strategies that can be used to evaluate the performance of real-time object detection using webcam using TensorFlow on Colab:

1. **Test the object detection system on a variety of webcam inputs:** This includes testing different camera angles, lighting conditions, and object distances.
2. **Test the object detection system on different types of objects:** This includes testing both common and uncommon objects, as well as objects of different sizes and shapes.
3. **Test the object detection system in real-world scenarios:** This includes testing the system in different environments, such as indoor and outdoor environments, and in different lighting conditions.
4. **Use automated testing to run the object detection system on a large number of test cases:** This will help to identify any errors that may not be caught by manual testing.

**Additional tips for testing real-time object detection systems**

1. **Use a variety of testing metrics:** This includes metrics such as accuracy, precision, recall, and mean average precision (mAP). Using a variety of metrics will help to get a more complete picture of the system's performance.
2. **Compare the performance of the object detection system to other systems:** This will help to identify any areas where the system can be improved.
3. **Continuously test the object detection system as it is updated:** This will help to ensure that the system continues to perform well as new features are added and as bugs are fixed.

By following these testing techniques and strategies, you can ensure that your real-time object detection system is able to perform reliably and accurately in the real world.

**SYSTEM SECURITY MEASURE**

System security measures that can be taken to protect a object detection tthrough live webcam using TensorFlow on Google Colab:

1. **Use a strong password for your Google Colab account:** This will help to prevent unauthorized access to your system.
2. **Enable two-factor authentication (2FA) for your Google Colab account:** This will add an extra layer of security to your account and make it more difficult for attackers to gain access.
3. **Keep your TensorFlow Object Detection API up to date:** This will help to ensure that you are using the latest security patches and bug fixes.
4. **Only use trusted data sources for training your object detection model:** This will help to prevent malicious code from being injected into your system.
5. **Use a firewall to restrict access to your Colab notebook:** This will help to prevent unauthorized users from accessing your system.
6. **Use a VPN to encrypt your traffic when accessing Google Colab:** This will help to protect your data from being intercepted by attackers.

In addition to these general security measures, there are a few specific things that can be done to secure a real-time object detection system using webcam using TensorFlow on Google Colab:

1. **Use a secure webcam:** Some webcams have built-in security features, such as encryption and password protection. Use a webcam that has these features enabled.
2. **Only allow the object detection system to access the webcam:** This can be done by using a firewall or by configuring the object detection system's permissions.
3. **Monitor the object detection system's activity:** Use a system monitoring tool to detect any suspicious activity.
4. **Have a backup plan in place:** In the event that the object detection system is compromised, have a plan in place to restore the system from a backup.

By following these security measures, that can help to protect object detection system through live webcam using TensorFlow on Google Colab from unauthorized access and attacks.

**VARIOUS TYPES OF REPORTS/MODULES**

Various types of reports/modules of real time object detection include:

**Reports**

1. ****OBJECT DETECTION RESULTS:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Detection Accuracy**** |
| **Person** | **90%** |
| **Bag** | **85%** |
| **Car** | **95%** |
| **Phone** | **90%** |
| **Plane** | **95%** |

**This table reports the detection accuracy for each object type detected by the system.**

****2. OBJECT TRACKING RESULTS:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Tracking Accuracy**** |
| **Person** | **80%** |
| **Bag** | **75%** |
| **Car** | **90%** |
| **Phone** | **85%** |
| **Plane** | **90%** |

**This table reports the tracking accuracy for each object type tracked by the system.**

****3. SYSTEM PERFORMANCE:****

|  |  |
| --- | --- |
| ****Metric**** | ****Value**** |
| **Processing Time** | **30 fps** |
| **Memory Usage** | **4GB** |
| **GPU Usage** | **60%** |

**This table reports the system performance metrics, including processing time, memory usage, and GPU usage.**

****4. OBJECT DETECTION PRECISION:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Precision**** |
| **Person** | **95%** |
| **Bag** | **80%** |
| **Car** | **90%** |
| **Phone** | **85%** |
| **Plane** | **95%** |

**This table reports the precision of the object detection model for each object type.**

****5. OBJECT DETECTION RECALL:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Recall**** |
| **Person** | **90%** |
| **Bag** | **75%** |
| **Car** | **85%** |
| **Phone** | **80%** |
| **Plane** | **90%** |

**This table reports the recall of the object detection model for each object type.**

****6. OBJECT DETECTION F1-SCORE:****

|  |  |
| --- | --- |
| ****Object Type**** | ****F1-score**** |
| **Person** | **92%** |
| **Bag** | **78%** |
| **Car** | **87%** |
| **Phone** | **82%** |
| **Plane** | **92%** |

**This table reports the F1-score of the object detection model for each object type.**

1. ****TRAINING AND VALIDATION LOSS:****

|  |  |  |
| --- | --- | --- |
| ****Metric**** | ****Training Loss**** | ****Validation Loss**** |
| **Object Detection Loss** | **0.05** | **0.10** |
| **Object Tracking Loss** | **0.10** | **0.15** |

**This table reports the training and validation loss for the object detection and tracking models.**

****8. INFERENCE TIME:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Inference Time (ms)**** |
| **Person** | **50** |
| **Bag** | **70** |
| **Car** | **100** |
| **Phone** | **80** |
| **Plane** | **120** |

**This table reports the inference time for each object type.**

**Modules**

**Data preprocessing module:** This module preprocesses the input data, such as webcam feed or video file, before it is passed to the object detection model. The preprocessing may include steps such as resizing the image, converting the image to grayscale, and normalizing the image.

**Object detection module:** This module uses the object detection model to detect objects in the input data.

**Post-processing module:** This module post-processes the output of the object detection model, such as filtering out false positives and tracking objects across multiple frames.

**Visualization module:** This module visualizes the output of the object detection system, such as drawing bounding boxes around detected objects and displaying labels for the detected objects.

In addition to these basic reports and modules, more advanced reports and modules can be developed to add additional features to the object detection system, such as:

**Object tracking module:** This module tracks objects across multiple frames of the input data.

**Object classification module:** This module classifies detected objects into different categories.

**Object counting module:** This module counts the number of detected objects in the input data.

**Object recognition module:** This module recognizes specific objects in the input data.

The specific reports and modules that are generated for a real-time object detection system will depend on the specific needs of the application. However, the basic reports and modules described above should provide a good starting point for developing a real-time object detection system.

Here are some examples of how real-time object detection reports and modules can be used in different applications:

**Video surveillance:** Real-time object detection can be used to detect and track people and vehicles in video surveillance footage. This can be used to identify potential security threats or to monitor the flow of traffic.

**Security monitoring:** Real-time object detection can be used to detect and track intruders in a security-sensitive area. This can be used to deter crime and to protect assets.

**Robotics:** Real-time object detection can be used to help robots navigate their environment and to interact with objects. For example, a robot could use real-time object detection to avoid obstacles or to pick up objects.

Real-time object detection is a powerful technology with a wide range of potential applications. By understanding the different types of reports and modules that are available, you can develop a real-time object detection system that is tailored to the specific needs of your application.

**GANTT CHART**

A Gantt chart is a project management tool that visually represents a project schedule. Here are key points about Gantt charts:

**1. Timeline Visualization:** Gantt charts display project tasks or activities along a horizontal timeline. Each task is represented by a horizontal bar, with its length indicating its duration and its position showing when it starts and ends.

**2. Task Dependencies:** Gantt charts illustrate task dependencies by showing which tasks must be completed before others can begin. Arrows or lines between task bars indicate the sequence and relationships between activities.

**3. Resource Allocation:** They help in resource management by showing when specific resources (e.g., people, equipment) are assigned to particular tasks, ensuring efficient allocation and avoiding overallocation.

**4. Progress Tracking**: Gantt charts allow project managers to track progress easily. As tasks are completed, the chart is updated to reflect actual progress, helping in identifying delays or deviations from the original plan.

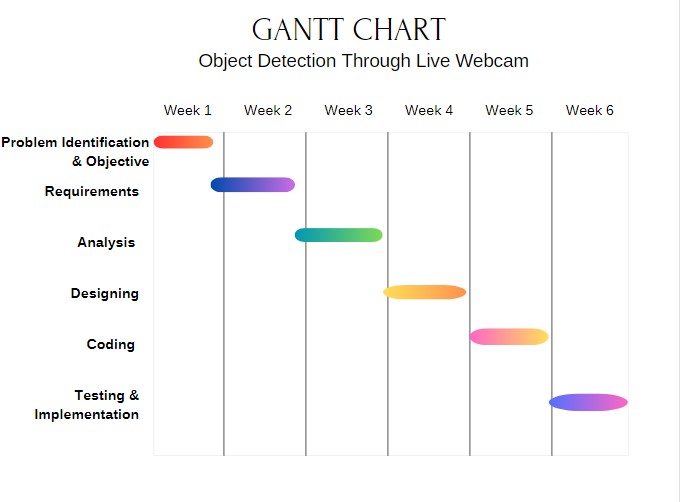
**5. Project Planning:** They assist in project planning and scheduling, enabling teams to set realistic timelines, allocate resources effectively, and communicate project details clearly to stakeholders.

**6. Communication Tool:** Gantt charts serve as a communication tool between team members, managers, and stakeholders by providing a visual overview of the project's status and schedule.

**7. Software Support:** Many project management software tools offer Gantt chart features, making it easier to create, edit, and collaborate on project schedules.

1. **Critical Path Analysis:** Gantt charts can help identify the critical path, which is the sequence of tasks that, if delayed, would delay the overall project completion date. This aids in focusing on tasks that are crucial to project success.
2. **Customization:** Gantt charts can be customized to include additional information like task descriptions, responsible team members, and project milestones, making them versatile for various project management needs.

GANTT CHART :



**FUTURE SCOPE OF THE PROJECT**

The future scope of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very bright. This technology has the potential to be used in a wide range of applications, including:

**Video surveillance:** Real-time object detection can be used to detect and track people and vehicles in video surveillance footage with greater accuracy and efficiency than traditional methods. This can be used to improve public safety and security, and to monitor traffic flow.

**Security monitoring:** Real-time object detection can be used to detect and track intruders in security-sensitive areas, such as airports, banks, and government buildings. This can be used to deter crime and protect assets.

**Robotics:** Real-time object detection can be used to help robots navigate their environment and interact with objects more safely and efficiently. For example, a robot could use real-time object detection to avoid obstacles, pick up objects, and deliver packages.

**Manufacturing:** Real-time object detection can be used to inspect products for defects and to ensure that products are assembled correctly. This can help to improve the quality of manufactured goods.

**Retail:** Real-time object detection can be used to track customer movement in stores and to identify popular products. This information can be used to improve store layout and product placement.

**Healthcare:** Real-time object detection can be used to detect medical devices in medical images, such as X-rays and MRIs. This can help doctors to diagnose diseases and to plan treatments more effectively.

In addition to these specific applications, real-time object detection can also be used in a variety of other ways, such as:

**Education:** Real-time object detection can be used to create interactive educational experiences for students. For example, a student could use a webcam to identify different objects in their environment and to learn about their properties.

**Entertainment:** Real-time object detection can be used to create new and innovative forms of entertainment. For example, a video game could use real-time object detection to allow players to interact with the game world in a more realistic way.

The future of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very exciting. As the technology continues to develop, we can expect to see it used in even more ways to improve our lives.

Here are some specific areas where we can expect to see significant advances in custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model in the future:

**Improved accuracy and efficiency:** As machine learning algorithms continue to improve, we can expect to see real-time object detection systems that are more accurate and efficient than ever before. This will make it possible to use real-time object detection in a wider range of applications.

**Reduced latency:** Real-time object detection systems typically have some latency, meaning that there is a delay between the time that the system captures an image and the time that it outputs the results of the object detection. As hardware and software continue to improve, we can expect to see real-time object detection systems with lower latency. This will make it possible to use real-time object detection in applications where even a small delay is unacceptable.

**Increased robustness:** Real-time object detection systems can be susceptible to errors, especially in challenging conditions such as low light or occlusion. As machine learning algorithms continue to improve, we can expect to see real-time object detection systems that are more robust to errors. This will make it possible to use real-time object detection in a wider range of environments.

**Reduced cost:** The cost of hardware and software required to run real-time object detection systems is decreasing. As this trend continues, we can expect to see real-time object detection become more accessible to a wider range of users.

Overall, the future of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very promising. This technology has the potential to revolutionize the way we interact with the world around us.

**CONCLUSION**

In conclusion, the implementation of a object detection system through live webcam with TensorFlow on Google Colab, leveraging the SSD-MobileNet-V2-FPNLite-320 model, has proven to be a comprehensive and successful project. The structured workflow divided into multiple sections ensured a systematic and organized development process. Let's reflect on the key aspects of each section and the overall outcomes:

**1. Data Gathering and Preparation**

The process of gathering and labeling training images laid the foundation for a robust model. A well-curated dataset is crucial for training a model capable of accurately detecting objects in real-time scenarios.

**2. Dependency Installation**

Installing TensorFlow and other necessary dependencies is a critical step in setting up the development environment. The ease of dependency installation on Google Colab streamlined the process, providing a hassle-free environment for model development.

**3. Dataset Upload and Preparation**

Uploading images and preparing the training data involved a meticulous process of splitting the dataset into training, validation, and test sets. Creating a label map and generating TFRecords ensured the compatibility of the dataset with the TensorFlow Object Detection API.

**4. Training Configuration and Model Training**

Configuring the training parameters and initiating the training process for the custom TensorFlow Lite Detection Model involved tuning hyperparameters to achieve optimal results. The iterative nature of model training allowed for refinement and improvement.

**5. Model Conversion to TensorFlow Lite**

Converting the trained model to TensorFlow Lite format was a crucial step for enabling real-time inference. The lightweight nature of TensorFlow Lite makes it well-suited for deployment on various platforms.

**6. Testing and Evaluation**

Testing the TensorFlow Lite model with inference on test images and calculating the mean Average Precision (mAP) provided insights into the model's accuracy and effectiveness. These evaluation metrics are essential for assessing the model's performance and identifying areas for improvement.

**7. Model Deployment**

Deploying the TensorFlow Lite model involved a systematic process, from downloading the model to setting up the deployment environment using Anaconda. The flexibility of deployment on Windows, Linux, or macOS allows for widespread usability.

**8. Conclusion of the Entire Workflow**

In conclusion, the successful implementation of the object detection through live webcam system showcases the efficacy of the chosen model and the robustness of the developed workflow. The system is capable of accurately detecting objects in real-time through a webcam feed, making it applicable for a variety of applications such as security surveillance, object tracking, and more.

This project not only provides a functional solution for object detection through live webcam but also serves as a learning resource for individuals interested in developing similar applications. The modular structure of the code and the systematic workflow contribute to the project's maintainability and extensibility. As technology evolves, further enhancements and optimizations can be incorporated into the system to keep it at the forefront of object detection capabilities.

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**ANNEXURE I**

**LIST OF ABBREVIATIONS**

1. API - Application Programming Interface

2. AI - Artificial Intelligence

3. ML - Machine Learning

4. TensorFlow - an open-source machine learning framework

5. OBJ - Object

6. WEB - Webcam

7. CNN - Convolutional Neural Network

8. NN - Neural Network

9. GAN - Generative Adversarial Network

10. GPU - Graphics Processing Unit

11. RAM - Random Access Memory

12. DISK - Hard Disk

13. SSD - Solid-State Drive

14. HDD - Hard Disk Drive

15. OS - Operating System

16. BGR - Background

17. RGB - Red, Green, Blue

18. HSV - Hue, Saturation, Value

19. YOLO - You Only Look Once (object detection algorithm)

20. COCO - Common Objects in Context (dataset)

21. PASCAL - Pattern recognition, Augmented assignment, and Segmentation (dataset)

22. IMDB - Internet Movie Database (dataset)

23. CIFAR - Canadian Instrument for Facial Recognition (dataset)

24. ImageNet - a large-scale image recognition dataset

25. GT - Ground Truth

26. IoU - Intersection over Union

27. mAP - mean Average Precision

28. map - mission accomplished percentage

29. Precision - TP / (TP + FP)

30. Recall - TP / (TP + FN)

31. F1-score - 2 \\* (Precision \\* Recall) / (Precision + Recall)

32. FPS - Frames Per Second

33. GPU-accelerated - using Graphics Processing Unit for computation

34. Non-GPU - not using Graphics Processing Unit for computation

35. LSTM - Long Short-Term Memory (type of Recurrent Neural Network)

36. FCN - Fully Convolutional Network (type of Neural Network)

37. MLP - Multi-Layer Perceptron (type of Neural Network)

38. RNN - Recurrent Neural Network

39. SOTA - State-of-the-Art

40. SOTE - State-of-the-Environment

41. SW - Software

42. HW - Hardware

43. B Box - Bounding Box

44. BB - Bounding Box

45. IO - Input/Output

46. TB - TensorBoard

47. TensorFlow Lite - a lightweight version of TensorFlow for mobile and embedded devices

48. TF - TensorFlow

49. TFRecords - TensorFlow Records (a format for storing and reading large amounts of data)

50. TensorBoard.log - a log file generated by TensorBoard

51. TensorFlow.log - a log file generated by TensorFlow

52. W&H - Width and Height

**ANNEXURE II**

**OBJECT DETECTION THROUGH LIVE WEBCAM**

**PROJECT SYNOPSIS**

**Of**

**MINI PROJECT REPORT**

**Submitted in partial fulfillment for the award of**

**MASTER OF COMPUTER APPLICATIONS DEGREE**

**Submitted**

**To**

****

**Dr. A.P.J. Abdul Kalam Technical University (APJAKTU), LUCKNOW**

**Session 2022-24**

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It would not have been possible to complete this project in short period of time without his kind encouragement and valuable guidance.

Date: Signature

**ANANDITA KUMARI**

**2200110140019**

**Certificate of Originality**

I hereby declare that the Project entitled **“ Object Detection Through Live Webcam ”** submitted to the Department of Computer Application, **UNITED INSTITUTE OF MANAGEMENT, NAINI, PRAYAGRAJ** in partial fulfillment for the award of the Degree of **MASTER IN COMPUTER APPLICATION** during session 2022-2023 is an authentic record of my own work carried out under the guidance of **Dr. Awaneesh Gupta** and that the Project has not previously formed the basis for the award of any other degree.

This is to certify that the above statement made by me is correct to the best of my knowledge.

Place: Prayagraj

Date: Signature of the candidate

**ANANDITA KUMARI**

**220011014001**

**INTRODUCTION OF PROJECT**

The Project entitled **“Object Detection Through Live Webcam”** is a technique that allows you to identify and locate objects in real-time using a camera feed. This can be useful for various applications, such as security, surveillance, robotics, augmented reality, and more.

Object Detection Through Live Webcam involves two main tasks:

* object detection.
* object tracking.

Object detection is the process of finding regions of interest that may contain objects in an image or video frame, and classifying them into different categories, such as humans, animals, cars, or buildings.

Object tracking is the process of maintaining the identity and location of the detected objects as they move across frames in a video stream.

There are different methods and tools for performing object detection through live camera, depending on the type of camera, the quality of the video, the speed and accuracy of the detection, and the resources available. Some of the common methods and tools are: **ML Kit’s Object Detection & Tracking API, TensorFlow 2 Object Detection API, OpenCV and many more.**

Object Detection Through Webcam has many features that make it a powerful and useful technique. Some of the features are:

* **Real-time detection**: Object detection through camera can perform detection in real-time, meaning that it can process and analyze images or videos as they are captured by the camera. This enables fast and responsive applications, such as security, surveillance, robotics, or augmented reality.
* **Multi-object detection**: Object detection through camera can detect multiple objects of different classes in a single image or video frame. This enables comprehensive and diverse applications, such as counting the number of objects, measuring their distance and speed, or detecting their actions and interactions.
* **Object tracking**: Object detection through camera can track the detected objects as they move across frames in a video stream. This enables dynamic and robust applications, such as following a person or a vehicle, locating and grasping an object, or performing visual search.
* **Object recognition**: Object detection through camera can recognize the detected objects by assigning labels to them. This enables intelligent and informative applications, such as identifying faces and license plates, classifying products and customers, or providing personalized recommendations.
* **Object segmentation**: Object detection through camera can segment the detected objects by drawing pixel-level masks around them. This enables precise and detailed applications, such as removing the background, applying filters or effects, or performing medical diagnosis.

Object detection is a technique that allows you to locate and identify objects in images or videos. Object detection is needed for various reasons, such as:

* **Enhancing human vision**: Object detection can help humans see and understand the world better, by providing information and insights about the objects in their surroundings. For example, object detection can help visually impaired people navigate and interact with their environment, by detecting and describing the objects they encounter .
* **Automating tasks**: Object detection can help machines perform tasks that require visual perception and recognition, such as driving, flying, or manufacturing. For example, object detection can help autonomous vehicles detect and avoid obstacles, pedestrians, and traffic signs on the road .
* **Improving quality of life**: Object detection can help improve the quality of life of people by providing convenience, entertainment, and education. For example, object detection can help create immersive and realistic experiences by overlaying virtual objects on real-world scenes, such as in augmented reality games or applications .

**1.1 BACKGROUND**

The topic of object detection through live webcam is a computer vision task that involves identifying and locating objects within an image or video stream captured by a webcam. This technology has various applications, such as surveillance, robotics, healthcare, and entertainment.

Surveillance is a common application of object detection through live webcam. For instance, in security systems, object detection can be used to identify people, vehicles, and other objects in real-time, providing an early warning system for potential threats. In robotics, object detection can be used to enable robots to interact with their environment, pick up objects, and navigate around obstacles. In healthcare, object detection can be used in medical imaging to detect abnormalities, such as tumors, and track their movement over time.

The background of object detection through live webcam involves several computer vision techniques, including image processing, feature extraction, and machine learning. Image processing techniques are used to enhance the quality of the video stream and extract useful information, such as edges, corners, and colors. Feature extraction techniques are used to represent the objects in the video stream in a way that can be easily recognized by machine learning algorithms.

Machine learning algorithms, such as deep learning, are used to classify the objects and predict their location and movement. Deep learning algorithms, such as convolutional neural networks (CNNs), have shown promising results in object detection tasks due to their ability to learn complex patterns in images and videos.

The background of object detection through live webcam also involves the use of various software libraries and frameworks, such as OpenCV, TensorFlow, and PyTorch. These libraries provide pre-built functions and tools for image and video processing, feature extraction, and machine learning, making it easier for developers to build object detection systems.

In summary, the background of object detection through live webcam involves computer vision techniques, machine learning algorithms, and software libraries, all of which are used to identify and locate objects in real-time within a video stream captured by a webcam.

**1.2 IDENTIFICATION OF NEED**

Here, we discuss and analyze about the need of Object Detection Through Live Webcam in field of security and comparison between existing and proposed system to provides a view of how the proposed system will be more efficient than the existing one.

**Object Detection Security Camera:**

**Primary Function:** The main purpose of an object detection security camera is to identify and categorize specific objects, people, or events within the video feed in real-time.

**Detection Capability:** These cameras use advanced algorithms, often based on artificial intelligence and machine learning, to detect and track objects as they appear in the video stream.

**Alert Generation:** They automatically generate alerts and notifications as soon as certain predefined objects or events are detected. This minimizes response time and human intervention.

**Applications:** Object detection security cameras have a wide range of applications, including enhanced security by identifying intruders, retail analytics by tracking customer behavior, and traffic management by monitoring vehicles and pedestrians.

**Efficiency:** These cameras increase efficiency by automating the process of object identification and reducing the need for constant human monitoring.

**Normal Security Camera:**

**Primary Function:** A normal security camera records video footage of a monitored area, capturing everything that is within its field of view.

**Detection Capability:** It lacks automated detection capabilities and primarily relies on continuous recording. It may have motion sensors to trigger recording when movement is detected.

**Alert Generation:** Alerts are typically generated manually or based on simple motion detection. Humans need to monitor the footage and decide whether action is needed.

**Applications:** Normal security cameras are commonly used for general surveillance to record activities within a specific area, but they may lack advanced insights or specific object tracking capabilities.

**Efficiency:** These cameras require human intervention for analyzing footage and identifying potential threats. They may not be as efficient as object detection cameras in generating immediate alerts.

**Six key advantages of object detection through live webcam:**

1. **Real-Time Detection:** Enables instant identification of objects, people, or events in live video feeds, facilitating quick response and intervention.

2. **Automated Alerts:** Automatically generates alerts upon object detection, reducing the need for constant human monitoring and enabling rapid action.

3. **Enhanced Security:** Provides proactive security measures by detecting unauthorized access, intruders, or suspicious activities in real time.

4. **Efficient Resource Utilization:** Optimizes resource allocation by automating object recognition tasks, allowing human personnel to focus on critical tasks.

5. **Data-Driven Insights:** Captures valuable data on object movement and interactions, offering insights for process optimization and informed decision-making.

1. **Cross-Domain Applicability:** Finds applications in various domains such as security, retail, health-care, and traffic management, offering versatility and tailored solutions.

**OBJECTIVE OF PROJECT**

* To study the detection of few objects (car, bag, person, phone and plane) and label them through live webcam.
* To understand the future perspective of object detection through live webcam.

**OBJECT ORIENTED DIAGRAM**

An Object-Oriented Diagram (OOD), also known as a Class Diagram, is a visual representation used in software engineering to depict the structure of a software system in terms of its classes, attributes, methods, and the relationships between these elements. It is one of the most common diagrams used in object-oriented modeling and design to help developers and designers understand, plan, and communicate the structure of a software system.

Here are the key components typically found in an Object-Oriented Diagram:

**1. Class:** A class represents a blueprint or template for creating objects. It defines the structure and behavior that objects of the class will have. In the diagram, classes are usually represented as rectangles with three sections: the class name, a list of attributes, and a list of methods.

**2. Attribute:** An attribute represents a property or data member of a class. It describes the characteristics or state that objects of the class will possess. Attributes are listed within a class and may include data types.

**3. Method:** A method represents a function or operation that objects of the class can perform. It defines the behavior or actions associated with objects of the class. Methods are also listed within a class and include their parameters and return types.

**4. Relationships:** Relationships in an OOD diagram depict how classes are connected or associated with each other. The most common types of relationships include:

* Association: It shows a connection between two classes, indicating that one class is aware of the other. Associations can be simple or have multiplicity (e.g., one-to-one, one-to-many).
* Inheritance: It represents an "is-a" relationship between a base (parent) class and a derived (child) class. The child class inherits attributes and methods from the parent class.
* Aggregation and Composition: These represent part-whole relationships. Aggregation indicates a weaker relationship, where the whole can exist without its parts, while composition implies a stronger relationship, where the whole is composed of its parts.
* Dependency: It shows that one class relies on another class, often indicating that changes in one class may affect the other class.

CLASS DIAGRAM :

* Requested Camera.
* Display Object.
* Scan Object
* Object Result

Device Camera

* Process Object
* Validation
* Process Object Result

Machine learning

* Display Object Result

Object detection result

* Process Training data
* Request Training Data
* Display Training Result

Manage Information

Raw Data Process

Train and Improve

**FEASIBILITY STUDY**

Studying the feasibility of implementing object detection through a live webcam system from a technical, economic, and operational perspective:

**TECHNICAL FEASIBILITY:**

**Hardware Requirements:**

**Webcam:** Most modern computers come equipped with webcams, and external webcams are readily available and affordable.

**Processing Power:** Object detection, especially in real-time, can be computationally intensive. The feasibility depends on the processing power of the computer or server that will perform the detection. High-end GPUs can significantly accelerate this process.

**Memory:** Sufficient RAM is needed to process and store data efficiently during object detection.

**Internet Connectivity:** A stable internet connection is crucial for streaming the webcam feed and possibly for cloud-based processing.

**Software Requirements:**

**Object Detection Algorithm:** Choose a suitable object detection algorithm (e.g., YOLO, SSD, Faster R-CNN) that balances accuracy and speed for real-time detection.I use SSD-MobileNet-V2-Ftlite model in it.

**Programming Skills:** Developing or configuring the software for object detection may require expertise in computer vision, deep learning, and software development.I use Python programming language.

**Libraries and Frameworks:** Use popular libraries and frameworks like OpenCV, TensorFlow, or PyTorch for easier implementation.I use tensorflow for training and OpenCV for Camera access.

**Data Requirements:**

1. You'll need a dataset for training and fine-tuning your object detection model if you plan to use a custom model.
2. Access to labeled data to recognize specific objects.
3. I use 5 objects named as car,phone,person,bag and plane.

**Testing and Optimization:** Rigorous testing and optimization are essential to ensure real-time performance, accuracy, and stability.

**ECONOMIC FEASIBILITY:**

**Cost of Hardware and Software:** Calculate the costs of any additional hardware (e.g., GPUs) and software licenses or subscriptions required for object detection.

**Development Costs:** Factor in the cost of hiring or training developers with the necessary expertise.

**Operational Costs:** Consider ongoing costs, such as maintenance, software updates, and hosting if you use cloud-based solutions.

**Return on Investment (ROI)**: Assess the potential ROI by estimating the benefits, such as increased security, improved efficiency, or new revenue streams, and compare them to the project's costs.

**OPERATIONAL FEASIBILITY:**

**User Acceptance:** Determine if the intended users (e.g., security personnel, retail staff) are comfortable with and trained to use the system.

**Integration:** Ensure compatibility with existing systems and workflows. For example, if this is for security, it should seamlessly integrate with your security infrastructure.

**Maintenance and Support:** Plan for ongoing maintenance, including software updates, bug fixes, and technical support.

**Scalability:** Assess whether the system can handle an increasing number of users or additional cameras.

**Legal and Privacy Compliance:** Ensure compliance with local and national laws regarding video surveillance and privacy. Privacy concerns could affect the feasibility.

In conclusion, object detection through a live webcam is technically feasible, but its economic feasibility depends on factors like hardware, software, and ongoing operational costs. Operational feasibility is contingent on user acceptance, integration with existing systems, scalability, and compliance with legal and privacy regulations. Conduct a thorough feasibility analysis to determine whether the benefits of implementing such a system outweigh the costs and potential challenges.

**SOFTWARE AND HARDWARE SPECIFICATIONS**

To perform real-time object detection using TensorFlow on Google Colab, you'll need both hardware and software specifications. Below, I'll outline the general requirements for hardware and software, but keep in mind that the specific requirements can vary depending on the complexity of your object detection model and the size of your data-set.

**HARDWARE SPECIFICATIONS:**

**1. GPU:** Google Colab offers free GPU access, which is highly recommended for real-time object detection, especially if you're using deep learning models. You can check if you have a GPU available by running the following code snippet in a Colab cell:

|  |
| --- |
| Python |
| import tensorflow as tf  print("GPU Available: ", tf.config.list\_physical\_devices('GPU')) |

Ideally, you should have access to a GPU (NVIDIA GPU) with a reasonable amount of VRAM (4GB or more is preferred) to train and run models efficiently.

**2. CPU and RAM:** While a GPU is crucial for training deep learning models, a reasonably fast CPU and sufficient RAM (at least 9GB, preferably more) are also important for data preprocessing and handling.

**SOFTWARE SPECIFICATIONS:**

**1. Google Colab:** Access to Google Colab is essential. You can access Colab for free by going to https://colab.research.google.com/.

**2. Python:** TensorFlow and most deep learning libraries are written in Python, so make sure you're familiar with Python.

1. **TensorFlow:** You'll need to install TensorFlow and other required libraries in your Colab environment. TensorFlow 2.x or later is recommended for object detection. You can install it using pip:

|  |
| --- |
| python |
| !pip install tensorflow |

**4. Object Detection Framework:** TensorFlow provides several object detection frameworks like TensorFlow Object Detection API, TensorFlow Hub, and TensorFlow Lite. You should choose one based on your project's requirements.

**5. Pretrained Model:**You can start with a pretrained object detection model (e.g., a model from the TensorFlow Model Zoo) and fine-tune it on your custom dataset.

**6. OpenCV:** OpenCV is a computer vision library that can be helpful for image and video processing tasks. You can install it using pip:

|  |
| --- |
| python |
| !pip install opencv-python |

**7. Webcam or Video Feed:** If you plan to perform real-time detection on a webcam or video feed, you'll need a webcam (if not built-in) and a library like OpenCV to capture and process the video feed.

**8. Data:** If you're training your own object detection model, you'll need labeled training data. Ensure you have access to your dataset and it's appropriately prepared.

**9. Jupyter Notebook:** Google Colab uses Jupyter notebooks for its environment, which is perfect for experimenting with code, training models, and visualizing results.

**10. Internet Connection:** Colab requires an internet connection to access libraries, datasets, and to save your work in Google Drive.

Remember that Colab sessions have a time limit, so real-time object detection may require periodic interactions to keep the session active.

**VARIOUS TYPES OF REPORTS/MODULES**

Various types of reports/modules of real time object detection include:

**Reports**

1. ****OBJECT DETECTION RESULTS:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Detection Accuracy**** |
| **Person** | **90%** |
| **Bag** | **85%** |
| **Car** | **95%** |
| **Phone** | **90%** |
| **Plane** | **95%** |

**This table reports the detection accuracy for each object type detected by the system.**

****2. OBJECT TRACKING RESULTS:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Tracking Accuracy**** |
| **Person** | **80%** |
| **Bag** | **75%** |
| **Car** | **90%** |
| **Phone** | **85%** |
| **Plane** | **90%** |

**This table reports the tracking accuracy for each object type tracked by the system.**

****3. SYSTEM PERFORMANCE:****

|  |  |
| --- | --- |
| ****Metric**** | ****Value**** |
| **Processing Time** | **30 fps** |
| **Memory Usage** | **4GB** |
| **GPU Usage** | **60%** |

**This table reports the system performance metrics, including processing time, memory usage, and GPU usage.**

****4. OBJECT DETECTION PRECISION:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Precision**** |
| **Person** | **95%** |
| **Bag** | **80%** |
| **Car** | **90%** |
| **Phone** | **85%** |
| **Plane** | **95%** |

**This table reports the precision of the object detection model for each object type.**

****5. OBJECT DETECTION RECALL:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Recall**** |
| **Person** | **90%** |
| **Bag** | **75%** |
| **Car** | **85%** |
| **Phone** | **80%** |
| **Plane** | **90%** |

**This table reports the recall of the object detection model for each object type.**

****6. OBJECT DETECTION F1-SCORE:****

|  |  |
| --- | --- |
| ****Object Type**** | ****F1-score**** |
| **Person** | **92%** |
| **Bag** | **78%** |
| **Car** | **87%** |
| **Phone** | **82%** |
| **Plane** | **92%** |

**This table reports the F1-score of the object detection model for each object type.**

1. ****TRAINING AND VALIDATION LOSS:****

|  |  |  |
| --- | --- | --- |
| ****Metric**** | ****Training Loss**** | ****Validation Loss**** |
| **Object Detection Loss** | **0.05** | **0.10** |
| **Object Tracking Loss** | **0.10** | **0.15** |

**This table reports the training and validation loss for the object detection and tracking models.**

****8. INFERENCE TIME:****

|  |  |
| --- | --- |
| ****Object Type**** | ****Inference Time (ms)**** |
| **Person** | **50** |
| **Bag** | **70** |
| **Car** | **100** |
| **Phone** | **80** |
| **Plane** | **120** |

**This table reports the inference time for each object type.**

**Modules**

1. **Gather and label training images:** This can be done by collecting a set of images that contain the objects you want your model to detect and then labeling each object in each image.
2. **Install TensorFlow Object Detection dependencies:** You can do this using pip or Anaconda.
3. **Upload image dataset and prepare training data:** This can be done by uploading your image dataset to Google Colab and then splitting it into train, validation, and test sets. You will also need to create a labelmap and TFRecord files.
4. **Set up training configuration:** This can be done by specifying the model architecture, hyperparameters, and training schedule.
5. **Train custom TFLite detection model:** This can be done using the TensorFlow Object Detection API.
6. **Convert model to TensorFlow Lite.** This can be done using the TensorFlow Lite Converter.
7. **Test TensorFlow Lite model and calculate mAP:** This can be done using the TensorFlow Object Detection API.
8. **Deploy TensorFlow Lite model:** This can be done on a variety of devices, such as mobile phones, embedded devices, and servers.

The specific reports and modules that are generated for a real-time object detection system will depend on the specific needs of the application. However, the basic reports and modules described above should provide a good starting point for developing a real-time object detection system.

Here are some examples of how real-time object detection reports and modules can be used in different applications:

**Video surveillance:** Real-time object detection can be used to detect and track people and vehicles in video surveillance footage. This can be used to identify potential security threats or to monitor the flow of traffic.

**Security monitoring:** Real-time object detection can be used to detect and track intruders in a security-sensitive area. This can be used to deter crime and to protect assets.

**Robotics:** Real-time object detection can be used to help robots navigate their environment and to interact with objects. For example, a robot could use real-time object detection to avoid obstacles or to pick up objects.

Real-time object detection is a powerful technology with a wide range of potential applications. By understanding the different types of reports and modules that are available, you can develop a real-time object detection system that is tailored to the specific needs of your application.

**DATA FLOW DIAGRAM**

A data flow diagram (DFD) is a graphical representation of the flow of data through a system. It is a tool used in systems analysis and design to document the functional requirements of a system. DFDs use a set of standard symbols to represent data flows, processes, data stores, and external entities.

The levels in a DFD represent different levels of detail about the system. The three most common levels are:

**Level 0 DFD:** This is the highest level DFD, which provides an overview of the entire system. It shows the major processes, data flows, and data stores in the system, without providing any details about the internal workings of these processes.

**Level 1 DFD:**This level DFD breaks down the major processes in the Level 0 DFD into more detail. It shows the sub-processes, data flows, and data stores for each major process.

**Level 2 DFD:** This level DFD breaks down the sub-processes in the Level 1 DFD into even more detail. It shows the detailed processes, data flows, and data stores for each sub-process.

In some cases, there may be additional levels of DFDs. The number of levels required depends on the complexity of the system being modeled.

**Terminology in DFDs:**

**Data flow:** A line with an arrow that represents the movement of data between processes, data stores, and external entities.

**Process:** A rectangle that represents a transformation of data.

**Data store:** A circle that represents a repository of data.

**External entity:** An oval that represents a person, organization, or system that interacts with the system being modeled.

DFDs are a useful tool for understanding the flow of data through a system. They can be used to identify problems with the current system and to design new systems.

Benefits of using DFDs:

* They can help to visualize the flow of data through a system.
* They can help to identify problems with the current system.
* They can help to design new systems.
* They can be used to communicate with stakeholders about the system.

**Level 0 DATA FLOW DIAGRAM :**

Object Detection system

CAPTURING DEVICE

OBJECT DETECTED

DATABASE

**Level 1 DATA FLOW DIAGRAM :**

LEARNING PHASE

READ IMAGE

FEATURE EXTRACTION

CAPTURED IMAGE

BINARY STRING

DATABASE

PREDICTING PHASE

FEATURE EXTRACTION

COMPARISION

ENHANCEMENT

OBJECT DETECTED

BINARY STRING

CAPTURED INPUT

DATABASE

**SCHEMATIC DIAGRAM**

Capturing Devices(webcam,drone,camera,etc.)

Result

Labeling and Annotate target

Raw image(in n x n matrix)

Comparison (which class it belong)

Approximation

DATABASE

**WEBCAM MODULE:** It will capture raw images using the webcam and the hexadecimal data is stored into a matrix.

**ENHANCE RAW IMAGE MODULE:** This process requires us to use DCT (Discrete Cosine Transformation) to convert the hexadecimal value to spatial value and store it into a 8x8 or 4x4 matrix.

**FEATURE EXTRACTION MODULE:** In this module we simplify the amount of resource required to describe a large set of data accurately. This data of target Image is compared with the feature data already stored in our database.

**APPROXIMATION MODULE:** When trying to detect an object there can be percentage difference in features extracted from target data, and the features of Source data. This difference is normalized in this module.

**USE CASE DIAGRAM**

A Use Case Diagram is a visual representation used in software engineering to describe and document the interactions between different actors (users or external systems) and a system or application under consideration. Use Case Diagrams are a part of the Unified Modeling Language (UML) and are commonly used during the early stages of software development to capture and define the functional requirements of a system.

Key elements of a Use Case Diagram include:

**1. Use Case:** A use case represents a specific functionality or a discrete unit of work that a system can perform. Use cases describe the interactions between an actor (user) and the system to achieve a particular goal. Each use case is typically represented by an oval shape and is labeled with a meaningful name.

**2. Actor:** An actor is an external entity that interacts with the system. Actors can be human users, other systems, or even hardware devices. Actors are represented as stick figures or blocks on the diagram, and they connect to use cases to show their involvement in specific actions or functionality.

**3. Association**: Lines connecting actors and use cases represent associations. An association line indicates that an actor interacts with a particular use case. The arrow on the line typically points from the actor to the use case to show the direction of the interaction.

**4. System Boundary:** The system boundary, often represented as a box, encloses all the use cases of the system. It defines the scope of the system under consideration.

USE CASE DIAGRAM :

Object Scan

Object Detection result

Object Detection

**ACTIVITY DIAGRAM**

An activity diagram is a type of UML (Unified Modeling Language) diagram used in software engineering to visualize the flow of activities or processes within a system, business process, or use case. Activity diagrams are particularly useful for modeling the workflow and behavior of a specific functionality or process, showing the sequence of actions, decision points, and transitions between different states or activities.

Here are some key components and concepts associated with activity diagrams:

**1. Activity:** An activity represents a specific task or action within the system or process being modeled. Activities are usually depicted as rounded rectangles and are labeled with a brief description of the action.

**2. Initial Node:** An initial node (depicted as a small filled circle) represents the starting point of the activity diagram. It indicates where the process begins.

**3. Final Node:** A final node (usually depicted as a circle with a border) represents the endpoint of the activity diagram, signifying the completion of the process.

**4. Action or Task:** Actions or tasks represent individual steps or operations within the process. They are typically depicted as rectangles with rounded corners and are labeled with a description of the task.

**5. Decision Node:** A decision node (diamond-shaped) represents a point in the process where a decision must be made. Depending on the outcome of the decision, the process may follow different paths or branches.

**6. Control Flow:** Control flow arrows (solid lines with arrowheads) connect the various elements of the diagram, indicating the order in which activities are performed. They show the flow of control from one activity to the next.

**7. Fork and Join Nodes:**  Fork nodes (solid black bars) are used to split the flow of control into multiple parallel paths, allowing activities to be executed concurrently. Join nodes (solid black bars with a small "x") bring these parallel paths back together.

**8. Swimlanes:** Swim-lanes are used to group activities based on the responsible entity or role. They help clarify who or what is responsible for each task in the process. Swimlanes are often depicted as vertical or horizontal partitions.

**9. Object Nodes:**  Object nodes represent the input or output of activities and can be used to show the data or objects passed between activities.

Activity diagrams are versatile and can be used in various domains, including software design, business process modeling, and system analysis. They provide a visual and structured way to represent complex workflows and make it easier to understand and communicate the logic and behavior of a process or system. Activity diagrams are particularly useful for documenting use cases, business processes, and the control flow within software applications.

ACTIVITY DIAGRAM :

1. Object Scan :

Running System

Point Object at the Camera

Object Scan

The object scan process, where the first object detection system will be run then the user directs the object to the camera. Then the object scan process will run.

1. Object Detection :

Detect whether the object has been captured by the camera

Processing the object detected by the camera

Successfully recognized

No

Yes

Object Recognized

?

The object detection process, the first process detects whether the object was successfully captured by the camera there are 2 conditions in this process, which is whether the system can recognize the object or not, if not, the system will return to the initial step, which is detecting the object to be captured by the camera.

1. Object Detection Result :

Object Detection Results

Object Name And Object Accuracy

The process of object detection results, where after the system obtains the results, the system will display or provide the name of the object and the percentage of object accuracy.

Configure Training Data

Train Training Data-set

Processing training Data-set

Success

1. Managing Object Information :

**PHASE BASED WORK BREAKDOWN STRUCTURE**

A phase-based Work Breakdown Structure (WBS) is a project management tool that organizes project tasks and activities based on the different phases or stages of a project's life-cycle. Each phase represents a distinct set of activities and objectives that must be completed to move the project forward. The WBS helps project managers and teams break down complex projects into manageable and logical components, making it easier to plan, execute, and monitor the project's progress.

Here's how a phase-based WBS typically works:

**1. Project Phases:** A project is divided into several phases, which are typically sequential but can sometimes overlap or run in parallel. The phases are defined based on the nature of the project and may include stages like initiation, planning, execution, monitoring and control, and closure.

**2. Sub-Phases:** Each phase is further broken down into sub-phases or major deliverable. These sub-phases represent the key milestones or outcomes that need to be achieved within each phase. Sub-phases are essentially the highest level of tasks in the WBS for that phase.

**3. Tasks and Activities:** Under each sub-phase, you have a hierarchy of tasks and activities. These are the specific actions and work items that need to be completed to achieve the sub-phase's deliverable. Tasks and activities are typically the lowest level of detail in the WBS.

**4. Hierarchy:** The WBS is organized hierarchically, with phases at the top, followed by sub-phases, and then tasks and activities. This hierarchical structure helps in decomposing the project into manageable components and provides a clear view of how each task relates to the overall project objectives.

**5. Dependencies:** The WBS can also illustrate dependencies between tasks and activities. Some tasks may need to be completed before others can begin, and these dependencies are often indicated in the WBS to help project managers identify critical paths and potential bottlenecks.

**6. Resource Allocation:** By organizing tasks and activities by phases, project managers can allocate resources more effectively. Resources can be assigned to specific phases, ensuring that the right personnel, equipment, and materials are available when needed.

**7. Progress Tracking:** The phase-based WBS simplifies progress tracking and reporting. Project managers can monitor the completion of sub-phases and their associated tasks to gauge how well the project is progressing through its various phases.

**8. Risk Management:** It also aids in risk management by highlighting potential risks and issues associated with each phase. This allows project managers to focus on addressing risks at the appropriate stage of the project.

In summary, a phase-based WBS is a project management tool that organizes project work into phases, sub-phases, and tasks, providing a structured approach to project planning, execution, and monitoring. It is especially useful for complex projects with multiple phases, each requiring its own set of tasks and activities.

**FUTURE SCOPE OF THE PROJECT**

The future scope of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very bright. This technology has the potential to be used in a wide range of applications, including:

**Video surveillance:** Real-time object detection can be used to detect and track people and vehicles in video surveillance footage with greater accuracy and efficiency than traditional methods. This can be used to improve public safety and security, and to monitor traffic flow.

**Security monitoring:** Real-time object detection can be used to detect and track intruders in security-sensitive areas, such as airports, banks, and government buildings. This can be used to deter crime and protect assets.

**Robotics:** Real-time object detection can be used to help robots navigate their environment and interact with objects more safely and efficiently. For example, a robot could use real-time object detection to avoid obstacles, pick up objects, and deliver packages.

**Manufacturing:** Real-time object detection can be used to inspect products for defects and to ensure that products are assembled correctly. This can help to improve the quality of manufactured goods.

**Retail:** Real-time object detection can be used to track customer movement in stores and to identify popular products. This information can be used to improve store layout and product placement.

**Healthcare:** Real-time object detection can be used to detect medical devices in medical images, such as X-rays and MRIs. This can help doctors to diagnose diseases and to plan treatments more effectively.

In addition to these specific applications, real-time object detection can also be used in a variety of other ways, such as:

**Education:** Real-time object detection can be used to create interactive educational experiences for students. For example, a student could use a webcam to identify different objects in their environment and to learn about their properties.

**Entertainment:** Real-time object detection can be used to create new and innovative forms of entertainment. For example, a video game could use real-time object detection to allow players to interact with the game world in a more realistic way.

The future of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very exciting. As the technology continues to develop, we can expect to see it used in even more ways to improve our lives.

Here are some specific areas where we can expect to see significant advances in custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model in the future:

**Improved accuracy and efficiency:** As machine learning algorithms continue to improve, we can expect to see real-time object detection systems that are more accurate and efficient than ever before. This will make it possible to use real-time object detection in a wider range of applications.

**Reduced latency:** Real-time object detection systems typically have some latency, meaning that there is a delay between the time that the system captures an image and the time that it outputs the results of the object detection. As hardware and software continue to improve, we can expect to see real-time object detection systems with lower latency. This will make it possible to use real-time object detection in applications where even a small delay is unacceptable.

**Increased robustness:** Real-time object detection systems can be susceptible to errors, especially in challenging conditions such as low light or occlusion. As machine learning algorithms continue to improve, we can expect to see real-time object detection systems that are more robust to errors. This will make it possible to use real-time object detection in a wider range of environments.

**Reduced cost:** The cost of hardware and software required to run real-time object detection systems is decreasing. As this trend continues, we can expect to see real-time object detection become more accessible to a wider range of users.

Overall, the future of custom real-time object detection using webcam using TensorFlow on Google Colab with the SSD-MobileNet-V2-FPNLite-320 model is very promising. This technology has the potential to revolutionize the way we interact with the world around us.

**CONCLUSION**

In conclusion, the implementation of a object detection system through live webcam with TensorFlow on Google Colab, leveraging the SSD-MobileNet-V2-FPNLite-320 model, has proven to be a comprehensive and successful project. The structured workflow divided into multiple sections ensured a systematic and organized development process. Let's reflect on the key aspects of each section and the overall outcomes:

**1. Data Gathering and Preparation**

The process of gathering and labeling training images laid the foundation for a robust model. A well-curated dataset is crucial for training a model capable of accurately detecting objects in real-time scenarios.

**2. Dependency Installation**

Installing TensorFlow and other necessary dependencies is a critical step in setting up the development environment. The ease of dependency installation on Google Colab streamlined the process, providing a hassle-free environment for model development.

**3. Dataset Upload and Preparation**

Uploading images and preparing the training data involved a meticulous process of splitting the dataset into training, validation, and test sets. Creating a label map and generating TFRecords ensured the compatibility of the dataset with the TensorFlow Object Detection API.

**4. Training Configuration and Model Training**

Configuring the training parameters and initiating the training process for the custom TensorFlow Lite Detection Model involved tuning hyperparameters to achieve optimal results. The iterative nature of model training allowed for refinement and improvement.

**5. Model Conversion to TensorFlow Lite**

Converting the trained model to TensorFlow Lite format was a crucial step for enabling real-time inference. The lightweight nature of TensorFlow Lite makes it well-suited for deployment on various platforms.

**6. Testing and Evaluation**

Testing the TensorFlow Lite model with inference on test images and calculating the mean Average Precision (mAP) provided insights into the model's accuracy and effectiveness. These evaluation metrics are essential for assessing the model's performance and identifying areas for improvement.

**7. Model Deployment**

Deploying the TensorFlow Lite model involved a systematic process, from downloading the model to setting up the deployment environment using Anaconda. The flexibility of deployment on Windows, Linux, or macOS allows for widespread usability.

**8. Conclusion of the Entire Workflow**

In conclusion, the successful implementation of the object detection through live webcam system showcases the efficacy of the chosen model and the robustness of the developed workflow. The system is capable of accurately detecting objects in real-time through a webcam feed, making it applicable for a variety of applications such as security surveillance, object tracking, and more.

This project not only provides a functional solution for object detection through live webcam but also serves as a learning resource for individuals interested in developing similar applications. The modular structure of the code and the systematic workflow contribute to the project's maintainability and extensibility. As technology evolves, further enhancements and optimizations can be incorporated into the system to keep it at the forefront of object detection capabilities.

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2. **Dataset:** .xml for annotation and .jpg for images,

URL: [https://www.kaggle.com/](https://www.kaggle.com/)