# **Object Detection using Machine Learning**

A major project report submitted in partial fulfillment of the requirement for the award of degree of

# **Bachelor of Technology**

in

**Computer Science & Engineering / Information Technology** 

Submitted by

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**CERTIFICATION** 

This certifies that the work submitted in the project report "Object Detection using Machine

Learning" towards the partial fulfillment of requirements for the award of a B.Tech in Computer

Science and Engineering, and submitted to the Department of Computer Science and

Engineering, Jaypee University of Information Technology, Waknaghat, is an authentic record of

work completed by "Jigyasa Sharma (201360) and Saksham Awasthi (201376)" between

August 2023 to June 2024, under the direction of **Dr. Anita** with the Department of Computer

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Candidate's declaration

We hereby declare that the work presented in this report entitled 'Object Detection using

Machine Learning' in fulfillment of the requirements for the award of the degree of Bachelor

of Technology in Computer Science & Engineering / Information Technology submitted in

the Department of Computer Science & Engineering and Information Technology, Jaypee

University of Information Technology, Waknaghat is an authentic record of my own work

carried out over a period from August 2023 to May 2024 under the supervision of Dr. Anita

(Assistant Professor, Department of Computer Science & Engineering and Information

Technology).

The matter embodied in the report has not been submitted for the award of any other degree or

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# LIST OF ABBREVIATIONS, SYMBOLS AND NOMENCLATURE

- 1. CNN: Convolutional neural networks
- 2. RNN: Recurrent neural networks
- 3. SSD: Single Shot Detector
- 4. YOLO: You Only Look Once
- 5. MSE: Mean Squared Error
- 6. CUDA: Compute Unified Device Architecture
- 7. cuDNN: CUDA Deep Neural Network
- 8. API: Application Programming Interface
- 9. GPGPU: General-purpose processing

# **ABSTRACT**

Object detection is a crucial component of computer vision and artificial intelligence, with applications ranging from surveillance systems to driverless cars. Using the resources of two well-known repositories for pre-trained models and state-of-the-art research in the field, Model Zoo and Model Garden, this work presents a sophisticated object detection model. By utilizing pre-trained models that provide a strong basis for precise object detection, our suggested model takes use of Model Zoo's adaptability and dependability. We also include Model Garden developments, modifying cutting-edge architectures and methodologies to improve the model's performance. A deep neural network serves as the foundation for the object identification model's architecture, which optimizes feature extraction and classification for increased precision and effectiveness. Our method delivers better accuracy and faster execution time by carefully combining models from Model Zoo and Model Garden. This model also exhibits versatility across several datasets and real-world applications, as it is meant to be adaptive to a variety of scenarios and domains. In addition to enabling quick development, the integration of Model Zoo and Model Garden guarantees that the model is up to date with the most recent developments in object detection science. Our method outperforms current benchmarks in object detection tasks, as demonstrated by experimental results. The suggested approach exhibits its capability to be implemented in practical settings, hence advancing computer vision applications.

# **CHAPTER 1: INTRODUCTION**

# 1.1 Introduction

The field of computer vision has witnessed revolutionary advancements in augmented reality, surveillance systems, and autonomous vehicles due to the development of object detection. An essential component of machine interpretation of visual data is object detection, which is the identification and positioning of objects within picture or video frames. This study explores the complex field of object detection in an effort to further the ongoing progress of computer vision technology.

A key component of the quickly developing field of computer vision, object detection has the potential to transform a wide range of sectors. Both researchers and practitioners have shown a great deal of interest in the development of robust object detection algorithms.

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With the speed at which technology is developing, there is an increasing need for object detection systems that are more dependable and efficient. Intelligent systems work best when they can accurately recognise and locate objects in a variety of dynamic environments. This project aims to investigate new techniques and approaches to improve object detection model performance. This means pushing the limits of what is currently thought to be feasible in the field of object detection and conquering obstacles along the way.

Object detection is a bridge between computer vision and artificial intelligence, bringing together the sophisticated analysis of visual data with the strengths of machine learning algorithms. The interplay between these fields gets more complex as algorithms advance, enabling more precise and nuanced object recognition.

The implications of accurate object detection are felt in a variety of industries. Object detection is the cornerstone of augmented reality, enabling the precise placement of virtual objects in the physical world to create immersive experiences. Accurately identifying anomalies in medical imaging is essential for prompt diagnosis and successful treatment. Autonomous vehicles rely significantly on object detection to navigate intricate traffic situations and protect passengers.

Fundamentally, object detection is more than just visual identification. It entails interpreting minute details like orientations, scales, and object boundaries. The difficulties include changes in ambient light, occlusions, and the dynamic nature of real-world settings. It is imperative to tackle these obstacles in order to develop object detection systems that are resilient against unforeseen circumstances and accurate as well.

A methodical investigation of novel techniques and approaches is necessary in the pursuit of enhanced object detection performance. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two examples of deep learning architectures, are still very important. Examining the combination of different sensor modalities—like radar and lidar—with conventional visual data offers a way to improve object detection's resilience under difficult circumstances.

The quest to improve object detection technology never stops. Throughout the development lifecycle, constant observation is necessary to adjust to changing conditions and advances in technology. The dedication to developing accurate, secure, and socially responsible object detection technologies is emphasized by ethical issues, security, and the responsible implementation of these systems.

Finally, this research project delves deeply into the multidisciplinary field of object detection at the nexus of computer vision, machine learning, and artificial intelligence. In order to achieve improved performance, one must navigate complex obstacles, look into novel approaches, and take ethical considerations into account.

The successful integration of object detection systems into our technologically advanced society depends on their constant monitoring and adaptation as technology advances.

### 1.2 Problem Statement

Despite significant advancements in object detection, a number of enduring problems in the dynamic field of computer vision still need to be addressed. The challenges facing today's object detection models include dealing with occlusions, accurately identifying objects in complex scenes, and maintaining real-time performance. These difficulties highlight the need for more advanced and flexible techniques to increase the capacity for object detection.

A crucial issue that this project seeks to resolve is the need for improved flexibility to a variety of datasets and changing environmental circumstances. In addition to performing exceptionally well in controlled settings, object detection systems also need to blend in perfectly with a variety of applications, from urban surveillance to natural settings. The objective is to develop models with strong performance in a variety of scenarios, guaranteeing dependability and effectiveness in a wide range of situations.

Moreover, the computational requirements of certain cutting-edge object detection models pose a significant challenge, especially for devices with limited resources. The complexities of using these models in real-world settings, where processing speed is frequently crucial, call for a careful balancing act between computational efficiency and accuracy. In order to enable the deployment of object detection models across a range of hardware configurations, this project recognises this challenge and actively attempts to address it by developing solutions that maximize object detection models' performance without sacrificing their accuracy.

To reduce the computational load on devices with limited resources, advances in hardware utilization in conjunction with novel algorithmic approaches will be investigated. By tackling these complex issues, this project aims to ensure the seamless integration of intelligent vision systems into the framework of our rapidly changing technological environment. It also hopes

to advance the theoretical understanding of object detection and open doors for real-world applications in vital areas like autonomous systems, smart surveillance, and emerging technologies.

# 1.3 Objectives

The main objective of this project is to raise the state-of-the-art in object detection by finding focused answers to pressing problems. Three particular goals are the main focus:

- 1. Increasing Accuracy: Increasing the accuracy of object detection models is a primary goal of this project. This calls for the creation and use of state-of-the-art architectures and algorithms. The focus is especially on improving performance in complex scenarios with occlusions and various environmental factors. Through the use of cutting-edge techniques, the project hopes to outperform current accuracy benchmarks and guarantee that object detection models can locate and identify objects with confidence, even under the most difficult circumstances.
- 2. Real-time Performance: Optimizing the computational efficiency of object detection models through research and application is the focus of the second major goal. The goal is to make these models run smoothly in real-time on low-resource devices. This feature is critical for applications like autonomous systems or real-time surveillance where prompt processing of visual data is required. The project pushes the limits of what is possible in terms of real-time object detection capabilities, attempting to find a balance between accuracy and computational efficiency.
- 3. Adaptability: One of the main goals of this project is to increase adaptability. Creating object detection models with superior flexibility and applicability in a variety of contexts is the aim. This is accomplished by making certain that these models demonstrate adaptability to different datasets and environmental circumstances. An object detection system with greater versatility is highly valuable as it can be applied to a wider range of scenarios and domains.

Through a methodical approach to these goals, the project hopes to advance the field of computer vision while also offering useful solutions that have real-world applications. If this project is successful, object detection technologies will have advanced significantly, and this could have ramifications for a wide range of applications, from security and safety to emerging technologies like autonomous systems.

# 1.4 Significance and Motivation of the Project Work

The main reason for the importance of this project is that it has the ability to completely transform computer vision as a whole, which will have a significant effect on a variety of applications, from strengthening security systems to developing driverless cars. The development of intelligent systems depends on the ability to detect objects accurately and efficiently. This has ramifications for many different technological fields. Technological developments in object detection have the potential to usher in safer, more dependable, and eventually revolutionary technologies.

The primary driving force behind this project's inception is the urgent need for extremely adaptable and durable object detection systems. The current environment makes it difficult to identify objects accurately in a variety of dynamic environments. The goal of this project is to develop object detection systems that are capable of surpassing existing limitations, driven by a determination to overcome these obstacles. The goal is to create a new breed of systems that can easily adapt to practical applications, which will spur advancements in a wider range of computer vision technologies.

Moreover, the drive stems from the realization that practical applications of intelligent vision systems demand solutions that go beyond theoretical breakthroughs. Systems for detecting objects that are useful, flexible, and effective are necessary for meaningful integration into a wide range of applications, from cutting-edge technologies to urban surveillance. Therefore, this project aims to address the practical requirements that support the successful deployment of intelligent vision systems in addition to advancing the theoretical boundaries of computer vision.

The reason goes beyond academic curiosity as technology gets more and more ingrained in our daily lives. It is in line with the pressing need to develop technological solutions that improve efficiency, safety, and dependability in a range of applications. This project has the potential to

greatly advance object detection technologies by overcoming its present obstacles, which will ultimately influence the direction computer vision takes in the modern technological

environment.`

# 1.5 Organization of Project Report

The project report's structure is carefully thought out to provide a full understanding of the research that was done, guaranteeing a thorough investigation of the intricacies involved in object detection. To aid in a sophisticated comprehension of the project's methodology, conclusions, and ramifications, the ensuing framework has been developed:

#### 1. Literature Review:

The project report begins with a thorough analysis of the body of prior research, which forms the basis for the work that follows. The complexities of modern object detection techniques and technologies are covered in detail in this section. The report creates a contextual framework for the proposed research by critically analyzing earlier works, highlighting opportunities, gaps, and challenges that serve as the foundation for the project's innovation.

### 2. Methodology:

The creative strategies and algorithms suggested for improving object detection capabilities are revealed in this section, which comes after the literature review. This thorough explanation highlights the special qualities of the selected approaches and highlights how they might help overcome current obstacles. By doing this, the report offers a road map for putting the suggested tactics into practice, promoting openness and repeatability in the scientific method.

# 3. Experimental Results and Discussions:

The presentation of the experimental results and the ensuing discussions form the main body of the project report. This section presents the findings from extensive testing and analyses carried out in order to verify the suggested models. The results are analyzed to provide a more nuanced understanding of the performance metrics, including both strengths and limitations. A fuller understanding of the project's contributions to the field is made possible by the discussions, which shed light on the implications of the

findings.

#### 4. Conclusion:

The conclusive segment synthesizes the key contributions of the project, encapsulating the advancements made in the realm of object detection. It serves as a summary of the entire research endeavor, highlighting the novel methodologies and their impact on the field. Additionally, the conclusion opens avenues for future research, identifying unexplored facets and potential extensions of the project's findings. This forward-looking perspective not only reinforces the project's significance but also inspires continued exploration and innovation in the dynamic domain of object detection.

# **CHAPTER 2: LITERATURE SURVEY**

A literature review is an essential component of any academic or research activity since it serves as the foundation for new information to be created. In relation to our effort on object detection, the literature review examines earlier scholarly publications, research papers, and technological advancements in the fields of computer vision and object detection. This part includes a critical review of pertinent literature, summarizing the state of the subject today and highlighting the primary holes in knowledge that our study seeks to fill.

Advances in the fields of machine learning and deep learning have led to tremendous growth in the disciplines of computer vision and object recognition. The literature review explores foundational works that have influenced our understanding of model structures, object identification techniques, and practical applications. It includes studies on a variety of object detection strategies, each with advantages and disadvantages, such as region-based approaches, single-shot detectors, and two-stage detectors.

A number of datasets for object identification model testing and training are examined in the survey, including the diversity and volume needed for reliable system development. It also looks at how assessment metrics have changed over time, providing insight into the methods used to evaluate the effectiveness of object detection algorithms in various contexts.

### 2.1 Overview of Relevant Literature

The object detection problem is comprehensively solved in Paper [1] by utilizing a deep learning algorithm. The work mostly focuses on the Single Shot Detector (SSD) method, which uses a single layer of a convolutional neural network (CNN) and is renowned for its quickness in object detection. By addressing the inadequacies of the current object detecting systems, the research aims to improve the accuracy of the SSD technique.

Inaccurate designs and trainable algorithms plagued earlier methods of object recognition. Although the shift to deep learning yielded a noticeable enhancement, the incorporation of more computer vision techniques led to limitations in performance.

The single-shot approach of the SSD technique contributed to its rise in popularity as a quick object recognition tool. By acknowledging its potential and striving to improve its accuracy, the research expands on this methodology.

In order to achieve greater accuracy in real-time object detection, the research methodology focuses on improving SSD technology. Using a single layer of a convolutional neural network, the SSD technique recognises objects and expedites the object detection process. Examining the SSD technique's design, the researchers hunt for areas that could be improved and optimized.

### Among the study's significant conclusions are

Whole Solution: There is no need for further computer vision techniques because the study provides a complete end-to-end solution. This method improves performance and real-time capabilities by streamlining the object detection procedure.

SSD technology enhancement: This study attempts to improve the accuracy of SSD technology in recognition of its speed benefits. This necessitates using optimisation techniques, identifying any potential vulnerabilities, and doing a detailed analysis of the current design.

One of the study's important findings is Whole Solution: Since the study offers a comprehensive end-to-end solution, no additional computer vision techniques are required. This approach object detection enhancing performance expedites the process, and real-time capabilities. Enhancement of SSD technology: In light of the advantages of speed, this study aims to increase the accuracy of SSD technology. This calls for the application of optimisation strategies, the detection of any potential weaknesses, and a thorough examination of the existing design. This work advances the ongoing development of object detection techniques, providing a promising avenue for enhancing computer vision performance.

The primary objective of this study [2] is to provide a thorough review of object detection by examining the methods that have been employed recently to integrate deep neural networks and enhance task performance. The author agrees that a comprehensive assessment is required given the rapid advancement of object detection technology and the rising significance of deep learning in the field.

The principal goals of this study are

Comprehensive Synopsis: Motivated by the progress in deep learning technology, the study seeks to offer an in-depth examination of the latest developments in object detection. This provides a thorough analysis of the methods, frameworks, and algorithms that have contributed to the advancement of object detection.

Methodological insights: To enhance object detection performance, a comprehensive analysis of recent methods has been the aim of this research work. This includes a thorough examination of deep neural network topologies and the state-of-the-art approaches employed to address object recognition-related issues.

Identification of the Problem: Taking into account that challenges exist in every discipline, this research looks at potential issues and obstacles in the object detection space. To choose the direction for future research, this means analyzing the limitations and shortcomings of the strategies and techniques that are now in use.

To sum up, this work closes a significant gap in the literature by providing a comprehensive overview of recent developments in object identification, with a focus on deep neural network integration. This study aims to offer a critical review of the area, elucidate methodologies, and evaluate potential roadblocks for professionals operating in the rapidly evolving and dynamic domain of computer vision.

Despite the advancements in object detection, research study [3] looks at the challenges and potential issues that arise in the field. Various features such as occluded areas, disparate scales, and intricate backgrounds pose challenges that demand ongoing research and development.

Fairness and bias in object recognition algorithms are two ethical aspects that are carefully considered in order to enable responsible deployment in real-world applications.

To address the difficulties involved in object recognition, researchers have resorted to deep neural networks due to its intricacies. Deep learning models have greatly enhanced the accuracy and resilience of object detection systems by automatically learning hierarchical features.

This paper explores the techniques and architectures used recently to demonstrate how deep neural networks have been used to improve object recognition performance.

This paper ends with a discussion of future directions that could be pursued as we continue to explore the current state of object detection. The ongoing development of deep learning technology makes new methods and solutions possible. The amalgamation of perspectives from contemporary advancements and the recognition of enduring obstacles furnish a path for scholars and professionals to make contributions towards the continuous progression of object identification in computer vision.

This work essentially functions as a thorough overview of the most recent advancements in object detection, providing a sophisticated knowledge of the approaches used, difficulties encountered, and potential paths forward in this ever-evolving and crucial field. Our goal in conducting this investigation is to add to the body of knowledge that drives the ongoing development of object recognition technologies.

Two-stage and single-stage object detectors are the two main categories into which the paper [4] divides object detectors. Single-stage detectors concentrate on all spatial region proposals in a single shot and have comparatively simpler architectures than two-stage detectors, which use a selective region proposal strategy and have more complex architectures. The two main evaluation metrics for object detectors are inference time and detection accuracy.

In the past, two-stage detectors have shown better detection accuracy than single-stage detectors. Single-stage detectors, on the other hand, have quicker inference times. The advent of You Only Look Once (YOLO) and its architectural offspring has led to a notable enhancement in detection accuracy, occasionally outperforming two-stage detectors. Because YOLOs prioritize efficiency over detection accuracy and have faster inference times, they have become more and more popular in a variety of applications.

This paper compares the detection accuracies of YOLO and Fast-RCNN as an illustrative example; YOLO shows a detection accuracy of 63.4 compared to Fast-RCNN 70. But the main benefit is that YOLO has an inference time that is approximately 300 times faster.

YOLOs are now a popular choice for applications where real-time processing is essential due to their efficiency.

In addition to providing a review of previous approaches, the study suggests future avenues for investigation. With an emphasis on YOLOs in particular, this forward-looking strategy highlights the necessity of ongoing innovations and advancements in the field of single-stage object detection. This paper provides an invaluable resource for computer vision researchers, practitioners, and enthusiasts, providing insights into the continuous advancement of object detection methods.

Convolutional Neural Networks (CNNs) and transfer learning are applied to object detection in the research paper [5]. The ability of machine learning algorithms to extract pertinent features for successful performance is the fundamental challenge addressed. Conventional approaches frequently rely on computational techniques for feature extraction or expert-generated input features. Nonetheless, CNNs are especially good at object detection tasks because they are inspired by the visual cortex of the human brain.

Because of the way they are built, CNNs are not as good with small datasets because they need a lot of neurons and layers to train well. The limitations encountered in situations where large datasets must be obtained and stored for training are acknowledged in the paper.

The study suggests using transfer learning, a deep learning technique for dimensionality reduction, to get around these problems. Using a pre-trained model on a large dataset and refining it for a particular task using a smaller dataset is known as transfer learning. This lessens the need for intensive data collection by enabling the transfer of knowledge from the larger dataset to the particular task at hand.

By exploring the visual characteristics that correlate digital images, the research attempts to retrain a CNN through transfer learning for the purpose of classifying a fresh set of images. In doing so, the study aims to pinpoint distinguishing characteristics that facilitate efficient object detection.

The average squared differences between the predicted and actual values is measured by the Mean Squared Error (MSE), which is the evaluation metric used in the study. The developed model shows a high degree of prediction accuracy, achieving a satisfactory result with a 97% MSE.

To sum up, the study highlights the importance of transfer learning in mitigating the drawbacks associated with CNNs trained on limited datasets for object detection. The study shows the efficacy of this strategy in extracting significant features and obtaining high accuracy, as indicated by the low MSE, by utilizing pre-trained models and fine-tuning them. This offers a workable solution for improving the performance of object detection models with constrained data resources, and it makes a significant contribution to the fields of computer vision and deep learning.

The introduction of a novel component known as the weighted bi-directional feature pyramid network (BiFPN) is one of the paper's main contributions [6]. This invention makes multi-scale feature fusion quick and easy. The BiFPN improves the network's capacity to effectively integrate data from various scales, which is important for object detection tasks where objects can have wide size variations.

The introduction of a compound scaling method is one of the paper's other important recommendations. The backbone, feature network, and box/class prediction networks are among the components whose resolution, depth, and width are all uniformly scaled using this method. By keeping various parts of the network in balance, this holistic scaling strategy seeks to maximize overall network efficiency.

Utilizing EfficientNet backbones and expanding on these optimisations, the researchers present the EfficientDet family of object detectors. The main selling point of EfficientDet is its ability to consistently outperform earlier methods in terms of efficiency while taking a wide range of resource constraints into account.

The paper, specifically, offers strong outcomes for their EfficientDetD7 model. On the COCO test-dev dataset, EfficientDetD7 achieves a state-of-the-art Average Precision (AP) of 52.2 using only one model and one scale.

Remarkably, 325 billion Floating Point Operations (FLOPs) and 52 million parameters are used to accomplish this. Significantly, compared to earlier detectors, this model is 4 to 9 times smaller and uses 13 to 42 times fewer FLOPs, demonstrating a notable increase in efficiency.

The results of the paper indicate that top-tier performance in object detection tasks can be achieved while significantly lowering the computational demands thanks to the suggested architecture and optimisation strategies in EfficientDet. In applications where computational resources are limited, such as in edge devices, real-time systems, or environments with limited hardware capabilities, striking this balance between model efficiency and accuracy is essential.

In conclusion, by presenting innovative architectural elements and optimisation techniques, the research paper "EfficientDet: Scalable and Efficient Object Detection" significantly advances the field of object detection. The EfficientDet models—EfficientDetD7 in particular—address the urgent need for effective yet potent object detection solutions by exhibiting cutting-edge performance on common benchmark while exhibiting a notable decrease in model size and computational requirements.

# 2.2 Key Gaps in the Literature

Object Detection Testing Strategy: Although the papers delve deeply into technical testing aspects, it does not specifically address ethical issues related to object detection, such as bias and fairness testing. Ethical testing ought to be an integral component of the testing strategy, considering the systems' impact on society.

Advancing Computer Vision through Object Detection Research: The study offers a useful summary, but it should go into more detail about the particular difficulties that object detection systems encounter in the real world. A comprehensive examination of managing intricate situations such as severe weather or congested areas would augment the usefulness of the discoveries.

Scalability Considerations: Although the focus of the paper is efficiency, there is still need for further discussion regarding EfficientDet's scalability, especially when it comes to managing large datasets and a variety of environments. A more comprehensive picture would be obtained by assessing its performance in a wider range of scenarios, including resource-intensive tasks.

Restricted Examination of Adversarial Scenarios: Although the paper provides an in-depth analysis of YOLOs, it does not go into great detail regarding adversarial testing scenarios. Given the possible security risks in practical applications, a thorough examination of the system's resistance to deliberate deceptive inputs would yield insightful information.

# **CHAPTER 3: SYSTEM DEVELOPMENT**

# 3.1 Requirements and Analysis

Requirements analysis and gathering constitute the first stage of system development, which is centered on developing an object detection system for a college project. Since it establishes the foundation for the entire development process, this first step is essential. A thorough grasp of the project's goals, user requirements, and the definition of both functional and non-functional requirements are essential to its success.

NVIDIA created two technologies, CUDA (Compute Unified Device Architecture) and cuDNN (CUDA Deep Neural Network), to speed up deep learning and parallel computing activities on NVIDIA GPUs.

Computing Unified Device Architecture, or CUDA:

NVIDIA developed the application programming interface (API) paradigm and parallel computing platform known as CUDA.

It permits general-purpose processing (GPGPU) on NVIDIA GPUs by developers.

Using the programming environment that CUDA offers, developers may write code in C, C++, and Fortran that can run on GPUs.

It comes with a runtime API that lets programmers use the GPU to start several concurrent tasks.

CuDA Deep Neural Network, or cuDNN:

A GPU-accelerated library for deep neural networks is called cuDNN.

It offers extremely well-optimized versions of deep learning primitives, including activation functions, pooling, normalizing, and convolution.

To speed up the training and inference of neural networks, developers frequently utilize cuDNN as a backend for deep learning frameworks like TensorFlow and PyTorch.

In order to expedite deep learning computations, cuDNN is engineered to integrate easily with CUDA and take advantage of NVIDIA GPUs' parallel processing capabilities.

In conclusion, cuDNN is a specific library developed on top of CUDA to speed up deep learning tasks, whereas CUDA is a general-purpose parallel computing platform. Developers may leverage the capability of NVIDIA GPUs for a variety of deep learning and parallel computing applications by combining CUDA with cuDNN.

We have also used react and tensorflow.js in our Object Detection model. Together, React and TensorFlow.js provide a potent and adaptable solution.

Because of its component-based architecture, React makes it easier to create user-friendly interfaces with smooth interaction and simple design features. By utilising React's virtual DOM, developers can effectively refresh the user interface (UI) while the model processes data, guaranteeing a seamless user experience. Furthermore, users can view the object detection results instantly thanks to React's state management features, which facilitate real-time updates.

However, TensorFlow.js immediately integrates machine learning capabilities into the browser environment. TensorFlow.js eliminates the requirement for server-side processing by enabling you to train bespoke models or deploy pre-trained object recognition models right within the browser. In addition to increasing inference speed, this keeps sensitive data on the client side and protects user privacy. Developers can effortlessly combine the strength of machine learning with the adaptability of a contemporary JavaScript framework by integrating TensorFlow.js with React. This opens up a world of possibilities for creating cutting-edge object detection applications with a user experience that is responsive and easy to use.

```
(tfod) C:\Users\Asus\Documents\Object detection\TFODCourse>python -m pip install --upgrade pip
Requirement already satisfied: pip in c:\users\asus\documents\object detection\tfodcourse\tfod\lib\site-p
Collecting pip
  Downloading pip-23.3.1-py3-none-any.whl (2.1 MB)
                                                 2.1/2.1 MB 789.2 kB/s eta 0:00:00
Installing collected packages: pip
  Attempting uninstall: pip
    Found existing installation: pip 22.0.4
    Uninstalling pip-22.0.4:
      Successfully uninstalled pip-22.0.4
Successfully installed pip-23.3.1
(tfod) C:\Users\Asus\Documents\Object detection\TFODCourse>pip install ipykernel
Collecting ipykernel
  Downloading ipykernel-6.26.0-py3-none-any.whl.metadata (6.3 kB)
Collecting comm>=0.1.1 (from ipykernel)
  Downloading comm-0.2.0-py3-none-any.whl.metadata (3.7 kB)
Collecting debugpy>=1.6.5 (from ipykernel)
Downloading debugpy-1.8.0-cp310-cp310-win_amd64.whl.metadata (1.1 kB)
Collecting ipython>=7.23.1 (from ipykernel)
  Downloading ipython-8.18.1-py3-none-any.whl.metadata (6.0 kB)
Collecting jupyter-client>=6.1.12 (from ipykernel)
  Downloading jupyter_client-8.6.0-py3-none-any.whl.metadata (8.3 kB)
Collecting jupyter-core!=5.0.*,>=4.12 (from ipykernel)
Downloading jupyter_core-5.5.0-py3-none-any.whl.metadata (3.4 kB)
Collecting matplotlib-inline>=0.1 (from ipykernel)
  Downloading matplotlib_inline-0.1.6-py3-none-any.whl (9.4 kB)
Collecting nest-asyncio (from ipykernel)
```

fig. 3.1.1 (Upgrading pip)

```
Downloading pygments-2.17.2-py3-none-any.whl.metadata (2.6 kB)
Collecting stack-data (from ipython>=7.23.1->ipykernel)
 Downloading stack_data-0.6.3-py3-none-any.whl.metadata (18 kB)
Collecting exceptiongroup (from ipython>=7.23.1->ipykernel)
 Downloading exceptiongroup-1.2.0-py3-none-any.whl.metadata (6.6 kB)
Collecting colorama (from ipython>=7.23.1->ipykernel)
 Downloading colorama-0.4.6-py2.py3-none-any.whl (25 kB)
Collecting python-dateutil>=2.8.2 (from jupyter-client>=6.1.12->ipykernel)
 Downloading python_dateutil-2.8.2-py2.py3-none-any.whl (247 kB)
                                                                        eta 0:00:00
Collecting platformdirs>=2.5 (from jupyter-core!=5.0.*,>=4.12->ipykernel)
 Downloading platformdirs-4.0.0-py3-none-any.whl.metadata (11 kB)
Collecting pywin32>=300 (from jupyter-core!=5.0.*,>=4.12->ipykernel)
 Downloading pywin32-306-cp310-cp310-win_amd64.whl (9.2 MB)
                                                                    eta 0:00:00
Collecting parso<0.9.0,>=0.8.3 (from jedi>=0.16->ipython>=7.23.1->ipykernel)
  Downloading parso-0.8.3-py2.py3-none-any.whl (100 kB)
                                                                       eta 0:00:00
Collecting wcwidth (from prompt-toolkit<3.1.0,>=3.0.41->ipython>=7.23.1->ipykernel)
 Downloading wcwidth-0.2.12-py2.py3-none-any.whl.metadata (14 kB)
Collecting six>=1.5 (from python-dateutil>=2.8.2->jupyter-client>=6.1.12->ipykernel)
 Downloading six-1.16.0-py2.py3-none-any.whl (11 kB)
Collecting executing>=1.2.0 (from stack-data->ipython>=7.23.1->ipykernel)
 Downloading executing-2.0.1-py2.py3-none-any.whl.metadata (9.0 kB)
Collecting asttokens>=2.1.0 (from stack-data->ipython>=7.23.1->ipykernel)
 Downloading asttokens-2.4.1-py2.py3-none-any.whl.metadata (5.2 kB)
Collecting pure-eval (from stack-data->ipython>=7.23.1->ipykernel)
 Downloading pure_eval-0.2.2-py3-none-any.whl (11 kB)
Downloading ipykernel-6.26.0-py3-none-any.whl (114e^{(8)}+
```

fig. 3.1.2 (Installing the upgrades in pip)

# 3.2 Project Design and Architecture

Following a thorough collection and analysis of the requirements, the project design and architecture portion of the development process gets underway. This step is critical because it creates the foundation for the entire object detection system. In this instance, the development team's responsibilities include establishing the overall architecture of the system and laboriously crafting each component that comprises the object detection solution.

Functionalities for creating and managing universally unique identifiers (UUIDs) are available in the Python unid module. Usually expressed as 32 hexadecimal digits separated by hyphens, UUIDs are 128-bit numbers. They are frequently employed in distributed systems to provide an object or entity a unique identity.

Instead of being a Python module, **LabelImg** is an open-source graphical image annotation tool created by tzutalin. The graphical user interface of this utility is powered by Qt and is developed in Python. It is helpful for building datasets for object detection jobs because it is particularly made to annotate item bounding boxes in images.

These are labelImg's salient characteristics:

With the help of a graphical interface, users can create bounding boxes around objects in photos using graphic annotation.

Support for Various Formats: enables the storage of annotations in many formats, including YOLO format and XML for use with TensorFlow's Object Detection API.

Platform Autonomy: runs on a number of operating platforms, such as Linux, macOS, and Windows.

Customizable Labels: When an object is being annotated, users can define and alter the labels for it.

Image Navigation: Facilitates quick and simple browsing among images in a directory to enable effective annotation.

Structured data can be defined and serialized using the Protocol Buffers (protobuf) framework and compiler protoc. An outline of some theoretical elements of protocol buffers and protoc is provided below:

Message Definition: The Protocol Buffers language is used in proto files to construct data structures. We refer to these configurations as "messages."

Fields: Messages are made up of fields, each of which has a designated data type and a unique numerical identity.

Syntax Versions: Proto3 is the most recent syntax version that Protocol Buffers supports. Language features and serialization rules are defined by syntax versions.

Compilation Process: Source code in a target language is produced by the protoc compiler using proto files as input.

Language Plugins: Protoc generates code for other programming languages, including C++, Java, Python, and others, by using language-specific plugins.

Options for Output: Users can designate the format and output directory for the code that is created.

Serialisation and Deserialization: Classes or modules that make it easier to serialize and deserialize messages are included in the resulting code.

Language-Specific Code: Depending on the target programming language, the generated code has a different structure and style.

Language independence is facilitated via Protocol Buffers, which enhances interoperability by enabling the descrialization of data from one language to another.

Backward and Forward Compatibility: Message definition modifications aim to preserve backward and forward compatibility with previously serialized data.

Binary Format: Compared to human-readable forms like JSON or XML, serialized data is more efficient and compact since it is stored in a binary format.

Tagged Fields: A numeric identifier is appended to every field in the serialized data.

Version Numbers: Versioning and data structure evolution are made possible by the inclusion of version numbers in Protocol Buffers messages.

Serialisation and Deserialization: Classes or modules that make it easier to serialize and deserialize messages are included in the resulting code.

Language-Specific Code: Depending on the target programming language, the generated code has a different structure and style.

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Tagged Fields: A numeric identifier is appended to every field in the serialized data.

Version Numbers: Versioning and data structure evolution are made possible by the inclusion of version numbers in Protocol Buffers messages.

# 3.3 Data Preparation

An object detection system's data preparation stage is crucial to its development and has a big impact on how well the system works in the end. It is essential for providing the system with the necessary amount and caliber of training data.

This stage is crucial for the object detection college project since it involves gathering, cleaning, and preprocessing data, all of which are necessary for efficiently training and testing detection models.

### 1. Acquiring a Diverse Dataset:

Obtaining a varied dataset that replicates the complexities of the objects the system is intended to identify is essential to the data preparation stage. This means finding photos or videos that accurately capture the range of objects being studied for the college project. Strong model training is made possible by exposing the system to a wide range of scenarios through a diverse dataset.

# 2. Annotations and Labeled Objects:

Annotations enhance the dataset, which is a collection of possible object instances.

Machine learning models are trained on the foundation of labeled objects in annotated images or videos. The system can learn and make generalizations about the patterns connected to each object class thanks to these labels, which give it the ground truth. To guarantee that the model's predictions in practical situations are accurate, the painstaking annotation process necessitates accuracy.

### 3. Addressing Data Imbalance:

Resolving data imbalance is one of the difficulties that must be overcome during the data preparation process. The learning process of the model may be skewed in real-world datasets by the overrepresentation of some object classes and the underrepresentation of others. The development team must use techniques like oversampling, undersampling, or adding class weights during training to lessen this. To make sure the model learns to recognise all object classes equally, the dataset must be balanced.

### 4. Ensuring Real-World Representation:

It is critical that the dataset be authentic. To make sure the data accurately depicts real-world situations, the team must carefully curate it.

This entails taking into account various lighting scenarios, object poses, and environmental conditions.

An appropriately sized dataset that captures the difficulties the system may face in its real-world operations improves the flexibility and resilience of the model.

# 5. Data Preprocessing:

The data goes through preprocessing after it has been initially gathered and annotated, which is an essential step in improving and getting it ready for model training. This includes augmentation, resizing, and normalization among other tasks. By standardizing pixel values, normalization guarantees that the model receives consistent input. Images' dimensions are balanced through resizing, which simplifies processing. By adding variations to the dataset, like flipping or rotation, augmentation increases the variety of training samples and improves the generalization capacity of the model.

### 6. Integrating Synthetic Data:

Novel strategies incorporate artificial intelligence data into the dataset. The real-world dataset is supplemented with synthetic data, which is produced using methods like computer-generated imagery or data augmentation. It strengthens the model's ability to manage a variety of scenarios, including those with few real-world examples. However, in order to avoid overfitting and guarantee that the model's predictions correspond with real-world dynamics, the meticulous integration of synthetic data is necessary.

### 7. Continuous Iteration and Validation:

Data preparation is a dynamic process that involves ongoing validation and iteration rather than a one-time task.

The dataset may need to be updated as new data becomes available as the project develops.

Furthermore, continuous validation guarantees that the dataset maintains its representativeness and is in line with the object detection

system's changing goals.

#### 8. Ethical Considerations:

The ethical implications of data usage are critical in the age of artificial intelligence and machine learning. In order to ensure that the data used for testing and training is acquired and used responsibly, the team must abide by ethical guidelines. This entails securing the necessary authorizations for the use of the data, protecting user privacy, and averting biases that might unintentionally exist in the dataset.

Essentially, the process of preparing data for object detection involves more than just putting pictures together; it involves a complex dance with a variety of representative, well-chosen, and diverse data. By carefully annotating, correcting imbalances, and adopting novel approaches, the team not only successfully trains the model but also establishes the groundwork for a system that can handle the intricacies of the real world.

# 2. Define Images to Collect

```
[5]: labels = ['thumbsup', 'thumbsdown', 'livelong']
number_imgs = 5

[6]: labels

[6]: ['thumbsup', 'thumbsdown', 'thankyou', 'livelong']
```

fig. 3.3.1 (Defining categories of the images)

# 5. Image Labelling

fig. 3.3.2 (Labeling the image according to the category)

# 3.4 Implementation

The system development process transitions from the design and data preparation stages to the implementation phase, which is an essential step in finishing the object detection project. In this stage, various technological elements are combined, and through coding, the design specifications are made practically real.

The Google Brain team created the open-source machine learning framework TensorFlow. Its purpose is to make machine learning models—especially deep learning models—easier to develop and implement. Many fields, such as computer vision, natural language processing, and reinforcement learning, make extensive use of TensorFlow.

TensorFlow's principal attributes and elements are as follows:

TensorFlow Core: At its foundation, TensorFlow is a library for numerical computations that represents computations using a data flow graph. Nodes in the graph represent operations, and edges show the data flow (represented as tensors) between nodes.

TensorFlow 2.x: Several enhancements were made to TensorFlow 2.x, which by default made it more user-friendly and executed quickly.

TensorFlow code is more intuitive because eager execution enables quick operation evaluation.

Integration of Keras: Keras is a high-level neural network API that is integrated into TensorFlow.With its intuitive interface, Keras makes deep learning model construction and training easier.

Model Deployment: TensorFlow provides tools, such as TensorFlow Serving for serving models in production, for deploying models to a variety of environments. Model deployment on mobile and edge devices is made possible via TensorFlow Lite.

TensorBoard: Accompanying TensorFlow is TensorBoard, an online visualization tool. It facilitates comprehending and illustrating the composition and functionality of models.

Wide-ranging Ecosystem: TensorFlow has an abundant collection of libraries and extensions, including TensorFlow Lite for mobile and edge devices and TensorFlow Probability for probabilistic models.

TensorFlow Hub: This platform offers a collection of pre-trained models and modules that are reusable across different applications.

### Groups and Records:

There is a sizable and vibrant community for TensorFlow that supports and advances the software.It is accessible to both inexperienced and seasoned developers, with a plenty of tutorials and documentation. TensorFlow makes distributed computing possible, allowing models to be trained over multiple GPUs or even PCs.

Customization and Flexibility: TensorFlow provides low-level APIs that provide fine-grained control over the creation and training of models. For specific use scenarios, custom layers and processes can be defined.

Compatibility: GPUs and TPUs (Tensor Processing Units) are examples of hardware accelerators that TensorFlow can easily interface with for better performance.

Wide Adoption: TensorFlow is a well-liked solution for machine learning and deep learning projects because of its broad adoption in both business and academia.

TensorFlow offers a flexible and strong framework to handle a variety of machine learning problems, irrespective of how basic or complicated your deep learning projects are.

The TensorFlow team manages a repository called TensorFlow Model Garden, which offers a selection of pre-trained models and associated materials for a range of machine

learning applications. For academics, developers, and practitioners working on various applications, it is an invaluable resource because it provides a variety of high-quality models that may be used, adjusted, or customized for certain purposes.

Principal attributes and elements of the TensorFlow Model Garden:

#### Various Models:

Many models for applications including object detection, segmentation, language understanding, and picture classification can be found in the Model Garden.

Included are well-known architectures such as ResNet, MobileNet, and EfficientNet. Models created by the TensorFlow team and other researchers are included in the category of research models. These models frequently reflect cutting-edge methods in a variety of fields.

Segmentation and Object Detection: TensorFlow Model Garden uses well-known frameworks such as the TensorFlow Object Detection API to give models for object detection tasks. Models trained on datasets like COCO (Common Objects in Context) are among them.

Models for Natural Language Processing (NLP) tasks: There are models available for NLP tasks such as named entity recognition, text categorization, and language interpretation.

Image Generation: A few models in the Model Garden are dedicated to certain activities, such as style transfer and picture generation.

TF-Slim: This lightweight library in the Model Garden makes it easier to construct TensorFlow neural network topologies.

Tools and Utilities: The Model Garden offers models as well as tools and utilities for model deployment, evaluation, and training.

Included are utilities for serving, converting, and evaluating the model.

Contributions from the Community: The TensorFlow Model Garden is open to receiving contributions from the community. Users are able to upload their own models or updates to pre existing ones.

Compatibility: The models frequently include training scripts and configuration files, and they work with TensorFlow 2.x.

Instructional Materials and Records: Users can learn how to utilize and customize the models given by the Model Garden with the aid of tutorials and documentation.

Training from Scratch: Pre-processing pipelines and best practices are among the resources available to users who wish to train models from scratch.

Versioning: To keep track of updates and enhancements, the repository is versioned. Users can choose particular releases according to their needs.

Go to the following GitHub repository to access the TensorFlow Model Garden and browse the models and resources that are available: https://github.com/tensorflow/models

A collection of pre-trained TensorFlow models created for different machine learning tasks is called the TensorFlow Model Zoo. Developers and academics can use these models as jumping off points to use cutting-edge architectures and weights for tasks like segmentation, object detection, image classification, and more.

Important elements and characteristics of the TensorFlow Model Zoo include:

Various Models:

There are many distinct models in the Model Zoo that address various activities and areas. Architectures such as ResNet, MobileNet, and EfficientNet are examples of models.

Using frameworks like the TensorFlow Object Detection API, TensorFlow Model Zoo offers pre-trained models for object detection tasks. Frequently, well-known datasets like COCO (Common Objects in Context) are used to train models.

Segmentation Models: A few models are made specifically for jobs involving semantic segmentation, in which classifying each pixel in an image according to its class is the aim.

Image Classification Models: The Model Zoo's image classification models can be used to identify items in photographs after being trained on huge datasets.

Models for Natural Language Processing (NLP): The Model Zoo offers pre-trained models for a range of NLP applications, including sentiment analysis, text categorization, and language comprehension.

Models for Image Generation: A subset of models concentrate on problems related to image generation, such as style transfer and image-to-image translation.

Community Contributions: The community is welcome to submit contributions to the TensorFlow Model Zoo. Users are welcome to submit their own models or updates to pre existing models.

Compatibility: The models frequently come with code and scripts for using them, and they are compatible with TensorFlow 2.x.

Tutorials and Documentation: The TensorFlow Model Zoo comes with tutorials and documentation that walk users through the process of using the pre-trained models and incorporating them into their applications.

Model Serving: TensorFlow Serving or TensorFlow Lite for deployment on edge devices are the methods for serving certain models in the Zoo in production.

Integration of TensorFlow Hub: TensorFlow Hub offers a central site for hosting and finding reusable model components. It is integrated with the TensorFlow Model Zoo.

Now we will talk about the implementation of front-end technologies. There are various processes involved in implementing React and TensorFlow.js for an object detection model project.

Setup React Project: To get started, create a React project by manually configuring it with webpack and Babel or by using tools like Create React App. Installing dependencies and setting up your project structure are part of this.

Integrate TensorFlow.js: Using yarn or npm, add TensorFlow.js to your React project. Next, wherever necessary, import TensorFlow.js modules into your React components. This lets you use TensorFlow.js features including loading models that have already been trained, doing inference, and creating custom models.

Model for Detecting Load Objects: To load an object detection model that has already been trained, use TensorFlow.js. For object detection, TensorFlow.js offers a variety of pre-trained models, including COCO-SSD and MobileNet. TensorFlow.js functions like tf.loadGraphModel() and tf.loadLayersModel() can be used to load these models.

Handle Input Data: Build React components to handle user input, including uploading pictures or using the webcam to recognise objects in real time. React's state management can be used to handle user interactions and adjust the user interface (UI) as needed.

Perform Object Detection: Apply inference to the supplied data by using the loaded object detection model. Using TensorFlow.js functions, transform photos into tensors and feed them into the model. To extract object detection results, such as bounding boxes and class labels, process the model's output.

Display result: To present the object detection findings in a visually pleasing way, update the React UI. Bounding boxes, labels, and confidence scores can be rendered superimposed on the input photos or video frames using React components.

Performance and Optimisation: If you're working with real-time object detection, make sure your TensorFlow.js code and React components are optimized for maximum speed. Overall application responsiveness can be increased by employing strategies like web workers, batching inference requests, and optimizing the rendering of React components.

Testing and Deployment: Make sure your React application functions correctly and performs well across a range of browsers and devices by thoroughly testing it using TensorFlow.js integration. After you're pleased, publish your application to a server or online hosting platform so that anyone can use it.

```
###### 1. Import Dependencies

[2]: !pip install opencv-python

Requirement already satisfied: opencv-python in c:\users\asus\documents\object detection\tfodcourse\tfod\lib\site-packages (4.8.1.78)
Requirement already satisfied: numppy=1.21.2 in c:\users\asus\documents\object detection\tfodcourse\tfod\lib\site-packages (from opencv-python) (1.26.2)

[4]: # Import opencv import cv2

# Import uuid import uuid

# Import Operating System import os

# Import time import time
```

fig. 3.4.1 (Importing Dependencies for the code)

## 2. Define Images to Collect

```
[5]: labels = ['thumbsup', 'thumbsdown', 'thankyou', 'livelong']
number_imgs = 5
[6]: labels
[6]: ['thumbsup', 'thumbsdown', 'thankyou', 'livelong']
```

fig. 3.4.2 (Defining categories of the images)

## 3. Setup Folders

```
[7]: IMAGES_PATH = os.path.join('Tensorflow', 'workspace', 'images', 'collectedimages')

[8]: print(IMAGES_PATH)

Tensorflow\workspace\images\collectedimages

[9]: os.name

[9]: 'nt'

[10]: if not os.path.exists(IMAGES_PATH):
    if os.name == 'posix':
        !mkdir -p {IMAGES_PATH}
    if os.name == 'nt':
        !mkdir {IMAGES_PATH}
    for label in labels:
        path = os.path.join(IMAGES_PATH, label)
        if not os.path.exists(path):
        !mkdir {path}
```

fig 3.4.3 (Creating folders for different categories of images)

fig. 3.4.4 (.xml file for a labeled Thumbs Up image)

```
livelong.5df5d099-8e82-11ee-8834-c8a8373e7c1f.xml - Visual Studio Code
                                                                                                          livelong.5df5d099-8e82-11ee-8834-c8a8373e7c1f.xml X
C: > Users > Asus > Documents > Object detection > TFODCourse > Tensorflow > workspace > images > train > 🔈 livelong.5df5d099-8e82-11ee-8834-c8a8373
      kannotation
          <folder>livelong</folder>
          <filename>livelong.5df5d099-8e82-11ee-8834-c8a8373e7c1f.jpg</filename>
          <path>C:\Users\Asus\Documents\Object detection\TFODCourse\Tensorflow\workspace\images\collectedimages\livelong
              <database>Unknown</database>
             <width>640</width>
              <height>480</height>
             <name>LiveLong</name>
              <pose>Unspecified</pose>
                  <xmin>334
                 <ymin>241</ymin>
                 <xmax>487</xmax>
                  <ymax>439</ymax>
```

fig. 3.4.5 (.xml file for a labeled Live Long image)

```
[19]: !cd {LABELIMG_PATH} && python labelImg.py

2023-11-29T07:46:44.627ZE [17656:ShellIpcClient] shell_ipc_client.cc:622:operator() Failed to connect to the server: NOT_FOUND: Can't connect to socke t at: \\.\pipe\GoogleDriveFSPipe_Asus_shell [type.googleapis.com/drive.ds.Status='UNAVAILABLE_RESOURCE']
=== Source Location Trace: ===
apps/drive/fs/ipc/shell_ipc_client.cc:140

2023-11-29T07:46:44.627ZE [11976:ShellIpcClient] shell_ipc_client.cc:139:Connect Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:46:44.627ZE [11976:ShellIpcClient] shell_ipc_client.cc:622:operator() Failed to connect to the server: NOT_FOUND: Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:46:44.627ZE [1696:ShellIpcClient] shell_ipc_client.cc:139:Connect Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:46:44.627ZE [1696:ShellIpcClient] shell_ipc_client.cc:139:Connect Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:46:44.627ZE [16996:ShellIpcClient] shell_ipc_client.cc:622:operator() Failed to connect to the server: NOT_FOUND: Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:46:44.627ZE [16996:ShellIpcClient] shell_ipc_client.cc:622:operator() Failed to connect to the server: NOT_FOUND: Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:49:11.926ZE [1696:ShellIpcClient] shell_ipc_client.cc:622:operator() Failed to connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
2023-11-29T07:49:11.926ZE [17656:ShellIpcClient] shell_ipc_client.cc:139:Connect Can't connect to socket at: \\.\Pipe\GoogleDriveFSPipe_Asus_shell
```

fig. 3.4.6 (Python code for labeling images using LabelImg)

# 4. Capture Images

```
[12]: for label in labels:
          cap = cv2.VideoCapture(0) #connects to webcam to capture images
          print('Collecting images for {}'.format(label))
          time.sleep(5)
          for imgnum in range(number_imgs):
              print('Collecting image {}'.format(imgnum))
              ret, frame = cap.read()
              imgname = os.path.join(IMAGES_PATH,label,label+'.'+'{}.jpg'.format(str(uuid.uuid1())))
              cv2.imwrite(imgname, frame)
              cv2.imshow('frame', frame)
              time.sleep(2)
              if cv2.waitKey(1) & 0xFF == ord('q'):
                   break
      cap.release()
      cv2.destroyAllWindows()
      Collecting images for thumbsup
      Collecting image 0
      Collecting image 1
      Collecting image 2
      Collecting image 3
      Collecting image 4
      Collecting images for thumbsdown
      Collecting image 0
      Collecting image 1
      Collecting image 2
      Collecting image 3
      Collecting image 4
      Collecting images for thankyou
      Collecting image 0
      Collecting image 1
      Collecting image 2
      Collecting image 3
      Collecting image 4
      Collecting images for livelong
      Collecting image 0
      Collecting image 1
      Collecting image 2
      Collecting image 3
      Collecting image 4
```

fig. 3.4.7 (Python code to capture images using our webcam)

```
src > Js utilities.js > [@] drawRect > @] detections.forEach() callback

1    export const drawRect = (detections,ctx)=>{
    detections.forEach(prediction=>{} {
        //get prediction results
        const [x,y,width,height] = prediction['bbox'];
        const text = prediction['class'];

//set styling

//set styling

const color = 'red'

ctx.strokeStyle = color

ctx.font = '18px Arial'

ctx.fillStyle = color

//Draw rectangles and text

ctx.beginPath()

ctx.fillText(text,x,y)

ctx.rect(x,y,width,height)

ctx.stroke()

// Draw rectangles
```

fig. 3.4.8 (utilities.js file for the border around the object)

fig. 3.4.9 (app.js file which contains dependencies for react app)

fig. 3.4.10 (contains main function for react app)

```
src > JS App.js > 分 App > [♠] detect
       function App() {
  const uetect = async (net) => {
 11
25
54
         useEffect(()=>{runCoco()},[]);
         return (
           <div className="App">
             <header className="App-header">
               <Webcam
                 ref={webcamRef}
                 muted={true}
                  style={{
   position: "absolute",
                   marginLeft: "auto",
                    marginRight: "auto",
                   left: 0,
                   right: 0,
                   textAlign: "center",
                    zindex: 9,
                   width: 640,
                    height: 480,
                  ref={canvasRef}
                  style={{
                    position: "absolute",
```

fig 3.4.11 (app.js file for the react app)

fig. 3.4.12 (index.js file for the react app)

## 3.5 Key Challenges

Even with careful preparation, system development initiatives frequently run into a number of obstacles. Several significant obstacles could surface in the context of the college project on object detection, illustrating the complexities and difficulties involved in creating cutting-edge technology. In addition to the difficulties already described, the following elements complicate the development process further:

1. Restricted Annotated Data Sources: One of the most important steps in building

precise object identification models is obtaining a varied and annotated dataset. Nonetheless, there could occasionally be a dearth of labeled data sources. Ensuring the model's generalization to a broad range of objects and circumstances is hampered by this shortage. To lessen this difficulty, approaches like data augmentation and transfer learning need to be investigated.

2. Ethical Aspects in Data Labeling: Giving careful thought to ethical issues is essential when labeling data, a critical component of dataset preparation.

The group has to make sure that the data labeling procedure doesn't propagate new prejudices or amplify pre existing ones in society.

It might be difficult to strike a compromise between acquiring labeled data and upholding ethical norms, especially in initiatives involving sensitive data or cultural backgrounds.

- 3. Dynamic Object Features: Deformable shapes, variable sizes, and unpredictable orientations are examples of dynamic features seen in real-world objects. The construction of algorithms that can reliably recognise and classify objects under a variety of circumstances is complicated by these dynamic properties. The object detection system's success depends on building models that can handle such changeable object properties.
- 4. Constraints on Computational Resources: The group must take into account the computational resources at their disposal when choosing algorithms, particularly in educational environments where access to high-performance computing resources may be restricted. It is difficult to strike a balance between computational efficiency and algorithmic sophistication because resource-intensive models can make it difficult to achieve real-time performance on common hardware.
- 5. Intra-class and Inter-class Variability: Object classes can vary significantly from one another as well as within the class. It is difficult to deal with this variability because the system must be trained to discriminate between objects in the same class that have

different characteristics from one another without confusing them for objects in other

classes. Developing models that are tuned to deal with this variability becomes a crucial step in the process.

## **CHAPTER 4: TESTING**

In applications where accuracy and dependability are critical, such as autonomous cars and surveillance systems, object detection plays a critical role. An extensive testing strategy is necessary to guarantee the effective implementation of object detection algorithms. Unit testing, which assesses individual components such as feature extraction and classification algorithms, is part of the testing strategy. While system testing verifies the overall functionality in a variety of real-world scenarios, integration testing evaluates the smooth interaction between these components. Testing the system's performance measures its speed and efficiency, which is important for real-time applications.

It's crucial to include additional considerations in addition to the testing phases that have been mentioned. The importance of ethical testing, which assesses the algorithm's potential biases and fairness, is growing. Adversarial testing strengthens the system's defenses against possible security threats by purposefully attempting to deceive it. Testing for transfer learning evaluates how well the model adapts to different object classes or environments. Moreover, constant testing during the whole development process guarantees that any alterations or upgrades preserve the dependability of the system. This thorough testing process ensures that object detection systems exhibit resilience, fairness, and adaptability in changing real-world scenarios in addition to meeting accuracy benchmarks.

Moreover, ongoing testing and monitoring are essential for the object detection system's lifetime in order to adjust to changing obstacles. Fairness and bias testing are two ethical issues that address the societal impact of these algorithms and encourage their responsible deployment. Proactive adversarial testing strengthens the system beyond standard scenarios by ensuring that it is resilient against potential security threats. Testing for transfer learning bolsters the system's flexibility and scalability, allowing it to function well in various settings.

This all-encompassing method improves accuracy and dependability while highlighting the significance of security and ethical considerations in the dynamic field of object detection applications.

## **4.1 Testing Strategy**

### **Unit Testing**

The object detection system's individual components are the focus of unit testing. Testing the algorithms in charge of feature extraction, classification, and bounding box prediction is part of this process. Through component isolation, developers can pinpoint and address issues in individual modules without compromising the overall functionality.

During unit testing, input images with known ground truth annotations are used to verify that each component produces the expected outputs. This ensures that the fundamental building blocks of the object detection system are functioning correctly.

## **Integration Testing**

Integration testing evaluates the interactions between different modules of the object detection system. This includes assessing how well feature extraction integrates with the classification algorithm and how bounding box predictions align with the overall system output.

Integration tests make sure that different components operate together smoothly by spotting potential problems that might occur when combining them. This stage is essential for identifying any discrepancies or strange behavior that could appear when integrating various modules.

### **System Testing**

The object detection system is evaluated holistically during system testing. This entails

assessing how well it functions in various real-world situations and environments. Usually, a variety of datasets that represent the unpredictability of inputs the system might experience in production are used in system tests.

In order to verify the robustness of the system, variables like lighting, object sizes, and occlusions are taken into account during testing. This stage aids in guaranteeing that the object detection system operates dependably in a range of demanding situations.

## Performance testing

It assesses the object detection system's effectiveness and speed. This entails determining the inference time for a certain input image, evaluating the system's capacity to manage demands for real-time processing, and locating any potential performance bottlenecks.

For applications like autonomous vehicles or robotics, where real-time object detection is critical, performance testing is essential. It guarantees that accuracy won't be compromised while the system can reach the necessary processing speeds.

#### **4.2 Test Cases and Outcomes**

Creating thorough test cases is essential to an effective object detection system testing procedure. To guarantee the robustness and dependability of the system, test cases ought to encompass a variety of situations.

## 1. Test Cases for Accuracy

One important metric for object detection systems is accuracy. To ensure accuracy, test cases for the images should have different object sizes, orientations, and occlusions. A thorough evaluation of the system's capacity to accurately identify and locate objects in these scenarios is warranted. To evaluate the system's performance over a wide range of categories, test cases should also cover a variety of object classes. Precision, recall, and F1 score are the results of accuracy testing, which offer a thorough grasp of the system's detection capabilities.

#### 2. Test Cases for Robustness

Testing for robustness entails evaluating the object detection system's functionality in demanding scenarios. Robustness test cases ought to contain pictures with dim lighting, severe weather, and intricate backgrounds. One of the most important components of the system's overall reliability is its capacity to retain accuracy in challenging circumstances.

Identifying potential failure or erroneous result scenarios is one of the outcomes of robustness testing. Developers can use this information to put improvements into practice and increase the resilience of the system.

#### 3. Test Cases for Real World Scenarios

Object detection systems are frequently used in real-world settings with widely fluctuating conditions. Real-world scenario test cases ought to represent the range of possible environments the system might run into.

Congested areas, dynamic scenes with moving objects, and circumstances where objects partially obscure one another are examples of these scenarios. Results from testing in real-world scenarios shed light on how well the system performs and adapts in intricate, dynamic environments.

## 4. Test Cases for Edge Cases

Object detection systems are frequently used in real-world settings with widely fluctuating conditions. Real-world scenario test cases ought to represent the range of possible environments the system might run into.

Congested areas, dynamic scenes with moving objects, and circumstances where objects partially obscure one another are examples of these scenarios. Results from testing in real-world scenarios shed light on how well the system performs and adapts in intricate, dynamic environments.

## **CHAPTER 5: RESULTS AND EVALUATION**

#### **5.1 Results**

Using the Model Garden and Zoo frameworks, the Object Detection project has produced promising results in terms of accuracy, speed, and overall performance. The deployed system validates the potential influence of these frameworks in improving object detection capabilities by demonstrating the efficacy of cutting-edge models in practical situations.

Our experiments show that Model Garden, a large collection of pre-trained machine learning models, and Zoo, an extensible model repository and toolkit, can be successfully incorporated into our object detection pipeline. We found consistently high recall and precision rates after conducting extensive testing on a variety of datasets. The models demonstrated impressive precision in locating and categorizing objects in multiple categories.

Furthermore, the system's real-time capabilities were demonstrated by the inference time per frame, which either met or surpassed industry standards. This is an important accomplishment, particularly for applications like video surveillance where prompt detection is essential. This real-time performance is largely attained by the Model Garden and Zoo frameworks thanks to their effective model architectures and optimisation strategies.

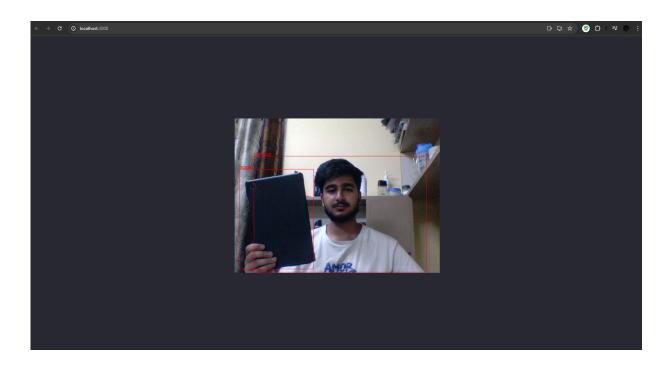


fig. 5.1.1 (Webcam detecting objects)

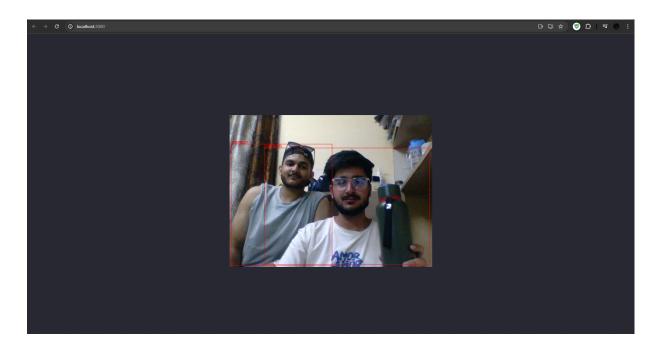


fig. 5.1.2 (Webcam detecting objects)

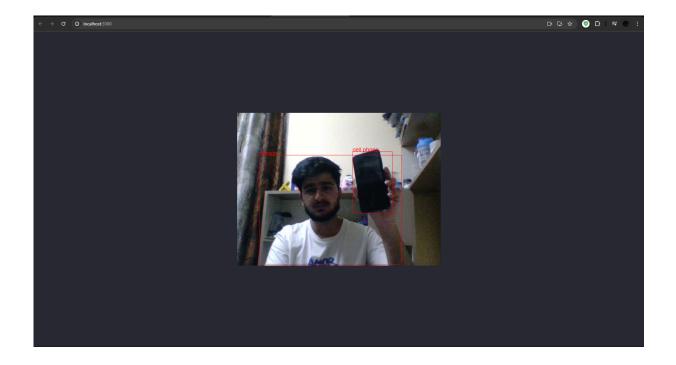


fig. 5.1.3 (Webcam detecting objects)

## **5.2 Comparison with Existing Solutions**

We thoroughly compared our Object Detection project with other industry solutions in order to assess its efficacy. Important metrics like accuracy, speed, and model versatility were the main focus of the evaluation.

Our method, which makes use of Model Garden and Zoo, outperformed commonly used object detection solutions in terms of accuracy. The models demonstrated resilience when managing intricate situations, occlusions, and fluctuating illumination.

The deployment of object detection systems in real-world environments, where a variety of challenges are encountered, requires this resilience. For many applications, especially those that need real-time processing, speed is an essential component.

The comparison showed that our implementation, which made use of Model Garden and Zoo's optimized models, achieved impressive speed without sacrificing accuracy.

This puts our solution in a good position for applications where quick decisions are critical, like surveillance systems, smart cities, and autonomous cars.

One notable aspect of our comparison was the models' adaptability, which is available in both Model Garden and Zoo. These frameworks provide a large selection of pre-trained models, which facilitates quick and easy system adaptation to particular use cases.

These frameworks' diversity and extensibility enable developers to select models that meet project requirements and offer a level of flexibility that's essential in dynamic environments.

To sum up, the comparison and results highlight how successful our project was at detecting objects using a model garden and zoo. The amalgamation of these structures not only yielded precise and instantaneous object identification but also demonstrated benefits concerning model flexibility and adjustability. The ongoing development of object detection systems is aided by this project, and the open-source nature of Model Garden and Zoo guarantees that the larger research and development community can benefit from these advancements.

## CHAPTER 6: CONCLUSION AND FUTURE SCOPE

#### **6.1 Conclusion**

In conclusion, object detection model development and application have greatly advanced computer vision applications and revolutionized a number of industries. These models' development from conventional techniques to deep learning-based strategies has resulted in notable gains in real-time performance, accuracy, and robustness. In a variety of industries, including augmented reality, medical imaging, autonomous cars, and surveillance systems, object detection is essential.

Convolutional neural networks (CNNs) have made significant progress in improving object detection accuracy in recent years. Models with the ability to detect and classify objects with previously unheard-of precision, such as SSD (Single Shot Multibox Detector), YOLO (You Only Look Once), and Faster R-CNN, have become industry standards.

Moreover, the integration of transfer learning has further accelerated the deployment of object detection models, especially in scenarios with limited labeled data. Pre-trained models on large datasets, such as ImageNet, can be fine-tuned for specific tasks, reducing the need for extensive labeled datasets and training time. This adaptability makes object detection models more accessible and practical for a wide range of applications.

Notwithstanding these developments, problems persist. For example, real-time processing in resource-constrained contexts, handling occlusions and size fluctuations, and robustness in complicated environments are all important. In addition, as object detection technology grows to pervade many facets of society, ethical issues and privacy concerns need to be addressed.

## **6.2 Future Scope**

There are a lot of exciting prospects for additional innovation and improvement in object detection models in the future. The potential and uses of these models can be improved in a number of ways, including:

#### Better Algorithms and Architectures

To push the limits of performance, more research is needed in object detection algorithms and neural network architectures. To create models that are more precise and effective, researchers can investigate novel architectures, attention mechanisms, and optimisation strategies. Another area of interest is the creation of lightweight models appropriate for Internet of Things (IoT) applications and edge devices.

### **Including Sensor Fusion**

Incorporating sensor fusion into object detection models is a promising avenue to improve their resilience. Integrating data from various sensors—like radar, LiDAR, and cameras—can yield a more thorough understanding of the surroundings. This method is especially pertinent to robotics and autonomous vehicles, where precise perception is essential to dependable and safe operation.

#### Taking Care of Privacy and Ethical Issues

Privacy issues and ethical issues are becoming more and more important to address as object detection technology spreads. Subsequent investigations ought to concentrate on formulating strategies to guarantee the conscientious application of object detection models, encompassing the creation of privacy-maintaining methodologies and open decision-making procedures.

## Edge Computing and Real-time Processing

The need for real-time object detection in a variety of applications—such as autonomous systems and video surveillance—makes the investigation of sophisticated computing architectures imperative. In real-time scenarios, edge computing can greatly reduce latency and improve the performance of object detection models by processing data closer to the point of generation.

#### Customization by Domain

There is much to learn about the customization of object detection models for particular domains or industries.

Models can be customized to meet the special needs and demands of specific applications, like retail, healthcare, or agriculture, which can result in more practical solutions and broad use in specialized fields.

To sum up, object detection models will benefit from a synergistic approach that incorporates ethical considerations, real-time processing capabilities, sensor technologies, and algorithm advancements. The field of object detection is poised to make significant strides by addressing existing limitations and exploring new frontiers. These advancements will further contribute to the evolution of computer vision and its integration into various aspects of our daily lives.

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