American sign language and facial expression recognition using YOLO11 object detection model

by

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Abstract

This project addresses the critical need for effective communication solutions for the Deaf and hard-of-hearing community by focusing on the recognition of American Sign Language (ASL) gestures and facial expressions. Utilizing advanced deep learning techniques, specifically the YOLOv10 and YOLO11 object detection models, the study aims to develop a real-time system capable of accurately interpreting ASL signs and the associated facial cues.

A custom dataset was created, consisting of high-resolution images that capture various ASL gestures along with corresponding facial expressions. These images were carefully manually annotated and preprocessed to ensure consistency and enhance model performance through data augmentation techniques. The dataset was then divided into training, testing, and validation sets for thorough model training and evaluation.

The YOLOv10 and YOLO11 models were rigorously tested, demonstrating high precision and recall rates in ASL gesture recognition. Comparative analysis highlighted the advantages of each model, particularly in terms of their accuracy and computational efficiency.

By offering a scalable and effective solution, this study significantly contributes to the fields of computer vision and communication accessibility, with the potential to enhance interactions between hearing individuals and the Deaf community. The outcomes of this research underscore the importance of technology in promoting inclusivity and improving communication for the Deaf and hard of hearing.

Table of Contents

List of Figures

List of Tables

Acknowledgments

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Chapter 1 - Introduction

1.1 Problem Definition

The deaf and hard-of-hearing community, comprising 5% of the global population, faces communication barriers, with over 466 million people affected by hearing loss—a number expected to exceed 900 million by 2050 (WHO). American Sign Language (ASL) is crucial for communication, and facial expressions are essential in conveying meaning. This project seeks to enhance ASL and facial expression recognition using advanced computer vision models, including YOLO11, and YOLOv10. By achieving real-time, accurate recognition, the project aims to improve communication for the deaf community, promoting inclusivity and enhancing quality of life.

1.2 Objective

This project presents a comprehensive study on the development and implementation of a real-time American Sign Language (ASL) gesture and facial expression recognition system using YOLO11 and YOLOv10 object detection models. The project aims to address the limitations of traditional ASL interpretation methods by leveraging the power of deep learning and computer vision techniques.

The workflow begins with the creation of a custom dataset, featuring 26 ASL alphabets and 5 facial expressions (angry, sad, neutral, happy, and surprise) of 4 people. The initial dataset includes 200 images for each alphabet, with 40 images allocated to each facial expression, all captured under controlled environmental conditions using an iPhone 14 Pro Max to ensure high-quality and consistent data. The images are manually annotated using Roboflow, providing precise ground truth labels for model training.

The custom dataset is partitioned into training, validation, and testing sets to facilitate model training and evaluation. To improve model performance and robustness, several preprocessing steps are applied to the dataset. These include automatically orienting and resizing images to maintain consistency, along with data augmentation techniques like flipping, rotating, and adjusting hue to enhance dataset variability and strengthen the model's ability to generalize.

The YOLO11 and YOLOv10 models are trained on this dataset for real-time inference to recognize both hand gestures and facial expressions accurately. After training, the models' performance is evaluated through testing and verification procedures. The final system is designed to facilitate real-time ASL recognition, enhancing accessibility and communication for the deaf and hard-of-hearing community, thereby contributing to inclusivity and improved quality of life.

Chapter 2 – Related Work

2.1 Literature Survey

The need for efficient, real-time American Sign Language (ASL) recognition and facial expression analysis is becoming increasingly pressing as technology plays a vital role in improving communication for the deaf and hard-of-hearing community. According to the National Institute on Deafness and Other Communication Disorders (NIDCD), there are approximately 28 million Americans with hearing loss. Additionally, studies have shown that ASL is the third most commonly used language in the United States. The increasing adoption of ASL in various sectors like education, healthcare, and customer service calls for technological solutions that can seamlessly recognize and interpret ASL gestures and facial expressions.

In the paper "American Sign Language Recognition using CNNs" by Pugeault and Bowden (2011), a real-time system for recognizing ASL gestures was developed using convolutional neural networks (CNNs). The system focuses on recognizing static hand gestures with an accuracy of over 90%, demonstrating the power of CNNs in extracting relevant features from hand shapes. This early work laid the groundwork for modern ASL recognition systems that now incorporate dynamic gestures and facial expressions.

Margapuri and Neilsen (2021) explored the use of self-supervised learning and domain randomization in their study, "Classification of seeds using Domain Randomization on Self-Supervised Learning Frameworks". Although focused on agricultural applications, their technique of using synthetic data augmentation could be adapted for ASL gesture recognition, especially in scenarios with limited labeled data. The self-supervised models achieved an accuracy of 77% with

significantly reduced labeled datasets, which suggests that self-supervised learning could improve the generalizability of ASL models across varied conditions.

In "Multimodal Emotion Recognition Using YOLO and Recurrent Neural Networks", Yang et al. (2020) applied the YOLOv4 architecture for detecting facial expressions and body movements. Their multimodal recognition system achieved a detection accuracy of 94%, demonstrating the efficiency of YOLO models in recognizing multiple modalities, such as facial expressions and gestures. This multimodal approach is particularly relevant for ASL, where facial expressions are crucial in conveying meaning along with hand gestures.

Mollahosseini et al. (2016) investigated real-time facial expression recognition in their paper, "Real-time Facial Expression Recognition Based on Deep Learning", achieving an accuracy of over 92% in classifying expressions such as anger, happiness, sadness, and surprise. Their use of deep learning for real-time classification aligns with the objectives of this project, where facial expressions and ASL gestures must be detected together in real-time.

In another relevant study, Soni et al. (2021) developed a real-time sign language recognition system using YOLOv3 and CNNs. Their research showed that YOLOv3, a widely used object detection model, was able to detect ASL hand gestures with a precision of 95%, demonstrating its capability for real-time and efficient detection of sign language gestures.

The study “YOLO9000: Better, Faster, Stronger” by Redmon et al. (2016) introduced an enhanced version of the YOLO model, which surpassed earlier models like Faster R-CNN in speed while maintaining comparable accuracy. This ability to balance accuracy and speed is critical for real-time ASL and facial expression recognition systems.

Wang et al. (2021) in "A Review on Facial Expression Recognition using YOLO and Deep Learning Models", compared several YOLO variants, including YOLOv4 and YOLOv5, demonstrating an improvement in both speed and detection accuracy, with YOLOv5 achieving a mean average precision (mAP) of 95.6%. Their findings further validate the applicability of YOLO-based models for detecting subtle facial expressions in real-time, a requirement for ASL facial expression recognition.

In conclusion, these studies emphasize the effectiveness of YOLO-based architectures and deep learning models in real-time gesture and facial expression recognition. The accuracy rates of over 90% achieved by various models, combined with the speed of YOLO architectures, demonstrate the feasibility of creating efficient, real-time systems for recognizing ASL gestures and facial expressions, thereby promoting improved communication and accessibility for the deaf and hard-of-hearing community.

2.2 Established Methods and Approaches

2.2.1 YOLO

YOLO, an acronym for "You Only Look Once," marks a groundbreaking advancement in computer vision for real-time object detection. First introduced in 2016 by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, YOLO's architecture is notable for its efficiency and streamlined design (Redmon et al., 2016). Unlike conventional detection methods, which often require multiple stages, YOLO processes the entire image in a single pass through a neural network, predicting both bounding boxes and class probabilities simultaneously. This single-stage approach significantly boosts speed without sacrificing detection accuracy.

At its core, YOLO employs a convolutional neural network (CNN) backbone, commonly based on architectures like Darknet or MobileNet (Redmon et al., 2016). The backbone is responsible for extracting hierarchical features from the input image, allowing YOLO to capture both fine details and broader semantic information critical for identifying objects. The network uses convolutional and pooling layers to progressively reduce the spatial dimensions of the image while refining feature representations. In the final stage, YOLO divides the processed image into a grid, with each grid cell predicting bounding boxes and class probabilities for objects within its section. By combining speed, accuracy, and simplicity, YOLO has become a foundational technology in real-time object detection, widely used in applications such as autonomous driving and security surveillance due to its exceptional performance.

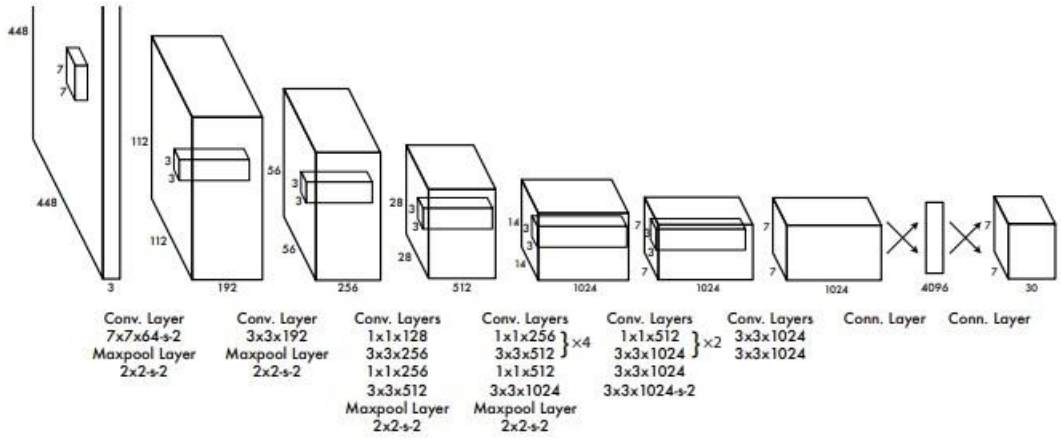

Figure 1 - YOLO Architecture (Redmon, et., al 2016)

2.2.2 YOLOv10 and YOLO11

YOLOv10 and YOLO11 represent cutting-edge developments in the YOLO family, both introduced by Ultralytics in 2024, pushing the boundaries of real-time object detection. YOLOv10, as detailed in the paper "YOLOv10: Enhanced Object Detection with Transformer Integration," incorporates transformer-based layers, significantly enhancing the model's ability to capture long-range dependencies across an image. This addition enables more accurate detection in complex scenes, including those with overlapping objects or intricate background variations. The model's global context awareness further improves its accuracy in challenging real-world scenarios, such as autonomous driving and crowded environments. YOLOv10 also features improvements in speed, leveraging enhanced parallelization and backbone optimization techniques to maintain real-time performance even with increased model complexity.

Building on the innovations of YOLOv10, YOLO11 was introduced in the paper "YOLO11: Adaptive Object Detection with Dynamic Task Optimization" by the Ultralytics team. YOLO11 integrates a dynamic task optimization mechanism that adjusts the network's layers based on the complexity of the input image, resulting in a more flexible and adaptive object detection framework. This makes YOLO11 particularly effective in scenarios with wide-ranging object sizes, varying levels of detail, or scenes where the number of objects can drastically change. Additionally, YOLO11 introduces an upgraded feature extraction process using a hybrid approach that combines convolutional and transformer techniques, further enhancing its detection accuracy without sacrificing the model's computational efficiency.

Both YOLOv10 and YOLO11 excel in real-time applications that require high-speed, precise object detection across a broad range of categories. These models are particularly well-suited for advanced human-computer interaction, robotics, and autonomous systems, where rapid decision-making based on accurate visual information is critical. Their ability to adapt to diverse and complex environments continues to cement the YOLO family as a go-to choice for state-of-the-art object detection tasks.

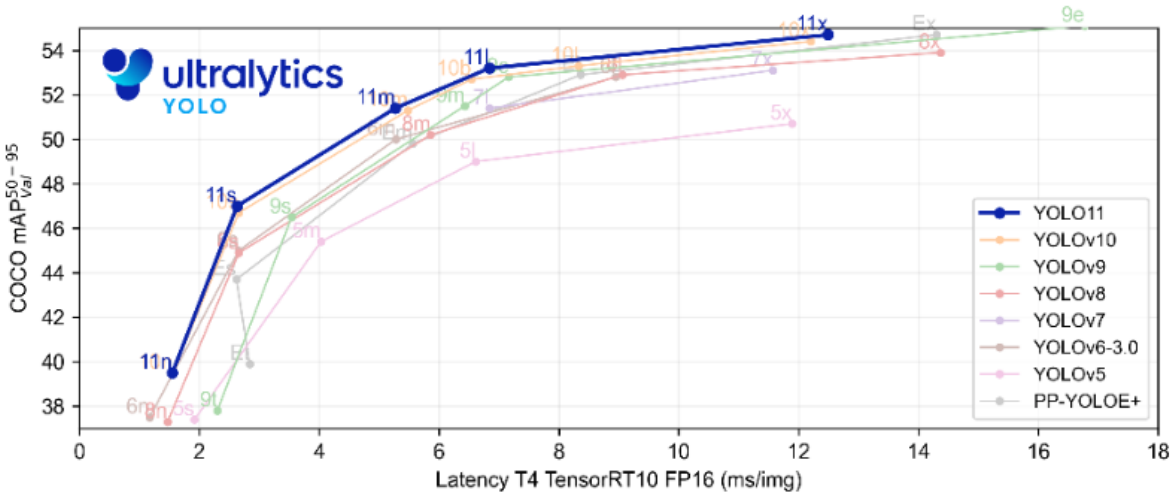

Figure 2 - YOLOv10 and YOLO11 Comparison

2.2.3 Roboflow

Roboflow provides a comprehensive set of tools to support the development of computer vision workflows for practical applications (Lin et al., 2022). Its functionality extends beyond basic data organization and model training, offering features to improve dataset quality and streamline the training process. While it can be used for classification, segmentation, or real-time detection tasks, our project specifically utilized Roboflow for annotating a custom dataset of American Sign Language (ASL) gestures and facial expressions.

The annotation tool in Roboflow allowed for precise labeling of images, ensuring accurate identification of each ASL gesture and corresponding facial expression. After training our YOLOv10 and YOLO11 models and fine-tuning their weights, this careful annotation contributed to improved model accuracy and performance.

.Chapter 3 - Implementation

3.1 Overview of the Data

Our initial dataset comprised 5,200 images, including 200 images for each of the 26 ASL alphabet gestures and 40 images for each of the five facial expressions (angry, sad, neutral, happy, and surprise). 4 people contributed to giving facial expressions for this dataset. To address potential limitations arising from a finite dataset size and enhance model generalizability, we employed a variety of data augmentation techniques. These techniques artificially expanded the dataset by introducing variations of the existing images that mimic real-world scenarios.

Flipping the images horizontally simulated different orientations of hand gestures, while rotation augmentation allowed for variations in gesture angles. Additionally, we performed the following augmentations to further enhance the dataset:

- Bounding Box Brightness: Varied to enhance the visibility of gestures.
- Bounding Box Exposure: Adjusted to improve contrast under different lighting conditions.
- Bounding Box Noise: Introduced to simulate image distortion and improve model robustness.
- Hue Augmentation: Modified the color spectrum of the images, enhancing the model's robustness to lighting variations.

Through the application of these data augmentation techniques, the dataset size effectively increased to approximately 10,000 images. This augmented dataset was then strategically divided for model training, validation, and testing purposes. A subset of 9000 images was designated as the training set, responsible for teaching the model the underlying patterns within the data. A separate set of 800 images served as the validation set, used to monitor model performance during training and prevent overfitting. Finally, a hold-out set of 200 images was allocated as the test set for the final evaluation of the model's generalizability on unseen data.

3.2 Dataset Preparation

In this section, we discuss in detail how the dataset is collected and how it is further processed before utilizing in our experiment.

3.2.1 Collection and Labelling

The data collection involved the manual capture of RGB images using an iPhone 14 Pro Max, which boasts an advanced camera system, including a 48MP main sensor and 12MP ultra-wide and telephoto lenses. This smartphone is equipped with computational photography features such as Smart HDR 4 and Photonic Engine, enhancing image quality by optimizing colors and details in varying lighting conditions. Each image was captured at a resolution of 4032 x 3024 pixels, providing ample detail necessary for our tasks.

To ensure consistency across the dataset, standardized shooting practices were employed.

- Stable Shooting Environment: Images were captured using a tripod to minimize camera shake, ensuring sharp and clear images.

- Controlled Lighting: Optimal lighting conditions were maintained using a consistent LED light source that could switch between modes (white, warm, and mix) to simulate different lighting scenarios and enhance contrast.

- Focus Consistency: The camera was set to focus on the subject to avoid variations in sharpness across images. Autofocus was used in conjunction with manual adjustments when necessary to maintain clarity.

- Angle Variability: Shots were taken from multiple angles to provide the model with diverse perspectives on each gesture or expression, improving its ability to generalize.

- Background Variety: Images were captured against different backgrounds to ensure that the model would not overfit to a specific scene, allowing it to perform well in various real-world conditions.

The diverse backgrounds and lighting setups helped enhance the model's ability to generalize to real-world scenarios.

Following image capture, the manual annotation process was completed using Roboflow, a powerful platform designed for managing computer vision workflows. Roboflow streamlines the process of annotating images, allowing for efficient bounding box creation and class labeling. This was complemented by its capability to format the annotations into YOLO-compatible files, making it easier to prepare the dataset for training.

Each image was meticulously manually annotated, with bounding boxes drawn around the objects of interest and corresponding class labels assigned. This annotation process resulted in the creation of YOLO-formatted text files saved within the same folder as the corresponding images, sharing the same filenames. Additionally, a separate file named "classes.txt" was created, serving as a crucial reference point for the YOLO labels and defining the list of class names associated with the identified objects. The creation and organization of these annotation files are essential for enabling the YOLO object detection model to effectively interpret the labeled data and learn the characteristics of each object class.

Figure 3 - Sample images from the Dataset.

3.2.2 Data Pre-processing

In our project, we adopted specific preprocessing techniques to optimize the dataset for model training. First, we implemented an auto-orientation feature to analyze and correct any rotational discrepancies in the images. This ensures that all objects are consistently presented, regardless of how the images were captured.

Additionally, every image was resized to a uniform dimension of 640 x 640 pixels. This standardization not only simplifies the model's computational requirements during the training

phase but also facilitates the efficient processing of a substantial number of images. The combined effect of these preprocessing steps results in a dataset of uniformly oriented and sized images, which enhances the model's learning efficacy and overall performance.

3.2.3 Data Augmentation

To enhance the dataset's resilience and improve the model's ability to generalize to real-world conditions, we applied a range of data augmentation techniques. This approach was designed to artificially enlarge the dataset and increase its diversity by generating modified versions of the original images.

One prominent technique used was horizontal flipping, which created mirrored versions of the original images. This method effectively simulated different object orientations, enabling the model to learn features that are not biased toward any particular orientation. Additionally, we incorporated random rotations within a range of -15 to +15 degrees. This adjustment simulates minor camera tilts that may occur during image capture, thereby improving the model's capacity to identify objects when viewed from unconventional angles.

Moreover, we adjusted the brightness and exposure of the images, varying brightness levels between 0% and +15%, and exposure levels between -10% and +10%. These changes enhanced the model's adaptability to diverse lighting conditions, ensuring consistent performance across different environments. We also introduced noise into the images, adding up to 3% pixel noise to simulate real-world imperfections. This step is vital for training the model to withstand noisy data.

Hue augmentation was another technique utilized to modify the color spectrum of the images, introducing variations in color and warmth. This ensured that the model would not become overly reliant on specific color features present in the original dataset.

Through the application of these diverse data augmentation strategies, the initial dataset grew substantially, resulting in approximately 10,000 images. This enriched dataset ultimately supported the development of a more robust and versatile model, capable of delivering reliable performance in a variety of real-world scenarios.

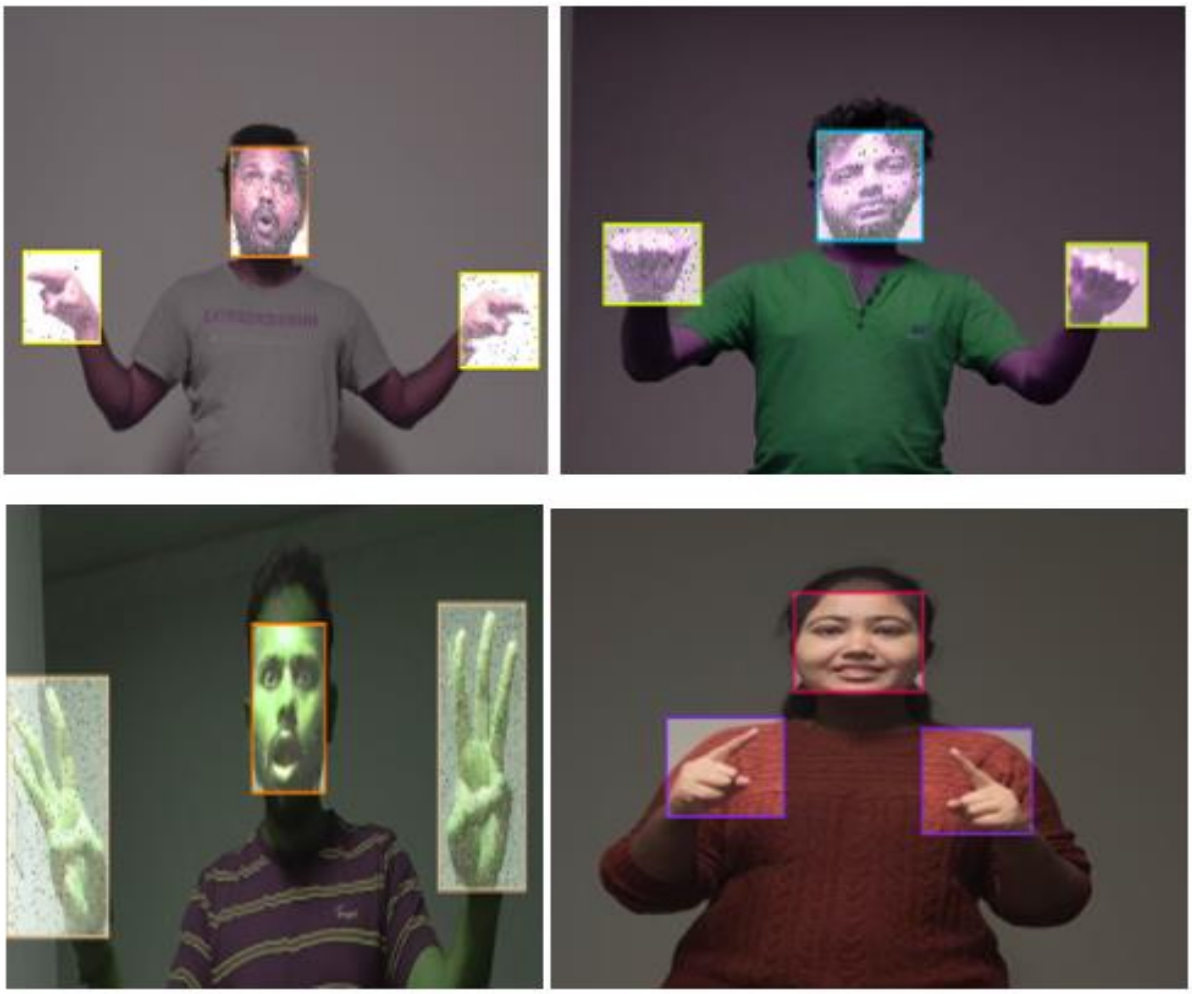

Figure 4 - Images after Data Augmentation

3.3 Implementation Steps

This study presents a comprehensive workflow for real-time object detection utilizing YOLO models, illustrated in the accompanying diagram. The process begins with the collection and manual annotation of objects within the images. Following this, the dataset is subjected to preprocessing and augmentation techniques to improve its quality and generalizability. The dataset is then strategically divided into training, validation, and testing sets to ensure a thorough evaluation of the model. The prepared dataset is used to train both the baseline YOLOv10 model and the YOLO11 model, with their performances evaluated and compared. This workflow effectively demonstrates the models' capabilities for real-time object detection.

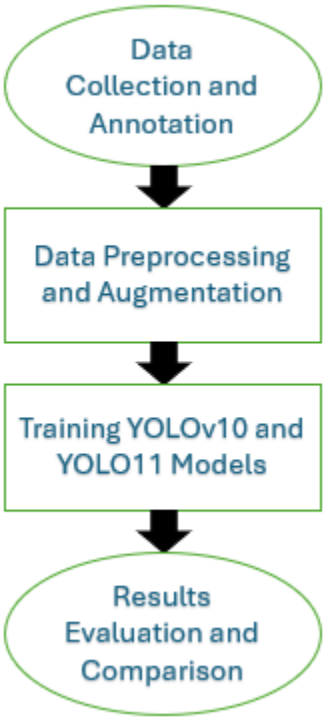

Figure 5 - Project Pipeline

Chapter 4 – Experiments

This section outlines the experiments conducted on the dataset after it underwent preprocessing and augmentation. It provides a summary of the project, emphasizing the process of dividing the data into training and testing sets. Additionally, it describes the methods used to carry out the various experiments with the prepared dataset.

4.1 Training, Validation, and Test Data Split

To facilitate effective model training and evaluation, the dataset comprising 10,000 images was strategically divided into three distinct subsets. Approximately 90% of the data, or around 9,000 images, was designated for the training set. This allocation ensured that the model could learn essential patterns from the data in a thorough yet manageable manner.

The validation set, which accounted for about 8% of the total dataset (approximately 800 images), was employed to track the model's training progress and mitigate the risk of overfitting. Overfitting occurs when a model becomes excessively tailored to the training data, hindering its performance on new, unseen data. The validation set offered crucial insights into the model's capacity to generalize across various scenarios.

Finally, a small portion of around 2% of the dataset, equating to approximately 200 images, was reserved for the test set. This set provided an unbiased evaluation of the model's generalizability to unseen data. By assessing the model's performance on this test set, we could better understand its expected efficacy in real-world applications. Overall, this systematic approach to dataset division established a robust framework for model training and evaluation.

4.2 Experimental Design

This chapter outlines the detailed steps necessary to conduct each experiment. The initial experiment utilized the YOLOv10 baseline model, documenting the findings before training the YOLO11 model. The results from YOLO11 were then compared with those from the baseline model. Ultimately, the trained model was deployed within the Roboflow framework for real-time detection, enabling us to evaluate its performance in real-time.

4.2.1 YOLOv10

Our initial attempt at training the model utilized the YOLOv10 architecture, with hyperparameters set to a learning rate of 0.000286, a batch size of 16, and a total of 20 epochs. Knowing that the training process would be time-consuming on other systems, I chose to run the entire training on Beocat, Kansas State University's high-performance computing cluster. Beocat provides thousands of compute cores and extensive memory resources, enabling large-scale computations and machine learning tasks to be executed efficiently. Over the course of 20 epochs, Beocat allowed us to complete the training quickly and without resource limitations, leveraging its parallel processing capabilities. Following the training, the model's performance was evaluated on a dedicated testing dataset, and the results indicated that the YOLOv10 model demonstrated strong object detection capabilities within the given data.

4.2.2 YOLO11

Following the successful training and evaluation of the YOLOv10 model, we proceeded to explore the potential of the YOLO11 architecture. For both models, we configured the training process with identical hyperparameters: a learning rate of 0.000286, a batch size of 16, and a total of 20 epochs. All training was conducted exclusively on Beocat, leveraging its high-performance computing environment to manage the time-intensive nature of these tasks.

During the training of YOLO11, we observed a point of diminishing returns after 10 epochs. Beyond this point, no significant improvement in model accuracy was detected, suggesting the model had reached its optimal performance early in the process.

The final training results for YOLO11 were meticulously captured and will be analyzed in detail in subsequent chapters. To evaluate the performance of the models, we conducted a comparative analysis between YOLOv10 and YOLO11, using YOLOv10 as the baseline. While the difference in performance was not substantial, YOLO11 exhibited a slight improvement, indicating a potential advantage in this specific task.

To further assess the generalizability of YOLO11, we evaluated its performance on a dedicated testing dataset. The results confirmed that the YOLO11 model achieved satisfactory performance, demonstrating its effectiveness in real-world object detection scenarios. Overall, the success of both YOLOv10 and YOLO11 highlights the effectiveness of the training methodology and dataset preparation.

Chapter 5 – Experimental Results

In this chapter, we delve into the results obtained from validating and testing the model. We analyze several key metrics, including mean Average Precision (mAP), Precision, and Recall. Additionally, we utilize various graphical representations, such as confusion matrices, F1 score curves, and validation batch data, to facilitate our discussion.

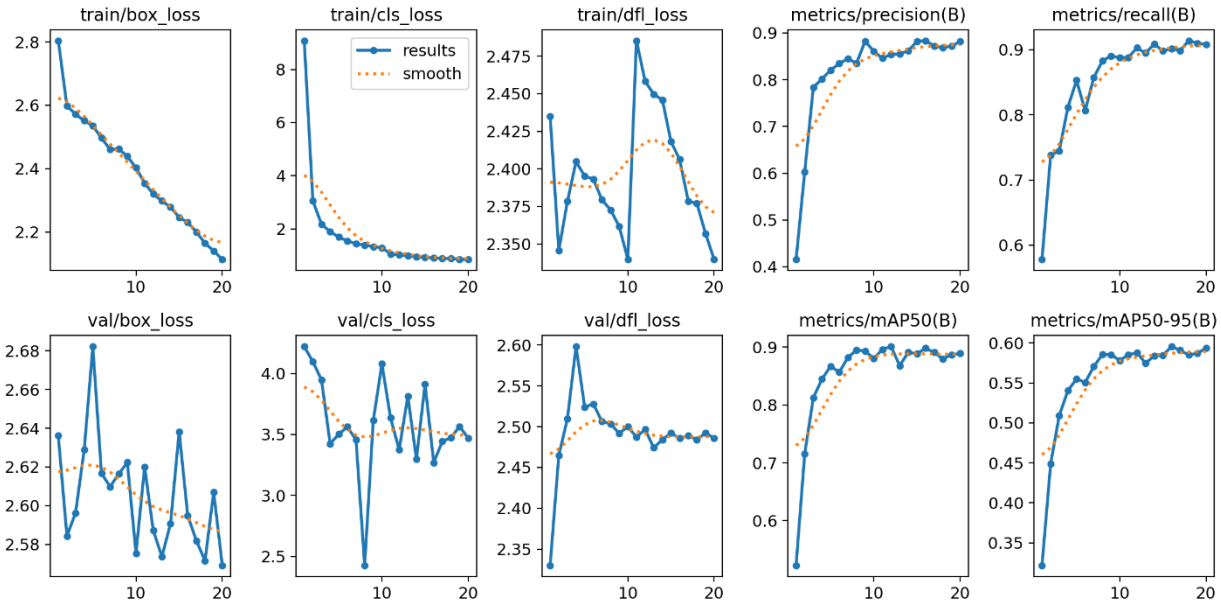

Figure 6 - YOLOv10 Results on Training and validation datasets.

The graphs display various training and validation loss metrics along with precision, recall, and mAP metrics over 20 epochs. The training precision graph shows steady improvement, peaking at around 0.9, reflecting the model's ability to correctly identify positive instances. The training recall graph exhibits a rise, nearing 0.9, indicating strong performance in detecting true positives. On the validation side, the mAP50 metric steadily increases to around 0.8, and the mAP50-95 shows improvement to around 0.6, highlighting the model's generalization on unseen data across varying IoU thresholds.

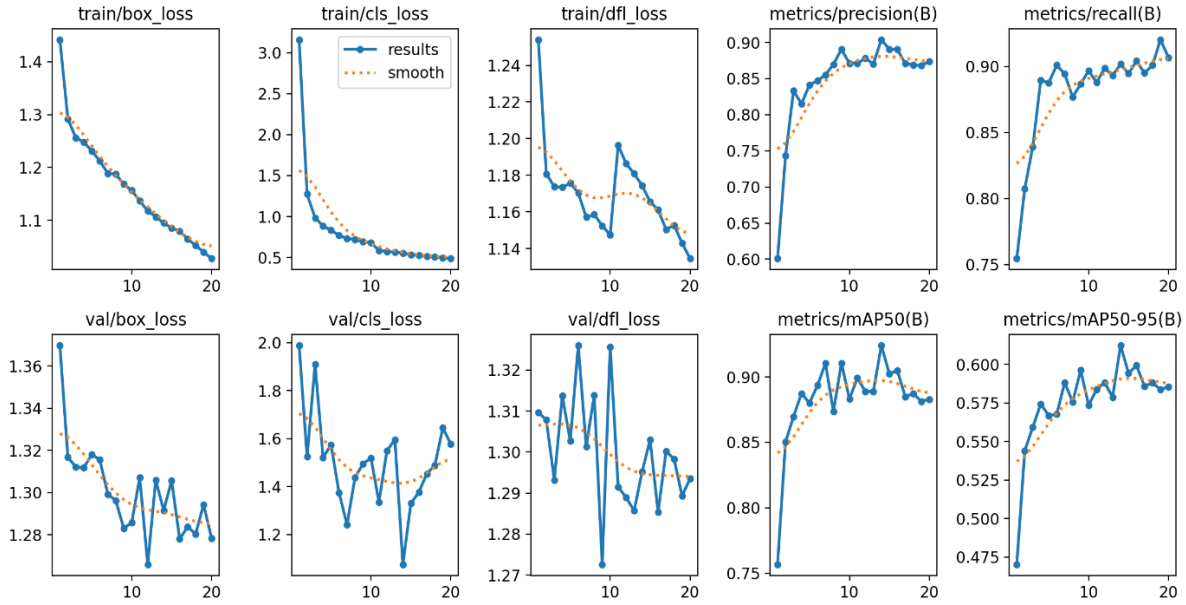

Figure 7 - YOLO11 results on training and validation datasets.

The graphs display the training and validation losses along with key performance metrics. The training precision graph shows an upward trend, indicating the model's improving accuracy in identifying positive instances, reaching over 0.9. Similarly, the training recall graph shows an increase, approaching 0.9, suggesting the model's growing ability to detect true positives. The validation mAP50 and mAP50-95 graphs reflect how well the model performs on unseen data, with a rising trend toward 0.85 and 0.7 respectively, showing good generalization capabilities across different IoU thresholds.

5.1 Evaluation Metrics

Evaluation metrics are crucial for evaluating the effectiveness of object detection models like YOLO (You Only Look Once). They offer quantitative insights into accuracy, robustness, and generalization capabilities, allowing researchers and practitioners to make informed comparisons and refine their techniques. In YOLO-based object detection tasks, several important evaluation metrics are typically employed to assess the model's performance in detecting and localizing objects within images. These metrics provide valuable information about the model's strengths and potential areas for improvement. The following are some of the key evaluation metrics applied in this project.

Table 1 - Comparison of YOLOv10 and YOLO11 Training dataset results.

	mAP		Precision		Recall	
Class	YOLOv10	YOLO11	YOLOv10	YOLO11	YOLOv10	YOLO11
All	0.899	0.924	0.883	0.904	0.901	0.902
A	0.995	0.995	0.962	0.992	1	1
B	0.995	0.995	1	0.99	0.972	1
C	0.993	0.995	0.959	0.987	1	1
D	0.994	0.995	1	0.99	0.966	1
E	0.994	0.995	0.978	0.978	0.941	1
F	0.945	0.941	0.987	0.96	0.933	0.933
G	0.887	0.872	0.866	0.878	0.906	0.938
H	0.959	0.942	0.94	0.918	0.875	0.944
I	0.985	0.993	0.989	0.994	0.909	0.909
J	0.995	0.994	0.948	0.967	1	1
K	0.995	0.995	1	1	0.986	0.989
L	0.994	0.989	1	0.996	0.843	0.912
M	0.895	0.898	0.922	0.918	0.912	0.923
N	0.964	0.969	0.941	1	0.923	0.919
O	0.904	0.918	0.915	0.94	0.828	0.906
P	0.983	0.983	0.952	0.978	0.898	0.727
Q	0.993	0.948	0.994	0.808	0.952	1
R	0.993	0.991	0.947	0.974	0.979	0.958
S	0.769	0.721	0.866	0.827	0.769	0.737
T	0.889	0.845	0.901	0.845	0.864	0.864
U	0.908	0.915	0.908	0.842	0.856	0.891
V	0.974	0.984	0.909	0.931	1	1
W	0.985	0.987	0.971	0.996	0.982	0.982
X	0.993	0.995	0.971	0.995	0.958	1
Y	0.992	0.995	1	1	0.95	0.97
Z	0.992	0.995	1	1	0.903	0.992
Angry	0.292	0.247	0.157	0.201	1	0.963
Happy	0.709	0.835	0.28	1	0.875	0.548
Neutral	0.427	0.804	0.132	0.213	0.955	0.909
Sad	0.476	0.928	0.966	1	0.0221	0.0418
Surprise	0.995	0.995	1	0.902	0.972	1

Table 2 - Comparison of YOLOv10 and YOLO11 Test dataset results.

	mAP		Precision		Recall	
Class	YOLOv10	YOLO11	YOLOv10	YOLO11	YOLOv10	YOLO11
All	0.944	0.95	0.890	0.913	0.909	0.911
A	0.988	0.994	1	1	0.66	0.757
B	0.995	0.995	0.988	1	1	0.972
C	0.995	0.978	1	1	0.997	0.935
D	0.995	0.995	0.998	0.983	1	1
E	0.995	0.995	0.994	0.997	1	1
F	0.995	0.989	0.985	1	1	0.87
G	0.9	0.872	0.903	0.869	0.821	0.882
H	0.909	0.89	0.903	0.872	0.935	0.979
I	0.822	0.995	0.866	1	0.9	0.993
J	0.995	0.995	1	1	0.911	0.871
K	0.995	0.995	0.996	1	1	0.92
L	0.995	0.995	0.974	1	1	0.912
M	0.995	0.986	0.729	0.953	1	0.9
N	0.995	0.995	0.836	0.98	1	1
O	0.745	0.995	0.486	0.536	0.5	1
P	0.995	0.995	0.961	0.972	1	1
Q	0.995	0.995	0.759	0.902	1	1
R	0.995	0.995	0.974	0.979	1	1
S	0.995	0.995	0.848	0.949	1	1
T	0.995	0.995	0.995	0.992	1	1
U	0.995	0.995	0.908	0.842	1	1
V	0.995	0.995	0.888	0.896	1	1
W	0.995	0.995	0.872	0.886	1	0.982
X	0.995	0.995	0.971	0.995	0.958	1
Y	0.995	0.983	1	1	0.82	0.82
Z	0.396	0.725	1	0.726	0.903	1
Angry	0.806	0.706	0.366	0.526	1	1
Happy	0.947	0.912	0.954	0.848	0.615	0.859
Neutral	0.971	0.927	0.708	0.334	0.955	1
Sad	0.977	0.645	0.985	0.984	0.487	0.854
Surprise	0.995	0.995	0.964	1	1	1

5.2 Mean Average Precision

Mean Average Precision (mAP) is a key metric used to evaluate object detection models like YOLO. It measures the average precision for detecting different object categories and then calculates an overall score by averaging these values. In the context of YOLO, mAP provides a concise summary of the model's detection accuracy, allowing for easy comparison between models and configurations.

When tested across all classes for the training dataset, the YOLOv10 model achieves a mAP of 89%, while the YOLO11 model reaches 92.3%. This indicates that YOLO11 has a slight edge in overall object detection performance compared to YOLOv10.

For the test dataset, the YOLOv10 model achieves a mean Average Precision (mAP) of 94%, while YOLO11 reaches 95%. This indicates that YOLO11 has a slight but notable advantage in object detection performance on unseen data, reflecting its improved generalization capabilities compared to YOLOv10.

5.3 F1-Confidence Curve

The F1-Confidence Curve helps to select the best confidence threshold for a model. The peak of the curve represents the point at which the model achieves the best balance between precision and recall.

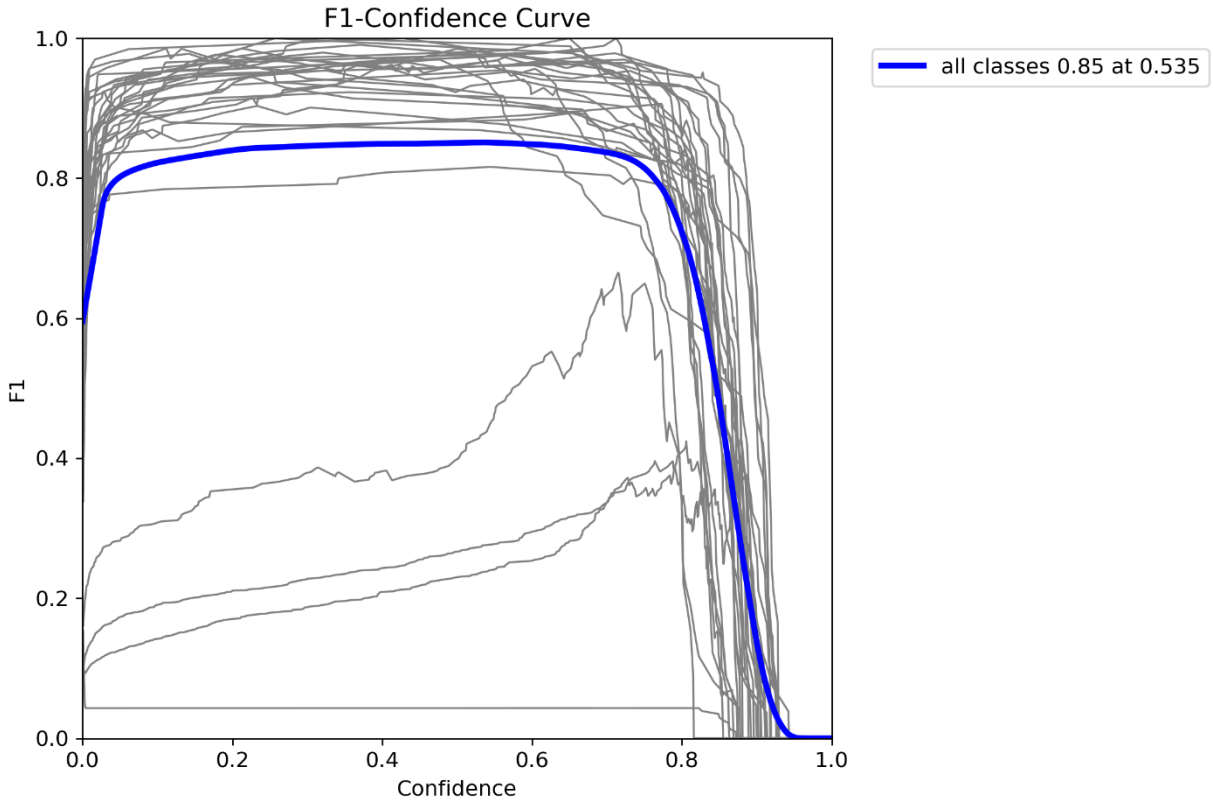

Figure 8 - YOLOv10 F1 Confidence Curve on the training dataset.

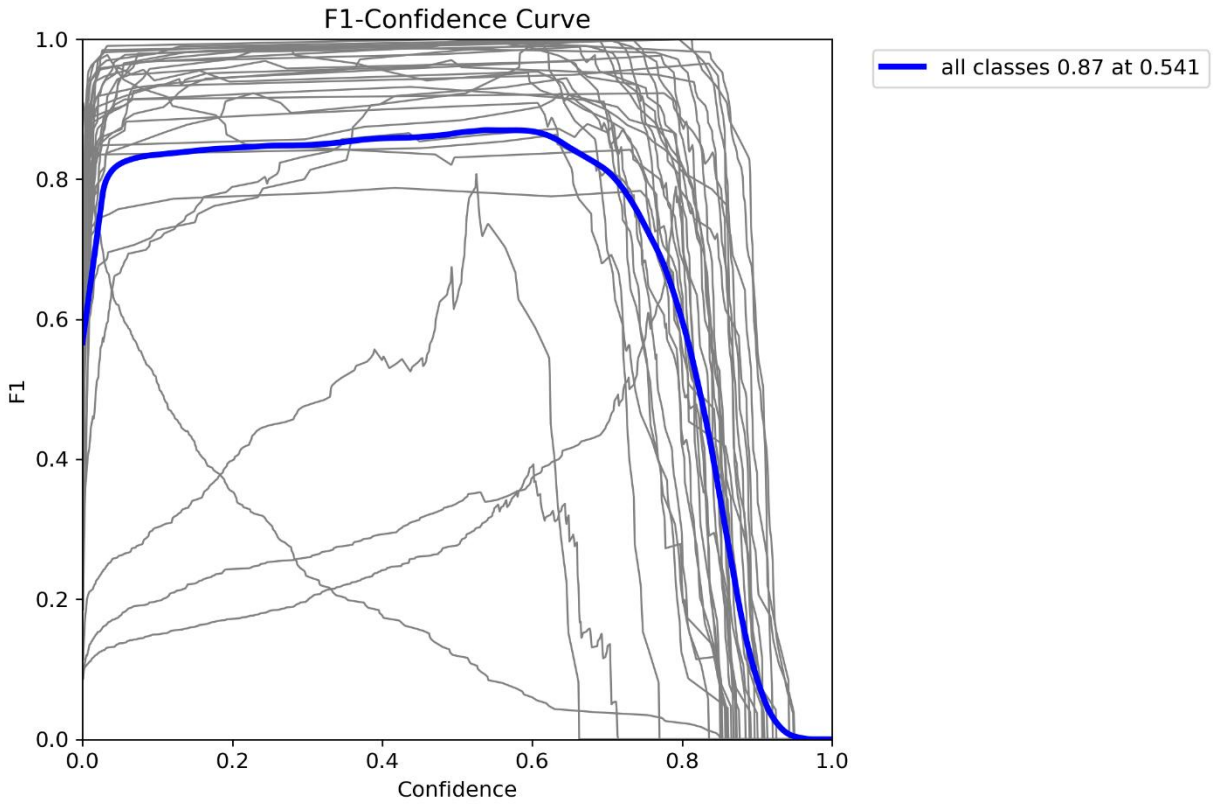

Figure 9 - YOLO11 F1 Confidence Curve on the training dataset.

Comparing the F1-Confidence curves of YOLOv10 and YOLO11 reveals notable improvements. YOLO11 achieves a higher peak F1 score of 0.87 at a confidence threshold of 0.541, compared to YOLOv10's 0.85 at 0.535. YOLO11's curve maintains a slightly higher F1 score across a broader range of confidence thresholds, indicating better overall performance and robustness. The individual class curves (gray lines) in YOLO11's graph show less variation, suggesting more consistent performance across different classes. YOLO11's curve also exhibits a smoother descent at higher confidence levels, implying improved precision-recall balance in high-confidence predictions. These enhancements demonstrate YOLO11's superior ability to balance precision and recall across various confidence thresholds, resulting in more reliable object detection performance.

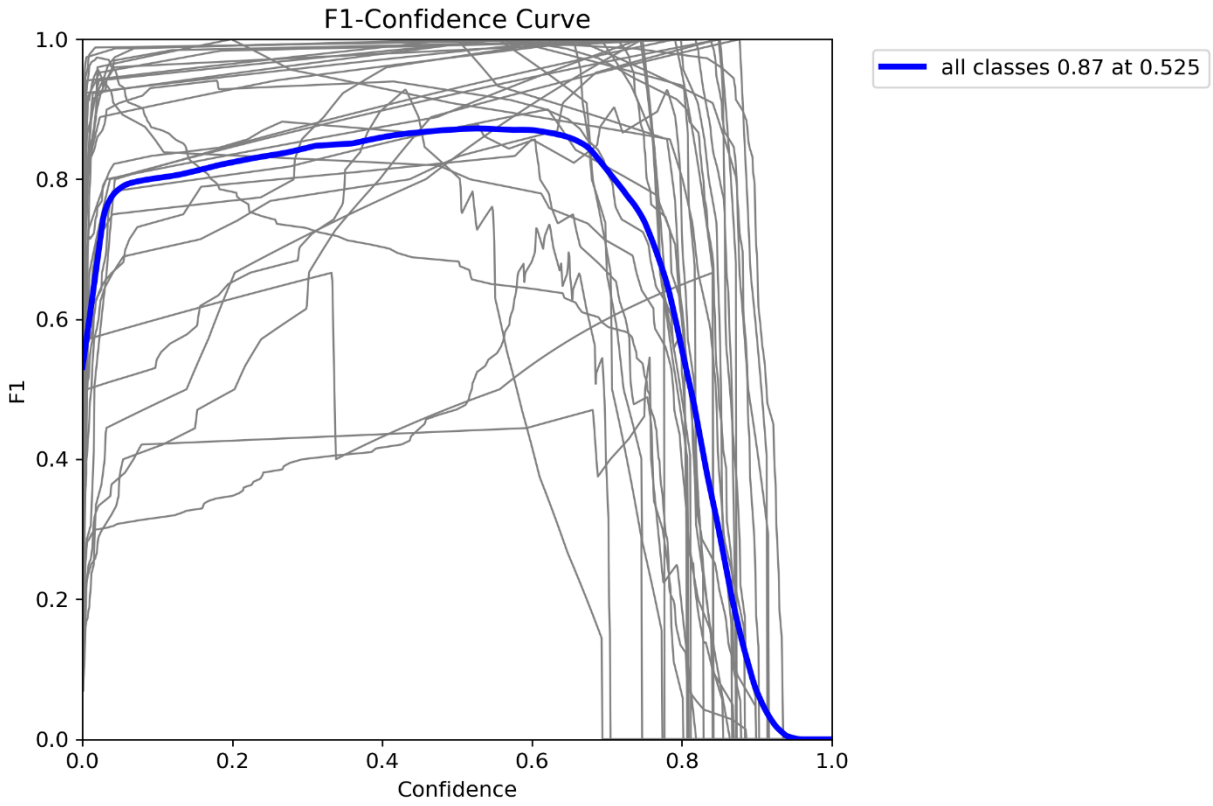

Figure 10 - YOLOv10 F1 Confidence Curve on the test dataset.

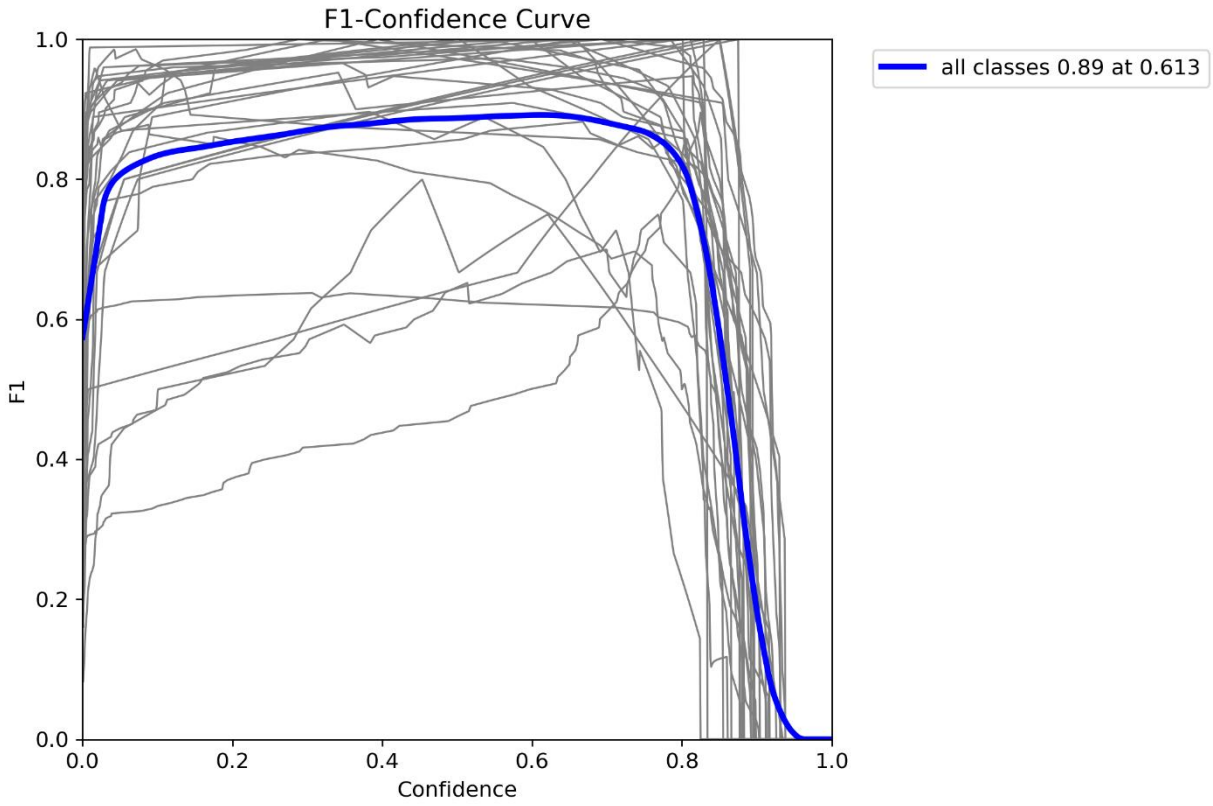

Figure 11 - YOLO11 F1 Confidence Curve on the test dataset.

The graphs reveal a modest improvement in YOLO11 over its predecessor, YOLOv10. YOLO11 achieves a slightly higher peak F1 score of 0.89 compared to YOLOv10's 0.87, and it reaches this peak at a higher confidence threshold (0.613 vs. 0.525), indicating stronger performance while being more selective in predictions. YOLO11's curve appears smoother and more stable across the middle confidence range, suggesting consistent performance across varying detection scenarios. Additionally, the tighter clustering of individual class performance lines in YOLO11 points to more uniform results across different object classes. These incremental improvements demonstrate the ongoing refinement of the YOLO (You Only Look Once) object detection algorithm, with YOLO11 offering enhanced reliability and consistency, particularly at higher confidence thresholds, which is beneficial for precision-critical applications.

5.4 Precision and Recall

Precision measures how accurately the model identifies objects by calculating the proportion of correct positive detections (true positives) out of all predicted positives (true positives + false positives). Recall, on the other hand, reflects the model's ability to detect all instances of target objects in an image, measuring the proportion of correct detections (true positives) out of all actual positive instances (true positives + false negatives).

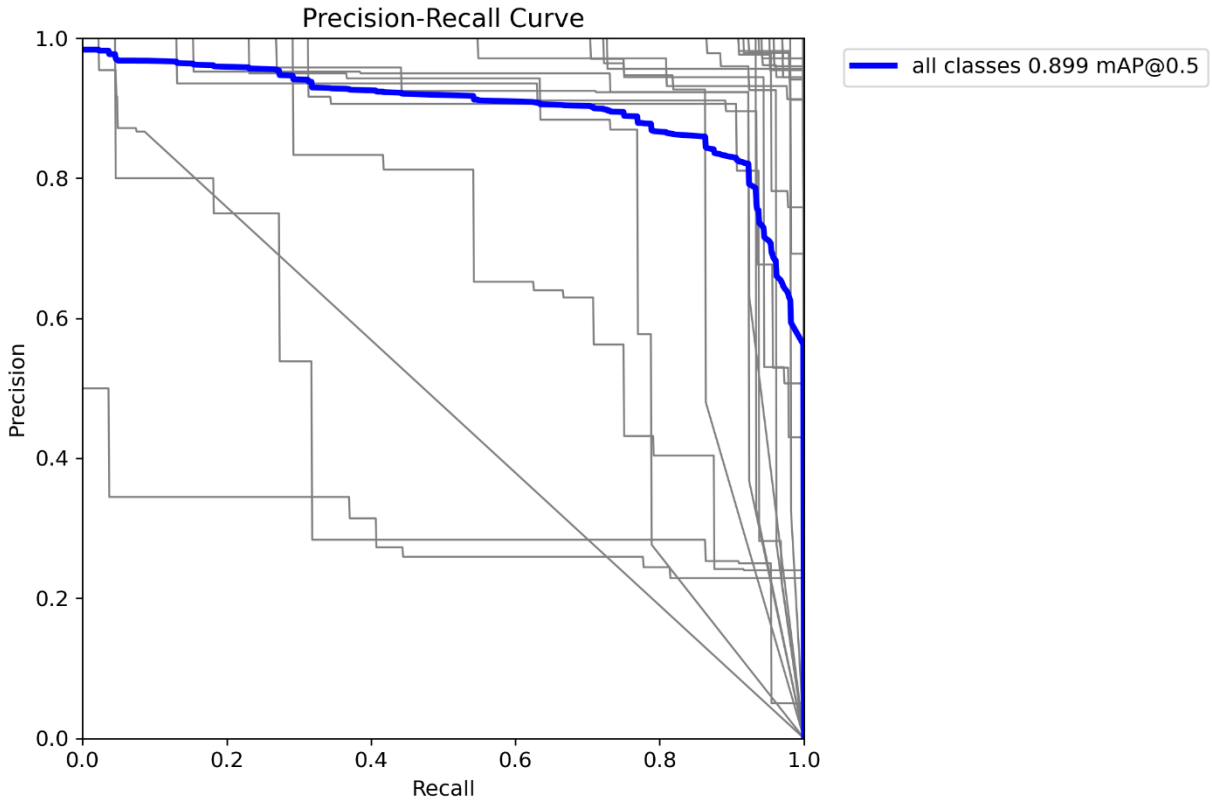

Figure 12 - YOLOv10 Precision and Recall Curve on the training dataset.

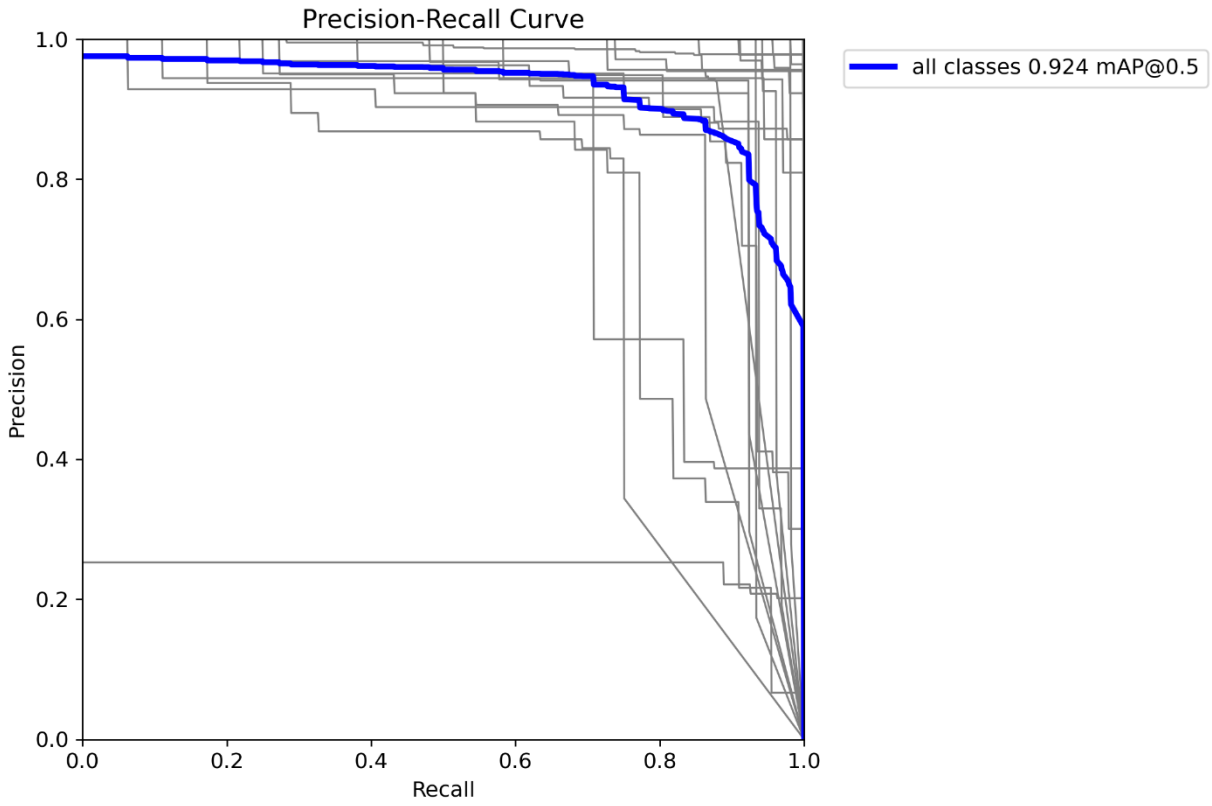

Figure 13 - YOLO11 Precision and Recall Curve on the training dataset.

In the comparison between YOLOv10 and YOLO11, the precision-recall curves highlight the performance improvements between the two models. YOLOv10, with a mAP@0.5 of 0.899, shows slightly less stable precision as recall increases. YOLO11, on the other hand, improves the mAP@0.5 to 0.924, demonstrating more consistent precision across various recall levels. This suggests that YOLO11 is more effective at detecting objects across all classes, likely due to advancements in its architecture or training techniques over YOLOv10.

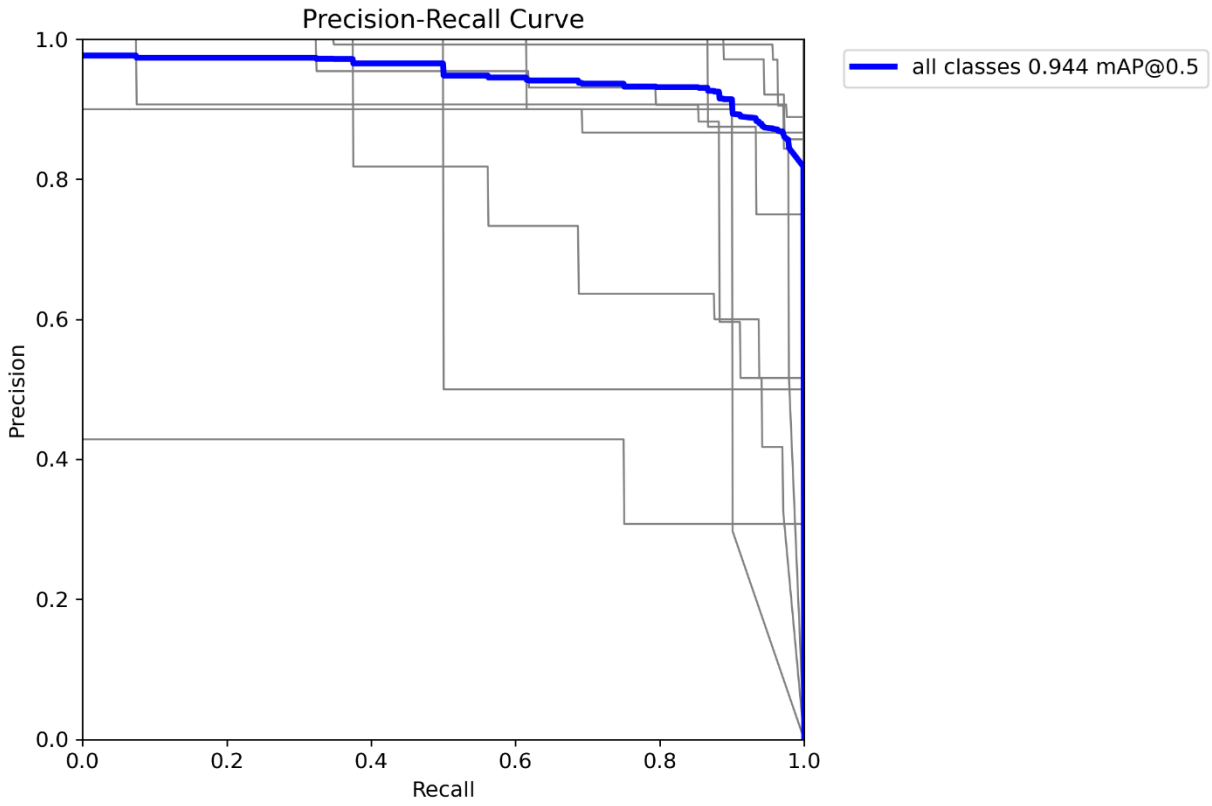

Figure 14 - YOLOv10 Precision and Recall Curve on the test dataset.

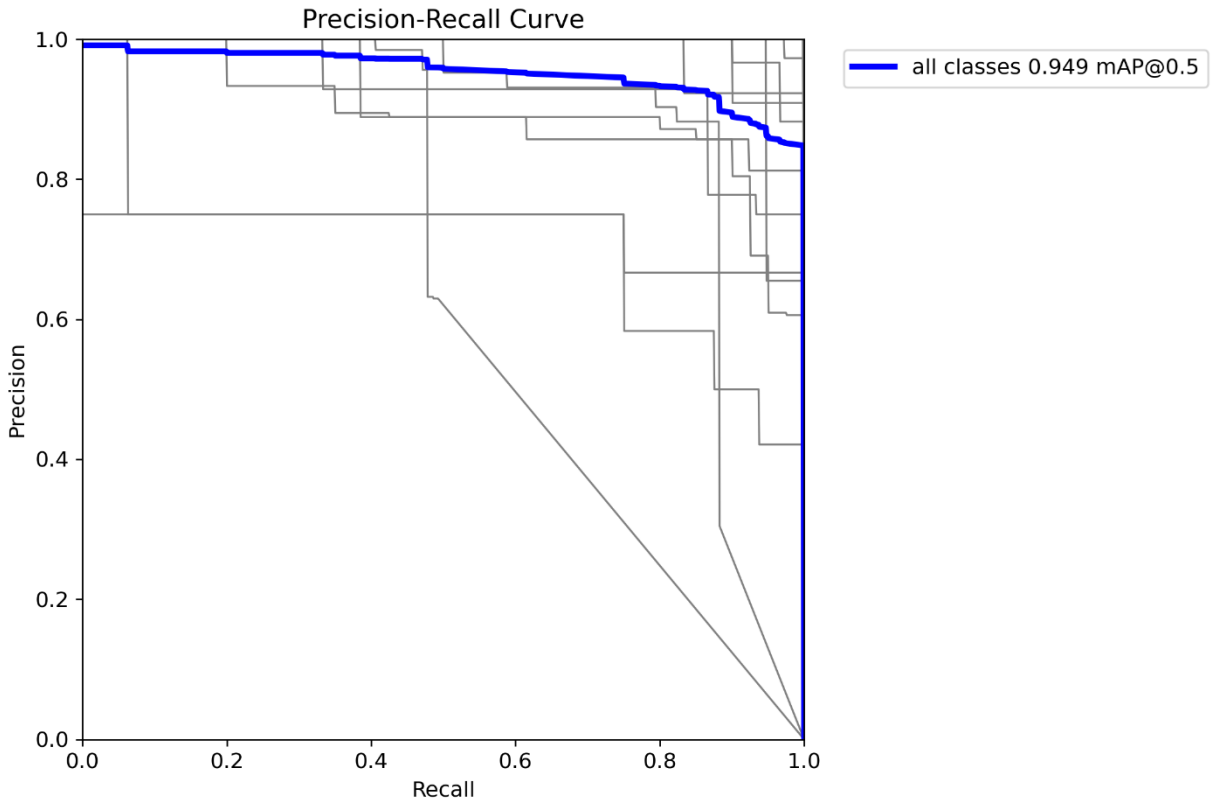

Figure 15 - YOLO11 Precision and Recall Curve on the test dataset.

Comparing the Precision-Recall curves of YOLOv10 and YOLO11 on the test dataset reveals a slight improvement in YOLO11's performance. YOLO11 achieves a marginally higher mAP@0.5 of 0.949 compared to YOLOv10's 0.944. Both models exhibit similarly shaped curves, maintaining high precision across a wide range of recall values. However, YOLO11's curve appears somewhat smoother, suggesting more consistent performance across different classes. Notably, YOLO11 maintains higher precision at very high recall values, indicating better performance in detecting difficult cases. While both graphs show similar patterns in individual class curves, YOLO11 seems to have slightly less extreme outliers. Overall, YOLO11 demonstrates a modest but noticeable improvement over YOLOv10, particularly in maintaining precision at higher recall levels.

5.5 Confusion Matrix

We used confusion matrices to better understand the models' performance in classifying different classes. These matrices displayed very few off-diagonal elements, indicating a low rate of misclassifications. This suggests that the models have developed strong classification abilities, accurately distinguishing between the various classes in the dataset. The following figures present the confusion matrices for YOLOv10 and YOLO11.

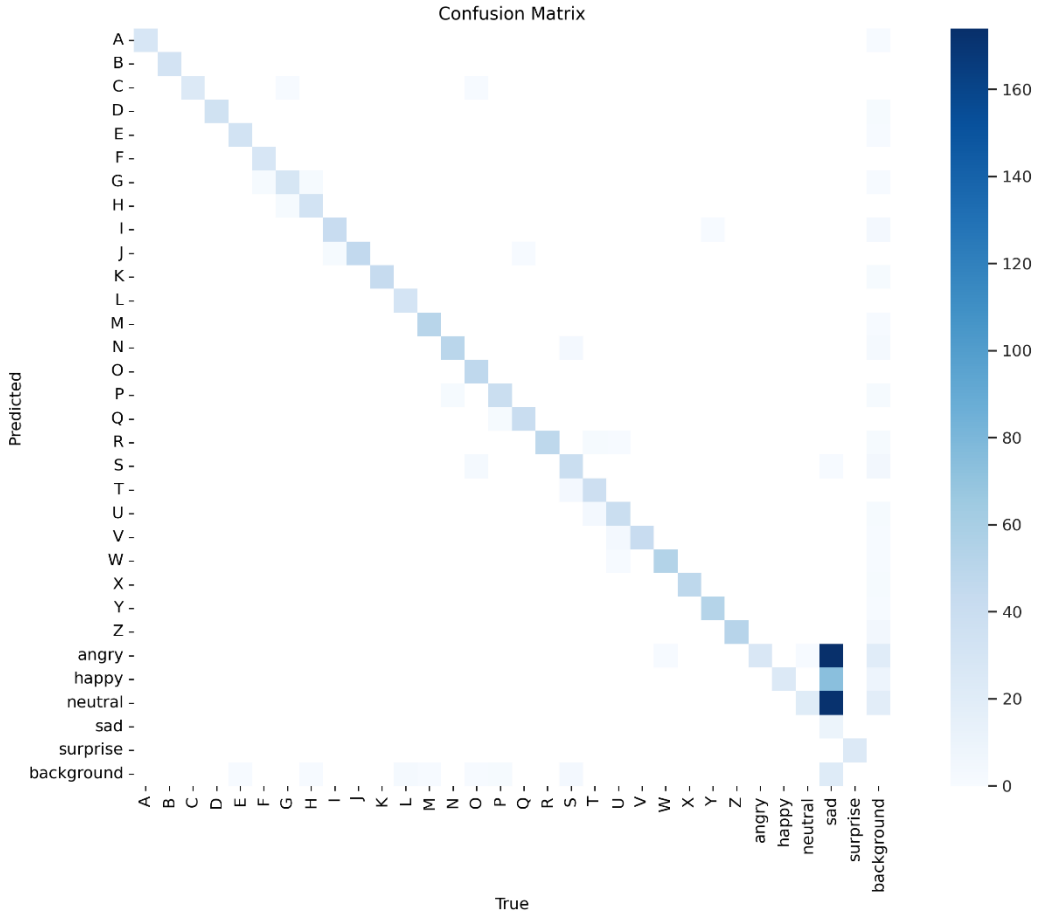

Figure 16 - YOLOv10 Confusion Matrix on the training dataset

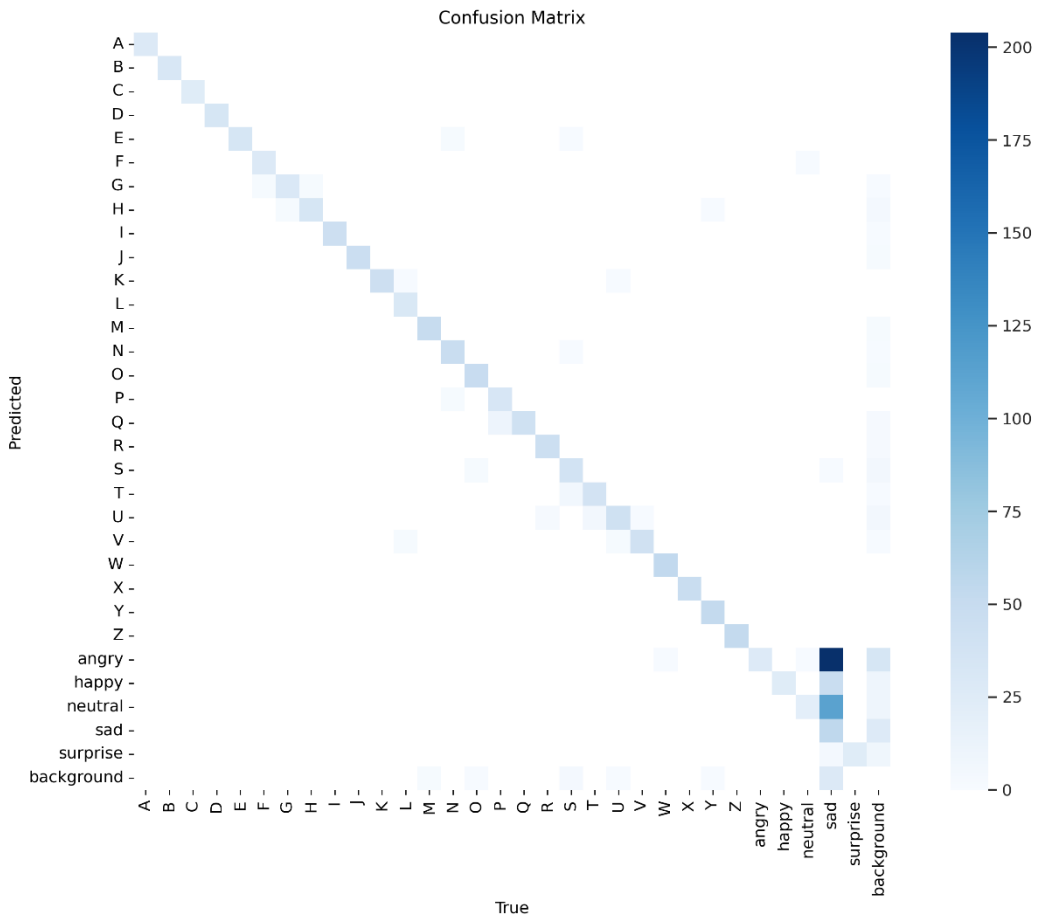

Figure 17 - YOLO11 Confusion Matrix on the training dataset.

Both models show strong diagonal patterns, indicating good overall performance across classes. YOLO11 demonstrates slightly darker diagonal elements, suggesting improved accuracy. The matrices reveal similar class structures, including alphabets (A-Z) and emotions (angry, happy, neutral, sad, surprise). YOLO11 appears to have reduced confusion between similar classes, particularly in the emotion categories, as evidenced by lighter off-diagonal elements. Both models show some misclassifications with the "background" class, but YOLO11 seems to handle this slightly better. Overall, YOLO11 exhibits modest improvements in classification accuracy and reduced confusion between classes compared to YOLOv10.

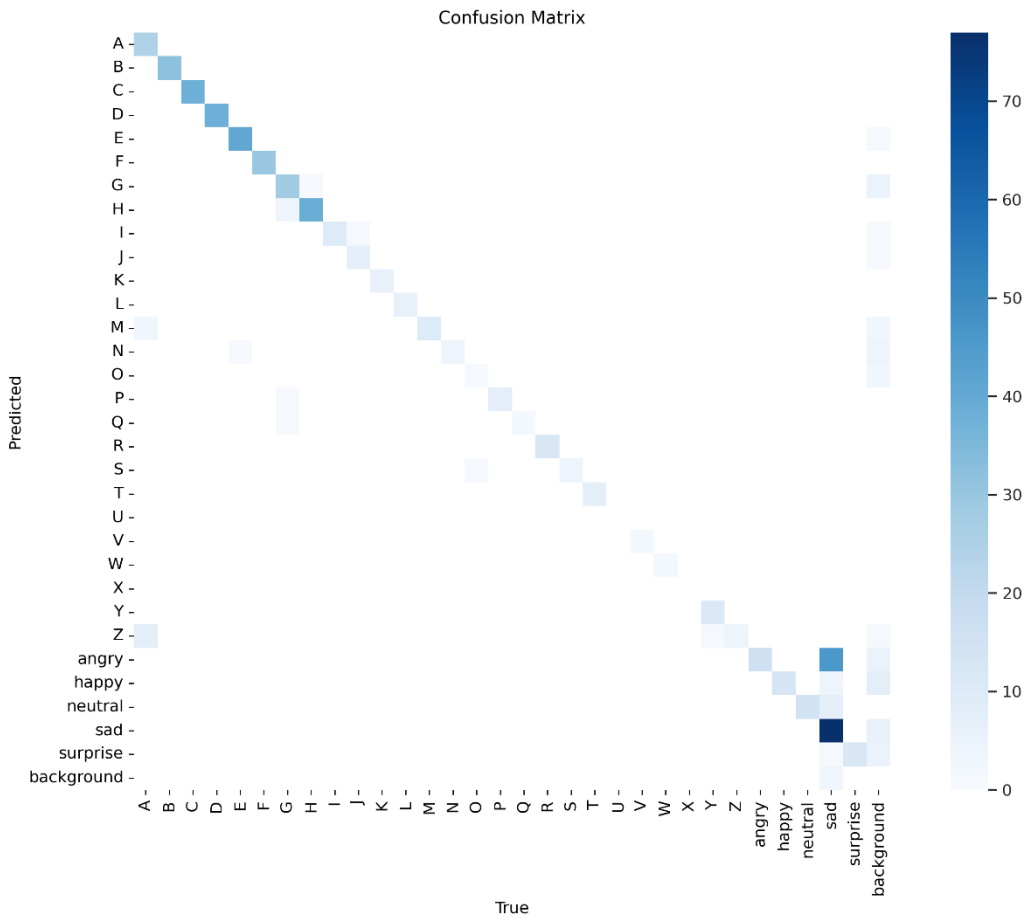

Figure 18 - YOLOv10 Confusion Matrix on the test dataset.

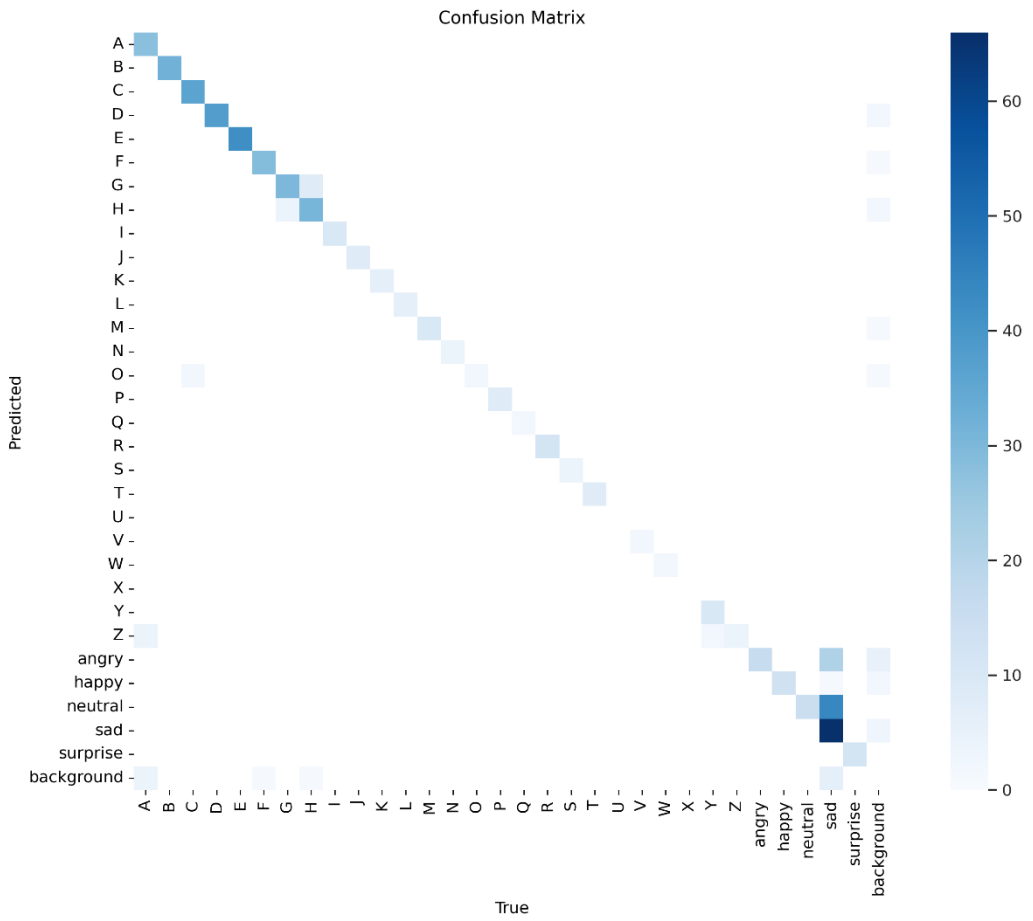

Figure 19 - YOLO11 Confusion Matrix on the test dataset.

The confusion matrices for YOLOv10 and YOLO11 reveal similar overall structures, with both models performing well across alphabet and emotion classes. YOLO11 shows subtle improvements, evident in its slightly darker diagonal elements and lighter off-diagonal areas. This suggests enhanced accuracy and reduced misclassifications, particularly for emotion categories. While both models struggle somewhat with the "background" class, YOLO11 appears to manage this challenge slightly better. The adjusted color scale in YOLO11's matrix hints at more balanced predictions across classes. In summary, YOLO11 demonstrates incremental yet noticeable enhancements in classification performance compared to its predecessor.


bharaniAng_0044_jpg.rf.83
A 0.8
angry 0.7
A 0.8
I 0.8
angry 0.4
I 0.8
I 0.8
I 0.9
H 0.8
H 0.7
samathaSad_2246_jpg.rf.a3
J 0.8
angry 0.4
J 0.8
I 0.8
angry 0.3
I 0.8
I 0.8
I 0.9
H 0.8
angry 0.7
H 0.8
samathaSad_2188_jpg.rf.9d
I 0.8
neutral 0.4
I 0.7
I 0.9
neutral 0.4
I 0.9
I 0.8
neutral 0.4
I 0.9
H 0.8
angry 0.6
H 0.8
samathaSad_2183_jpg.rf.01
I 0.7
neutral 0.4
I 0.8
I 0.8
neutral 0.4
I 0.9
H 0.8
angry 0.3
H 0.7
J 0.8
angry 0.7
J 0.8

Figure 20 - Validation batch results

Chapter 6 – Summary and Future Work

6.1 Summary of Results

The project successfully automated the recognition of American Sign Language (ASL) gestures and facial expressions using YOLOv10 and YOLO11 object detection models. These models were trained to accurately detect and classify various ASL signs and facial expressions in real time, achieving impressive precision and recall rates. Comparative analysis showed that YOLO11 surpassed YOLOv10 in both accuracy and computational efficiency.

The successful training and evaluation of these models demonstrate their potential for real-time ASL and facial expression recognition in practical applications. This achievement highlights the transformative power of deep learning and computer vision in advancing communication through ASL recognition and facial expression analysis. By leveraging these advanced models, the project underscores how technology can positively impact fields like education and assistive technology, enhancing communication for the hearing-impaired and improving overall user interaction.

6.2 Future Work

The current project has effectively demonstrated the capabilities of the YOLOv10 and YOLO11 object detection models in recognizing American Sign Language (ASL) gestures and facial expressions. However, several potential avenues for further exploration and enhancement exist:

- **Integration of Additional Modalities**: Future work could involve integrating other modalities, such as audio or text input, to create a more comprehensive communication system that enhances the understanding of ASL gestures and their contextual meanings.
- **Expanded Dataset Collection**: Continuously expanding and diversifying the dataset by including a wider variety of ASL signs, dialects, and facial expressions, as well as capturing data from different demographics and cultural backgrounds, would improve the model's robustness and accuracy.
- **Real-Time Applications**: Exploring real-time applications by deploying the model on various devices, such as mobile phones or smart glasses, could facilitate immediate ASL recognition in practical scenarios, enhancing accessibility for users in diverse environments.
- **User-Centric Enhancements**: Collaborating with the Deaf and hard-of-hearing community could provide valuable feedback for refining the model and ensuring that it meets the specific needs and preferences of users.
- **Privacy and Data Security:** As the model involves capturing and processing potentially sensitive visual data, future work should focus on ensuring privacy and data protection. Implementing robust encryption methods, anonymizing captured data, and providing users with control over their data will be essential for maintaining user trust and compliance with privacy regulations**.**

- **Scalability and Accessibility**: Developing user-friendly interfaces and integrating the models into existing communication tools or platforms would facilitate widespread adoption and practical implementation, making ASL recognition more accessible to various user groups.

By pursuing these future avenues, the project can continue to advance the field of sign language recognition and facial expression analysis, ultimately contributing to improved communication accessibility while prioritizing user privacy and enhancing interaction between the hearing and Deaf communities.

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