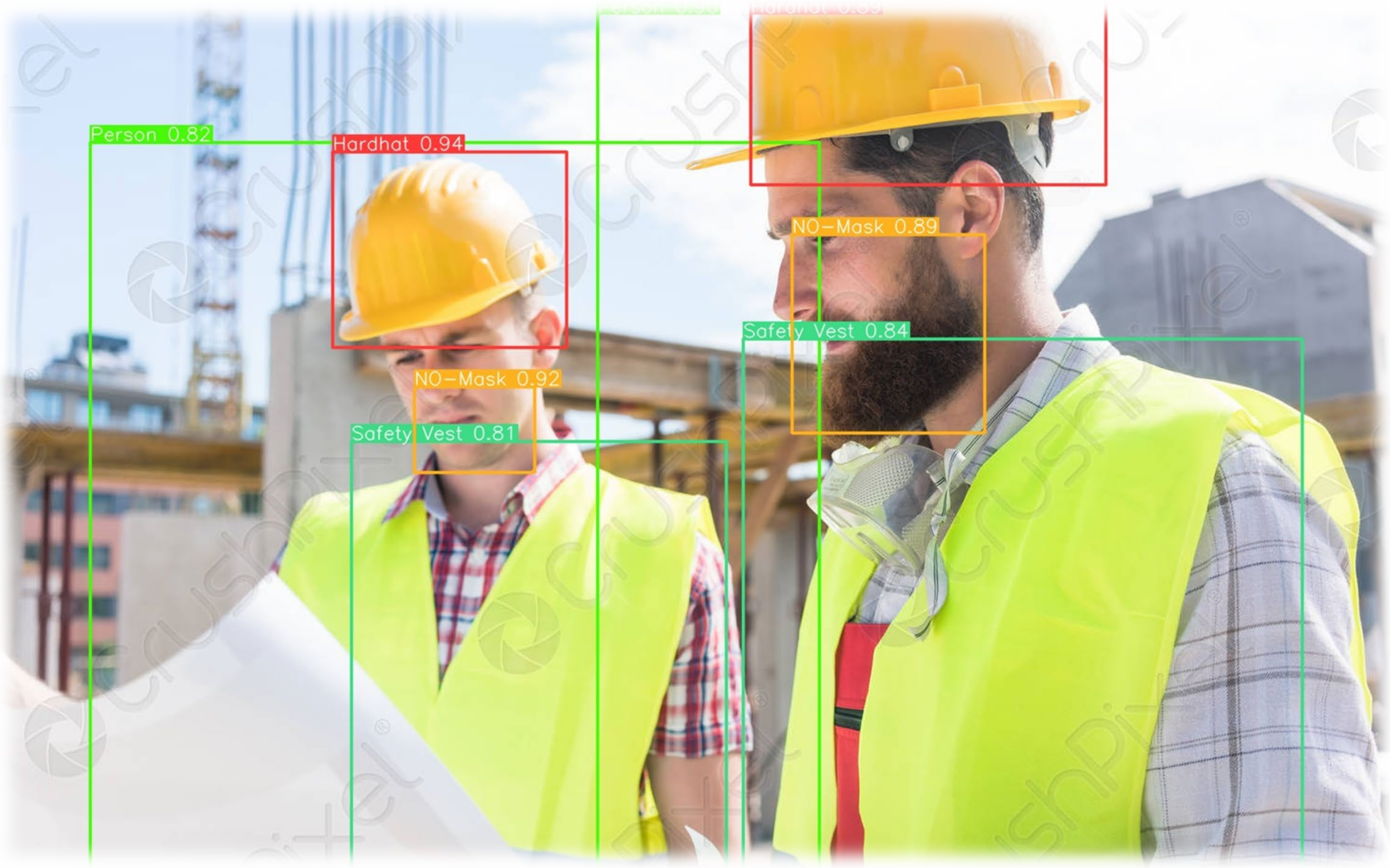

Leveraging Yolo for Real-Time Prediction and Detection of Personal Protective Equipment (PPE)

Enhancing Safety Compliance on Construction Sites

GROUP 3

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Objective

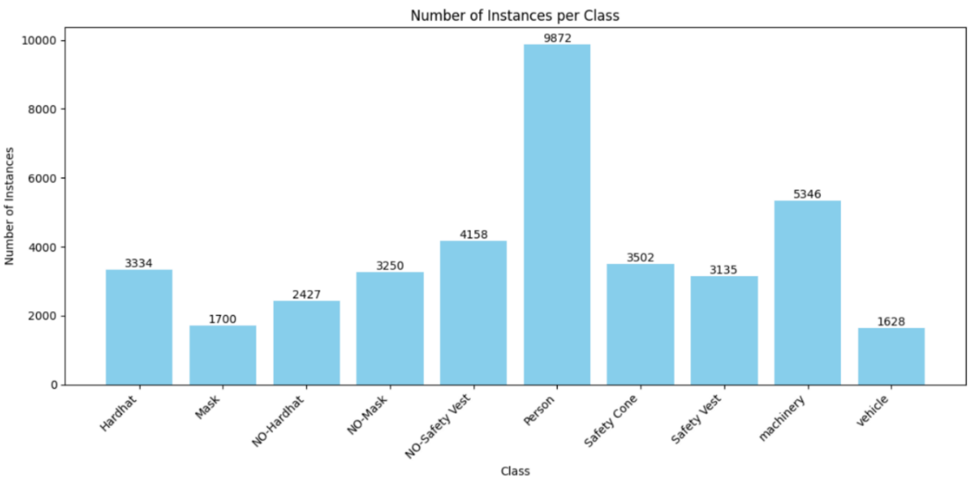
The objective of this project is to leverage YOLO (You Only Look Once) for real-time detection and prediction of Personal Protective Equipment (PPE) on construction sites. This aims to enhance safety compliance by accurately identifying whether workers are wearing necessary safety gear, thereby reducing the risk of accidents, and improving overall site safety.

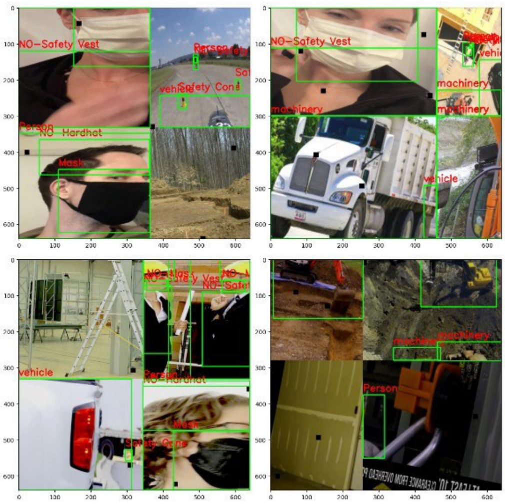
Dataset Description

- ✓ ***Overview / Description**: The dataset focuses on detecting safety-related elements at construction sites, specifically PPE such as hardhats, masks, and safety vests.*
- ✓ ***Number of Rows and Columns**: The dataset includes 2,801 images: 2,605 for training, 114 for validation, and 82 for testing.*
- ✓ ***Sample Predictors**: Hardhat, Mask, No-Hardhat, No-Mask, No-Safety Vest, Person, Safety Cone, Safety Vest, Machinery, and Vehicle.*
- ✓ ***Link to Dataset**: https://universe.roboflow.com/roboflow-universe-projects/construction-site-safety/dataset/28*

Preliminary Data Exploration

In my exploration of the dataset, I began by loading and examining the distribution of instances across different classes. To visualize this distribution, I created a bar chart:





As expected, the "Person" class has the highest number of instances, typical for construction site imagery. I have run 3 epochs to verify that it does not require more computing resources outside Colab, so I do not need to reduce the dataset size, allowing me to utilize the full range of data for robust model development. The dataset was pre-processed in Roboflow, applying several preprocessing and augmentation techniques to enhance model training. These included auto-orientation, resizing images to 640x640, and various augmentations like horizontal flipping, zoom, rotation, and more. Each training example was augmented five times with techniques like grayscale conversion, hue and saturation adjustments, brightness changes, blur, cutout, and mosaic.

Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640
Augmentations	Outputs per training example: 5 Flip: Horizontal Crop: 0% Minimum Zoom, 20% Maximum Zoom Rotation: Between -12° and +12° Shear: ±2° Horizontal, ±2° Vertical Grayscale: Apply to 10% of images Hue: Between -15° and +15° Saturation: Between -20% and +20% Brightness: Between -25% and +25% Exposure: Between -20% and +20% Blur: Up to 0.5px Cutout: 6 boxes with 2% size each Mosaic: Applied

Proposed Data Exploration Insights

- ✓ ***Class Distribution Analysis****: I will analyze the distribution of classes in the dataset to identify the most frequently present PPE items, helping to uncover potential biases. I already have a bar plot for the entire dataset and will create separate plots for each subset (training, validation, and test) after the split. This will allow me to compare class distributions and ensure each set is representative of the PPE items.*
- ✓ ***Image Resolution Variance****: I will examine the image resolutions to determine the range used in the dataset. Although the images are resized to 640x640 during preprocessing, I need to verify that this resizing is consistent across all images. This insight is essential for ensuring the YOLO model is trained on images of uniform quality.*
- ✓ ***Class Co-occurrence****: I will investigate how often different PPE classes appear together in the same images. This analysis will reveal common combinations of safety gear worn by workers and may inform the model's ability to recognize multiple classes simultaneously.*

Proposed Predictions

Safety Compliance Prediction: *I predict that by leveraging YOLO, the model will be able to detect PPE on workers in real-time with high accuracy, identifying safety violations:*

- ✓ ***Hardhat****: The model will accurately detect whether workers are wearing hardhats, which is one of the most critical pieces of PPE. Any instances of "No-Hardhat" will be flagged in real-time, helping prevent head injuries.*
- ✓ ***Mask****: The model will distinguish between workers wearing masks and those not, which is essential for environments with dust, chemicals, or health risks. "No-Mask" detections will trigger safety alerts, ensuring respiratory protection compliance.*
- ✓ ***Safety Vest****: The model will ensure that high-visibility safety vests are worn by workers, reducing the risk of accidents involving heavy machinery. It will flag "No-Safety Vest" detections for immediate action.*
- ✓ ***Person****: The detection of persons will be highly accurate due to the prevalence of the "Person" class. The model will identify individuals on-site and verify their PPE compliance.*
- ✓ ***Safety Cone****: Safety cones are key for site boundary markers. The model will predict and detect these to ensure areas are correctly marked for worker safety, reducing the chances of hazardous zone entry.*
- ✓ ***Machinery****: The model will detect machinery in proximity to workers, and combined with PPE detection, this can provide insights into high-risk situations, such as workers operating near heavy equipment without adequate protection.*
- ✓ ***Vehicle****: Detecting vehicles is important to ensure workers are visible and out of the way of moving equipment. The model will cross-reference vehicle detections with the presence of workers without safety gear to prevent accidents.*