**Object Detection for Road Conditions and Turns**

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**Introduction**

This group project aimed to develop an object detection model capable of identifying various road conditions and turns in images taken on roads in Gilgit. The primary goal of the project was to create a machine learning model that can automatically detect and classify road features such as right turns, left turns, straight roads, and unexpected road conditions like landslides, helping improve road safety and navigation in the Gilgit region. The project was based on the implementation of the YOLO (You Only Look Once) object detection framework, providing students with hands-on experience in data gathering, labeling, model development, and evaluation.

**Objectives**

The objectives of the project were clearly defined as follows:

1. Data Collection: Gather a dataset of road images from Gilgit, ensuring a minimum of 50 images for model training and evaluation.

2. Data Annotation: Annotate the collected images to label road conditions, including right turn, left turn, straight, and unexpected conditions such as landslides.

3. Classifier Development: Train a classifier to categorize the images into predefined classes: right turn, left turn, straight, and unexpected.

4. Implementation of YOLO Model: Use YOLO, a state-of-the-art real-time object detection model, to detect and classify these road conditions in the images.

5. Model Evaluation: Evaluate the model's performance and adjust parameters or model architecture as necessary to improve accuracy.

6. Documentation: Document the entire process, from data collection and labeling to model training, evaluation, and results.

**Methodology**

**Data Collection**

The first step in the project was to collect a set of road images from Gilgit. Each group of students was tasked with capturing at least 50 images showing different road conditions. These images were taken using smartphones or cameras and covered various road types and conditions, such as:

- Curved roads (left and right turns)

- Straight roads

- Roads with unexpected conditions (e.g., landslides or road blockages)

The data was diverse, covering different weather conditions, lighting, and road types to ensure a robust dataset for model training.

**Data Annotation**

After collecting the images, the next task was to annotate and label them according to the following categories:

1. Speed Limits: Images showing a speed limits on the road.

2. Traffic Signs: Images showing traffic signals.

3. Straight Road: Images showing a straight road with no turns.

4. Unexpected Road Conditions: Images showing unforeseen road conditions, such as landslides, roadblocks, or obstacles.

The images were labeled using annotation tools such as roboflow. Annotations were saved in the YOLO format, which specifies bounding boxes and class labels for each identified object or road condition in the image.

**Model Selection: YOLO (You Only Look Once)**

For object detection, the team decided to implement YOLO, a powerful real-time object detection model known for its speed and accuracy. YOLO divides the image into a grid and assigns a bounding box for each object detected within each grid cell. It predicts both the bounding box coordinates and the probability of different classes within the image.

**Advantages of YOLO**

- Fast and efficient, making it suitable for real-time applications.

- Can detect multiple objects in an image with high accuracy.

- End-to-end training, allowing for fast deployment.

**Model Training**

The training process involved the following steps:

1. Data Preprocessing: Images were resized to 416x416 pixels to match YOLO’s input requirements. The dataset was split into training (80%) and testing (20%) sets.

2. Model Architecture: The YOLOv4 model architecture was chosen, which provides a good balance between speed and accuracy. YOLOv4 uses a convolutional neural network (CNN) with several enhancements such as CSPDarknet53 as the backbone for feature extraction.

3. Hyperparameter Tuning: Hyperparameters such as learning rate, batch size, and number of epochs were optimized to achieve the best performance.

4. Training: The model was trained on the annotated dataset using the pre-trained YOLOv4 weights as a starting point, which was fine-tuned on our specific dataset of road images.

**Model Evaluation**

To evaluate the performance of the YOLO model, the following metrics were used:

- Precision: The percentage of correct positive detections (e.g. correct identification of traffic signals or obstacle).

- Recall: The percentage of actual objects correctly detected by the model.

- F1 Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.

- Intersection over Union (IoU): A metric to measure the overlap between the predicted bounding boxes and the ground truth.

The model was initially evaluated on the test set, and based on the results, adjustments were made to the architecture and hyper parameters to improve performance. For instance, the learning rate was reduced to avoid over fitting, and additional augmentation techniques (e.g., rotations, flips) were applied to the images to increase the dataset size and diversity.

**Fine-Tuning and Optimization**

After the initial training, fine-tuning was conducted by adjusting the following:

-Anchor Boxes: Adjusted to better fit the size and aspect ratio of the road conditions and turns.

- Model Parameters: Adjusted based on performance metrics to improve recall and precision, particularly in detecting landslides and road blockages.

- Testing on Real-World Data: The model was also tested on a few real-world images to assess how well it generalized outside of the training set.

**Challenges and Limitations**

Some challenges faced during the project included:

Limited Dataset: With a relatively small dataset (less than 300 images in total), the model struggled to detect rare road conditions such as landslides and road blockages accurately.

- \*\*Diverse Road Conditions\*\*: The variety of road conditions and environmental factors (e.g., lighting, weather) led to some false positives and false negatives.

Class Imbalance: Some classes, such as “straight road,” were overrepresented in the dataset, leading to potential biases in detection.

To address these, future work could include gathering a larger and more balanced dataset, as well as incorporating additional techniques such as data augmentation and domain adaptation.

**Conclusion**

The project successfully developed an object detection model capable of identifying road conditions and turns using the YOLO framework. Through careful data collection, labeling, model training, and evaluation, the team was able to create a functional model that can assist in road navigation and safety monitoring. Although there were challenges related to data size and class imbalance, the results demonstrate the potential for real-time object detection in road conditions, which could be used in navigation systems or road monitoring applications.

Future work will focus on expanding the dataset, refining the model, and integrating the detection system into a real-world application.

This concludes the report on the object detection model for road conditions.