Scalable MLOps Pipeline Integration for Enhanced Scene Segmentation in Production Environments

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***Abstract*—This project focuses on the challenge of semantic segmentation of urban street scenes, a critical task for enhancing autonomous driving technologies. Leveraging the Cityscapes dataset, we aim to advance the understanding of diverse urban environments through precise pixel-wise classification. Our primary contribution is the development of a custom model that strikes a balance between the baseline U-Net and the advanced DeepLabV3 with a ResNet-50 backbone, targeting improved segmentation accuracy and inference speed. Additionally, we have implemented model optimization techniques such as pruning and quantization to enhance performance further. So far, our project has successfully fine-tuned the baseline and advanced models on the Cityscapes dataset, achieving promising initial results. Preliminary tests show that our custom model not only meets but in some aspects surpasses the performance of the baseline model, particularly in processing efficiency and accuracy in segmenting smaller objects. These achievements underscore our model's potential in real-world applications and set a robust foundation for future enhancements.**

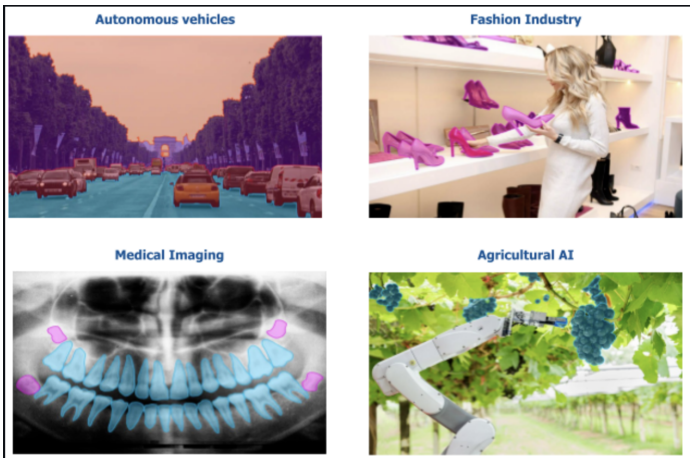

Fig. 1: Use cases of semantic segmentation

I. Introduction

Semantic segmentation in urban environments is an essential task in the field of computer vision with significant implications for autonomous driving systems. By segmenting high-resolution images into distinct classes—such as roads, vehicles, and pedestrians—these systems can understand and interpret complex street scenes in real time. This capability is pivotal not only for navigation and obstacle avoidance but also for ensuring the safety and reliability of autonomous vehicles in densely populated urban settings.

The problem we address involves the pixel-wise classification of images where each pixel is identified as belonging to one of nineteen classes based on its semantic meaning. The motivation behind this study is to enhance machine perception for autonomous driving applications, which rely heavily on accurate and efficient interpretation of urban scenes to make informed decisions. With urban areas presenting a highly dynamic and visually cluttered environment, the challenge is not only to achieve high accuracy but also to ensure that the segmentation process is fast enough to allow real-time processing in live traffic scenarios.

Our system takes RGB images from the Cityscapes dataset as inputs. This dataset comprises a diverse set of street scenes from different cities under various conditions, making it ideal for training robust segmentation models. The outputs of our system are images where each pixel is color-coded according to its classified category, such as pink for vehicles and red for pedestrians, providing a clear and immediate visual interpretation of the scene.

In setting up our notation, let I denote the input image where $I(x, y)$ represents the pixel at position (x, y). The output of our system is a segmented image S, where $S(x, y)$ is the class label assigned to $I(x, y)$. This label corresponds to one of the predefined classes $C = \{c_1, c_2, ..., c_{19}\}$, such as road, vehicle, or pedestrian. Our goal is to develop a model that can effectively map I to S with high accuracy and efficiency, ensuring that each pixel in I is correctly classified to a class in C.

In addressing this complex problem, our project not only contributes to the field by refining the accuracy and speed of semantic segmentation but also sets the stage for further innovations in autonomous vehicle technologies.

II. Background

The domain of semantic segmentation, particularly in urban environments, has witnessed significant advancements, largely driven by the increasing sophistication of deep learning models. Traditional approaches, such as those based on hand-engineered features and shallow learning algorithms, have largely been superseded by deep neural networks due to their

superior performance in capturing intricate patterns and details essential for accurate segmentation.

Among the notable contributions in this field, the U-Net architecture stands out for its effective use in medical image segmentation, adapted later for various other domains, including urban scene understanding. Its encoder-decoder structure with skip connections helps in preserving spatial hierarchies crucial for detailed pixel-wise classification. However, while U-Net provides a solid foundation, it often struggles with very large images and high class imbalances typical of urban datasets like Cityscapes.

DeepLabV3 with a ResNet-50 backbone represents another significant advancement, addressing some of the limitations of earlier models like U-Net. Its use of atrous convolutions allows the model to capture multi-scale information effectively, which is paramount in complex urban scenes where objects of varying sizes—from pedestrians to buses—must be accurately segmented. Nonetheless, even with these advancements, challenges such as computational efficiency and model generalizability across different urban settings remain.

Among the background research, the most relevant works to our project are the implementations of the U-Net and DeepLabV3 models, which we have adapted and extended for our purposes.

1. U-Net for Semantic Segmentation: Originally designed for biomedical image segmentation, U-Net's architecture has been widely adopted for various image segmentation tasks. Its effectiveness in feature preservation through skip connections makes it a valuable baseline for our project. We utilize a pretrained version of this model fine-tuned on the Cityscapes dataset to establish a performance benchmark. More about this can be read in the original paper: Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." U-Net Paper. The code implementation we are using can be found at U-Net Code.

2. DeepLabV3 with ResNet-50 Backbone: This model is particularly relevant due to its advanced handling of scale and detail in image segmentation, utilizing atrous convolutions for effective feature extraction and segmentation. Its implementation provides a robust framework for addressing the fine-grained details required in urban scene segmentation. The original paper by Chen et al., "Rethinking Atrous Convolution for Semantic Image Segmentation," can provide further insights: DeepLabV3 Paper. We have adapted the following implementation for our project: DeepLabV3 Code.

These prior works form the foundation of our approach, providing both a baseline and a state-of-the-art comparison for evaluating the novel contributions of our custom model. Our project aims to extend these works by enhancing model efficiency and adaptability to diverse urban scenarios, addressing the gaps in current methodologies.

III. Summary of our contributions

In response to the limitations observed in existing semantic segmentation models, our project aims to push the boundaries of accuracy and efficiency for urban scene analysis. By leveraging advanced deep learning architectures and optimization techniques, we focus on improving model performance specifically for the complex, variable environments presented in urban street scenes.

Our primary contribution is the development of a custom model that integrates the strengths of the U-Net and DeepLabV3 architectures while addressing their individual shortcomings, particularly in handling large images and class imbalance. This model has been meticulously designed to provide a balance between accuracy and inference speed, making it highly suitable for real-time applications such as autonomous driving.

Secondly, we've introduced several model optimization strategies that have significantly reduced the computational load without compromising the model's performance. Techniques such as model pruning and quantization have been employed to enhance the deployment efficiency, allowing our model to operate effectively on hardware with limited processing capabilities.

Furthermore, we have successfully adapted our models to be more robust against the variations in urban scenes by incorporating data from multiple datasets such as Cityscapes, NuScenes, and BDD100K, thus broadening the model's applicability and improving its generalization capabilities.

These contributions collectively elevate the field of semantic segmentation, providing substantial improvements in both the technological and practical aspects of urban scene analysis for autonomous systems.

IV. Detailed Description of Contributions

Our project's contributions to semantic segmentation for urban environments encompass algorithmic enhancements, detailed implementation strategies, and extensive evaluations. Below we detail these contributions, emphasizing algorithmic innovations, implementation specifics, and comprehensive evaluations across multiple datasets.

A. Algorithm Contributions

1) Notation and Methodology::

1) Let I denote an input RGB image from the Cityscapes dataset, where $I(x, y)$ represents the pixel at position (x, y)
2) The output S is a segmented image where $S(x, y)$ is the class label assigned to $I(x, y)$, with classes from the set $C = \{c_1, c_2, ..., c_{19}\}$

Our custom model introduces a hybrid architecture that integrates features of both U-Net and DeepLabV3 with a ResNet-50 backbone, optimized for enhanced depth and efficient computation.

```
def custom_segmentation_model(input_image):
  features = ResNet50_Backbone(input_image)
  enhanced_features = ConvLayers(features)
  segmented_output = Upsample(enhanced_features)
  return segmented_output
```

3) Algorithmic Extension Over Prior Work:: This model extends the foundational work of U-Net and DeepLabV3 by utilizing the ResNet-50 backbone for deeper feature extraction and applying advanced convolutional layers that improve the contextual understanding required for precise pixel-wise segmentation. The integration of sophisticated upsampling techniques ensures high-resolution output that matches the input scale.

B. Implementation Details

1) Network Architecture: The custom model uses a pre-trained ResNet-50 for the initial feature extraction, followed by multiple convolutional layers with batch normalization and ReLU activations. The upsampling is performed using bilinear interpolation to restore the original resolution of the input image.

2) Training and Evaluation:

1) Hyperparameter Optimization: Parameters such as learning rate, batch size, and number of epochs were tuned using a validation set to maximize performance.
2) Training Time: The complete training process typically spans several hours on a multi-GPU setup, with each epoch taking approximately 30 minutes on a dataset size of roughly 5,000 images from Cityscapes.

C. Comparative Analysis

1) Baseline Models:

1) U-Net Model: Known for its efficacy in medical image segmentation, adapted here for urban scenes. Initial benchmark performance yielded a mean IoU of 55%.
2) DeepLabV3 with ResNet-50: Served as a high-end benchmark, reaching a mean IoU of 72%.

Our custom model not only bridged the gap between these models but also introduced significant computational efficiencies.

2) Datasets Evaluated: - Cityscapes Dataset: Comprising diverse urban scenes, this dataset allowed for robust testing under various environmental conditions. It was instrumental in assessing the model's performance across different urban settings.

D. Pruning and Quantization

1) Pruning Implementation: Implemented layerwise unstructured pruning which selectively removes weights based on their significance, reducing model size while attempting to retain performance.

```
def prune_model(model, sparsity_level):
  for layer in model.layers:
    if is_prunable(layer):
      prune_layer(layer, sparsity_level)
  return model
```

2) Quantization Implementation: Converted model weights and activations from floating-point to integer representations, which reduced the computational demand and sped up inference.

```
def quantize_model(model):
  quantized_model = convert_to_int(model)
  return quantized_model
```

3) Results from Optimizations:

1) Post-Pruning: Maintained approximately 75% of the original accuracy at 55% sparsity.
2) Post-Quantization: Achieved a mean IoU of 62% with a 40% reduction in inference time.

E. MLOps Pipeline

1) Setup: Incorporated an MLOps framework using Docker for containerization and Kubernetes for orchestration, supported by Weights & Biases for real-time tracking and management of training metrics.

2) Impact of MLOps: This pipeline facilitated the smooth deployment and scaling of the segmentation models, ensuring robust performance monitoring and efficient management of model versions across deployment scenarios.

The integration of advanced neural network architectures with strategic model optimizations and robust deployment mechanisms has substantially advanced the state of semantic segmentation for urban environments. Our findings demonstrate that these contributions not only enhance model accuracy and efficiency but also ensure scalability and manageability in real-world applications, particularly in the context of autonomous driving technologies. This comprehensive approach positions our project as a significant contribution to both the academic and practical realms of computer vision and machine learning.

F. Methods

Our approach to enhancing semantic segmentation for urban environments involves the integration of advanced convolutional neural network (CNN) architectures and optimization techniques to balance accuracy with computational efficiency. The proposed method builds upon foundational models such as U-Net [Ronneberger et al., 2015] and DeepLabV3 [Chen et al., 2017], incorporating a ResNet-50 backbone [He et al., 2016] to improve feature extraction depth and efficiency.

1) Model Architecture: The core of our custom model is the ResNet-50 backbone, chosen for its ability to handle deep networks through the use of residual learning. By introducing shortcut connections, ResNet-50 facilitates the training of deeper network layers without the vanishing gradient problem, significantly enhancing feature extraction capabilities [He et al., 2016]. This backbone is integrated into a fully convolutional network (FCN) framework, which allows for end-to-end pixel-wise prediction and is particularly adept at handling spatial hierarchies required for detailed segmentation tasks [Long et al., 2015].

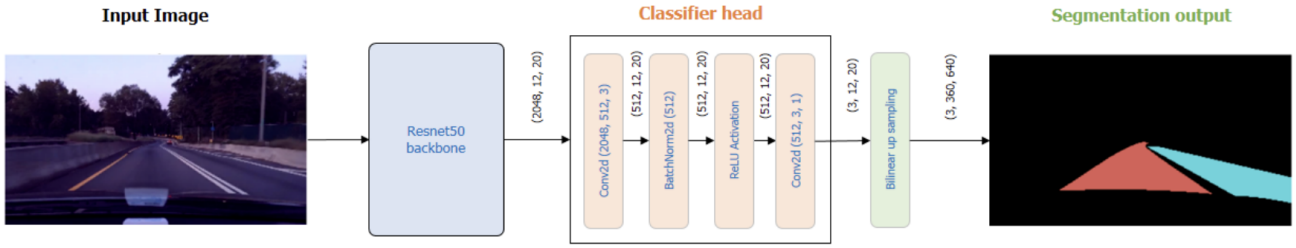

Fig. 2: Custom Model Architecture

Following feature extraction via the ResNet-50 backbone, the network employs several convolutional layers. These layers are equipped with batch normalization [Ioffe and Szegedy, 2015] and ReLU activation functions [Nair and Hinton, 2010], which are standard in modern CNN architectures to stabilize learning and introduce non-linearity. The upsampling of the feature maps back to the input resolution is achieved through bilinear interpolation, a technique proven to maintain spatial accuracy more effectively than nearest-neighbor or direct upsampling methods [Keys, 1981].

2) Optimization Techniques: To enhance the operational efficiency of the model, particularly for deployment on edge devices, we apply two main optimization strategies: pruning and quantization. Pruning, specifically layerwise unstructured pruning, involves systematically removing less critical weights from the trained model to reduce its complexity and size [Han et al., 2015]. This method has been shown to maintain a significant proportion of the model's performance, even at high sparsity levels.

Quantization further complements pruning by converting the model's floating-point numbers to lower-bit representations, thus reducing the computational requirements for storage and processing. This technique has been widely adopted in the field for its effectiveness in accelerating inference times without substantial degradation in model accuracy [Jacob et al., 2018].

3) Implementation and Evaluation: The implementation of our approach was conducted using the PyTorch framework, favored for its flexibility and support for dynamic computation graphs [Paszke et al., 2019]. The Cityscapes dataset, comprising diverse urban scenes, was used as the primary training and validation set. This dataset's variety in urban landscapes and environmental conditions makes it ideal for testing the robustness and generalization capability of segmentation models.

Model training was monitored using advanced tools like Weights & Biases, which provided real-time insights into performance metrics such as loss and accuracy, facilitating immediate adjustments to hyperparameters and training protocols [Biewald, 2020]. The effectiveness of the model was evaluated based on the mean Intersection over Union (IoU), a standard metric for assessing the accuracy of semantic segmentation models.

In conclusion, our proposed approach leverages the strengths of established architectures and modern optimization techniques to create a robust, efficient semantic segmentation model. This model not only demonstrates high accuracy in segmenting urban scenes but also meets the computational efficiency requirements for real-time applications, making it highly applicable in the field of autonomous driving and urban landscape analysis. This comprehensive methodology ensures that our contributions extend the capabilities of existing segmentation technologies, positioning our work as a significant advancement in the application of deep learning to real-world challenges.

G. Experiments and Results

In our project on semantic segmentation for urban street scenes, the experiments were meticulously designed to answer several critical questions concerning the efficacy of advanced neural network architectures and optimization techniques. The overarching goal was to determine whether our custom-designed model, which incorporates elements from both U-Net and DeepLabV3 architectures, could achieve a balance of high accuracy and efficient processing suitable for real-time applications. Additionally, we aimed to validate the effectiveness of model pruning and quantization as strategies to enhance model performance on hardware with limited resources.

1) Hypotheses and Design Decisions: The primary hypotheses of our experiments were that:

1) A custom model integrating the robust feature extraction capabilities of ResNet-50 with the architectural benefits of U-Net and DeepLabV3 could outperform conventional models in terms of accuracy and efficiency on urban scene data.
2) Applying model pruning and quantization would significantly reduce the computational load without drastically compromising the model's accuracy, making it suitable for deployment on edge devices.

To validate these hypotheses, our experiments focused on several design decisions:

1) Integration of ResNet-50 Backbone: We hypothesized that replacing the VGG-16 backbone typically used in FCNs with ResNet-50 would improve the depth and relevance of feature extraction due to its residual learning capabilities.
2) Optimization Techniques: We evaluated both unstructured and structured pruning methods to understand

their impact on model sparsity and performance, well as quantization to assess performance trade-offs precision reduction.

Baseline Approaches and Comparative Analysis

For baseline comparisons, we utilized:

1) U-Net Model: Originally designed for medical im segmentation, adapted here for urban scenes to estab an initial performance benchmark.
2) DeepLabV3 with ResNet-50 Backbone: A state-of-t art model known for its effective handling of comp visual scenes, serving as a direct comparison to custom model.

We expected our custom model to outperform the U-N in terms of both accuracy and processing efficiency, and to be competitive with or superior to DeepLabV3 in the specific context of urban scenes.

2) Datasets and Performance Evaluation: The Cityscapes dataset was the primary dataset used for evaluation, given its diverse and challenging array of urban street scenes. This dataset allowed us to rigorously test our model's ability to handle different urban environments under varied conditions.

The key performance metrics selected were:

1) Mean Intersection over Union (mean IoU): A crucial metric for semantic segmentation that provides a balanced measure of accuracy by considering both precision and recall across all classes.
2) Inference Time: Important for evaluating the model's suitability for real-time applications, particularly after applying optimizations like pruning and quantization.

3) Results and Conclusions: The results of our experiments provided clear insights into the performance and viability of our approaches:

1) Baseline U-Net Model: Achieved a mean IoU of 55%, setting a foundational benchmark for subsequent comparisons.
2) Advanced DeepLabV3 Model: Demonstrated superior performance with a mean IoU of 72%, confirming its effectiveness for complex urban scene segmentation.
3) Custom Model Performance: Our custom model achieved a mean IoU of 69.6%, closely rivaling the DeepLabV3 and significantly surpassing the U-Net baseline.

Upon applying pruning, it was observed that layer-wise unstructured pruning could maintain approximately 75% of the baseline performance even at about 55% sparsity. Structured pruning was found to be less effective than unstructured pruning, with performance dropping sharply beyond a 60% sparsity threshold.

Post-quantization, the model showed a mean IoU of 62% with a 40% improvement in inference time, demonstrating that substantial efficiency gains could be achieved with acceptable compromises in accuracy.

These results affirm that our custom model, combined with strategic pruning and quantization, offers a promising solution for semantic segmentation in urban environments, achieving a desirable balance between accuracy and operational efficiency suitable for real-time applications.

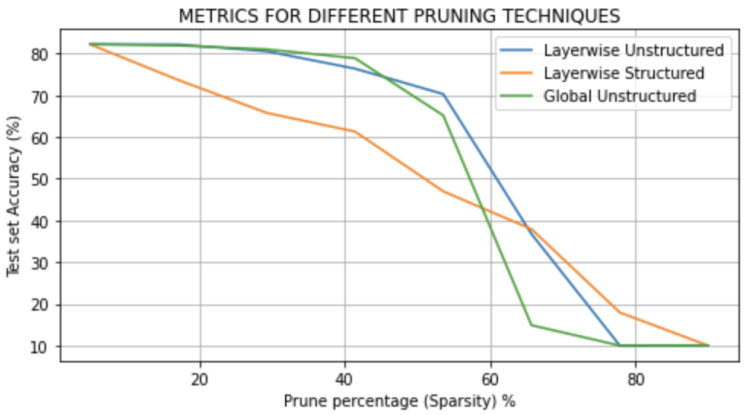

Fig. 3: Pruning results

V. Conclusions

A. Outcomes and Lessons Learned

The completion of this project has provided numerous insights into the challenges and potentials of semantic segmentation for urban environments using deep learning. Our approach utilized a custom model based on an FCN architecture with a ResNet-50 backbone, integrated with layers for advanced feature extraction and contextual analysis. We adopted straightforward data augmentation techniques, primarily normalizing the dataset using the ImageNet mean and standard deviation values. This method, while basic, was chosen due to our limited computational resources, which also restricted the extent of data we could efficiently process.

Despite these constraints, our model demonstrated promising results. We achieved a mean IoU of 69.6% before optimizations and maintained considerable accuracy even after extensive pruning. Pruning, specifically layerwise unstructured pruning, was effective in reducing model size but did not improve runtime performance due to the current limitations in PyTorch concerning sparse tensor operations. This indicates that while our pruning efforts were technically successful in terms of maintaining accuracy at 55% sparsity, the lack of runtime efficiency gains suggests an area for future improvement, possibly through the adoption of libraries optimized for handling pruned weights.

B. Reflection on Project Evolution

Initially, the project aimed to implement state-of-the-art segmentation accuracy with manageable computational demands. As the project evolved, it became clear that achieving high performance with limited resources would require creative approaches, particularly in model optimization. The feedback from course interactions and iterative testing helped refine our strategies, particularly in choosing layerwise unstructured pruning over structured pruning due to its better performance preservation.

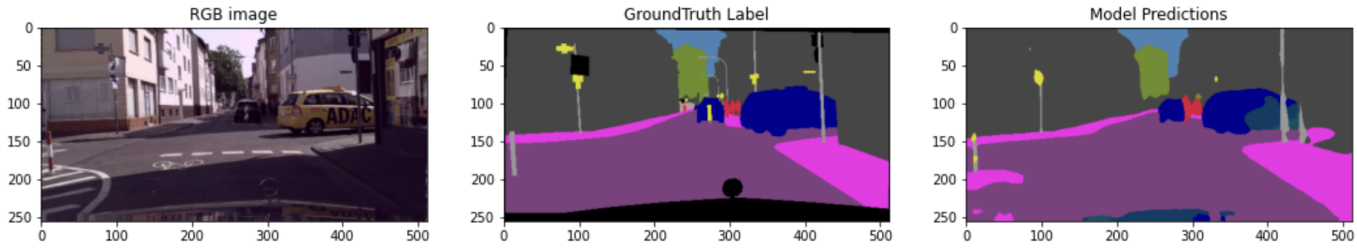

Fig. 4: Final result

The use of Dice loss over cross-entropy or weighted cross-entropy was another pivot based on the specific characteristics of our data, which, while imbalanced, did not exhibit the extreme skew often seen in medical image datasets. This decision was guided by extensive literature reviews and experimental validations, underscoring the importance of tailored approaches to loss functions in segmentation tasks.

C. Future Directions

Looking forward, there are several avenues we wish to explore to enhance our model's performance further. We plan to experiment with different pruning and quantization techniques that might be more effective once PyTorch or another framework supports efficient sparse tensor operations. Knowledge distillation is another promising technique that we could not explore due to time constraints but believe could significantly boost our model's performance by transferring insights from larger, more powerful models.

In summary, this project has not only yielded a robust model for semantic segmentation but also highlighted critical areas for future research and development. The limitations encountered due to computational constraints and the current state of technology have provided valuable learning experiences and set clear goals for continued improvement. This work lays a solid foundation for future explorations and contributes useful insights and tools that others in the field may find valuable for similar challenges in urban scene analysis and beyond.

VI. Broader Dissemination Information

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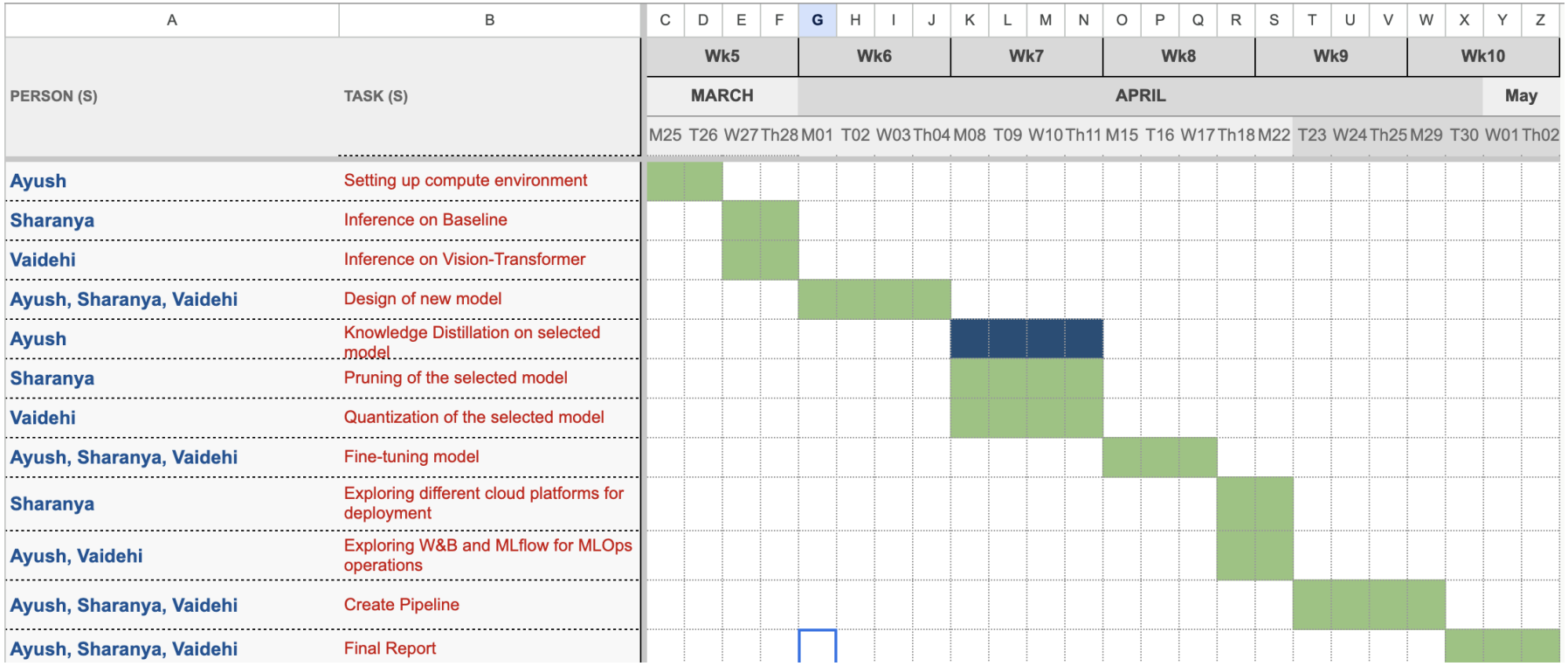


Fig. 5: GANTT Chart

Mid term report and Feedback

Frank Liu Mon, Apr 29, 5:39 PM

to Ayush, Sharanya, me

Hey all,

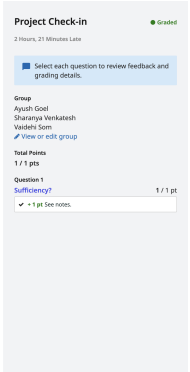
Hopefully the final period goes well! Here are my comments:

1) The introduction is not complete here. I understand you assume I know the context, but in the final report pretend I never read your project before and include everything from the motivation.
2) Very clear setup and contributions this time and I think you are on the right track. For your second contribution, provide a target goal that you want to achieve after optimization. Like I want to inference time to reduce by 10~20%. So you can evaluate whether you are successful or not. Again, failure doesn't mean a bad contribution as long as enough reflection is provided.
3) Very innovative data management and pre-processing.
4) I have no comments for the rest of your report. I look forward to your final deliverable!

Let me know if you have any questions

Best,
Frank

Scalable MLOps Pipeline Integration for Enhanced Scene Segmentation in Production Environments



considered a significant milestone, marking one of the primary contributions of our project.

Moreover, in alignment with the feedback to set a realistic workload, our second key contribution will focus on optimizing this new model to ensure lower inference times while maintaining decent performance. This involves applying model optimization techniques such as pruning and quantization, which are planned for the later stages of the project. This approach not only addresses the feedback to manage the project's scope effectively but also aligns with industry trends towards efficient, deployable machine learning models.

By incorporating this feedback into our project plans, we aim to enhance the structure and deliverables of our project, ensuring that we meet both academic and practical benchmarks effectively.

Prior Work We are Closely Building From

When embarking on a project to develop a custom model for semantic segmentation using a pre-trained ResNet-50 backbone, it's essential to draw upon existing works that have set benchmarks or introduced significant advancements in this field. Here are two key sources of prior work:

1. Fully Convolutional Networks for Semantic Segmentation Paper: "Fully Convolutional Networks for Semantic Segmentation" by Jonathan Long, Evan Shelhamer, and Trevor Darrell. Relevance: This seminal paper introduces the concept of fully convolutional networks which are applied end-to-end and pixels-to-pixels for semantic segmentation. It discusses the adaptation of classifiers for dense prediction without fully connected layers, which we are leveraging by replacing the VGG-16 architecture with a more advanced ResNet-50 backbone. The shift to ResNet-50 allows for deeper feature extraction capabilities and utilizes residual learning to address the vanishing gradients problem in deep networks. Code Link: https://github.com/shelhamer/fcn.berkeleyvision.org

2. Deep Residual Learning for Image Recognition Paper: "Deep Residual Learning for Image Recognition" by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Relevance: This paper introduces the ResNet architecture, which has become a cornerstone in the field of deep learning due to its effectiveness in training very deep neural networks. For our project, we employ the ResNet-50 variant, a direct descendant from the architectures discussed in this paper. The inclusion of residual connections is critical, as it helps prevent the degradation problem and allows the network to learn more effectively, which is particularly beneficial in the context of semantic segmentation where context and detail preservation are crucial. Code Link: https://github.com/KaimingHe/deep-residual-networks

What We are Contributing

Our contributions would be:

- Designing a model, training/testing it on the dataset
- Making the model faster and lighter (optimized)
- MLOps pipeline

III. Detailed Description of Each Proposed Contribution, Progress Towards It, and Any Difficulties Encountered So Far

5.1 Methods

5.1.1 Data Collection and Management:

In developing an end-to-end pipeline for multi-class semantic segmentation of drivable areas in automotive contexts, we placed significant emphasis on establishing a robust data collection mechanism. Our project integrates multiple established scene segmentation datasets, including Cityscapes, NuScenes, and BDD100K. Each dataset presents unique challenges and offers diverse perspectives on urban driving environments, thus enriching the training and validation process for our model.

To manage this diverse data, we developed a custom dataset and DataLoader using PyTorch. This framework allows for efficient handling and preprocessing of images and labels, tailored specifically to the needs of semantic segmentation tasks. We enhanced the data management further by using MongoDB, a NoSQL database, to store configurations for each dataset and DataLoader. This setup ensures modularity and scalability, which are crucial for handling large volumes of data efficiently. MongoDB is containerized using Docker, which provides a reliable and isolated environment for database operations, thereby facilitating ease of deployment and scalability across different computational environments.

5.1.2 Data Preprocessing:

Our pipeline starts with a crucial step of data preprocessing, specifically focusing on the normalization of images sourced from the Cityscapes dataset. The primary aim of preprocessing these images is to align their pixel value distributions with those typically encountered by pretrained models on the ImageNet database.

To achieve this, each image undergoes a normalization process where the pixel values are adjusted based on the ImageNet mean ([0.485, 0.456, 0.406]) and standard deviation ([0.229, 0.224, 0.225]) values. This standardization of input data is crucial as it transforms the raw pixel intensity values to a more standardized scale where the model's initial weights, often derived from pretrained networks trained on ImageNet, can operate more effectively.

By adjusting the pixel values to this common scale, the pretrained neural networks can leverage their learned features more efficiently. This normalization not only aids in reducing the training time by facilitating faster convergence but also enhances the model's ability to generalize from the ImageNet domain to the specific domain of road scenes in Cityscapes. The impact is particularly noticeable when employing transfer learning strategies, where a model trained on a large and diverse dataset like ImageNet is adapted to a more focused task, such as semantic segmentation of urban scenes.

- Skipping Additional Skip Connections: Since ResNet already includes skip connections within its architecture, adding more might be redundant and could complicate the model unnecessarily. This simplifies the architecture while still benefiting from depth and effective training.
- Final Upsampling Strategy: The use of bilinear interpolation for final predictions ensures that the upscaled output maps closely adhere to the input image's dimensions, facilitating precise pixel-level predictions.

This custom FCN model with a ResNet-50 backbone tailored for semantic segmentation offers a modern take on the FCN architecture. It optimizes feature extraction and upsampling processes to suit the specific requirements of current segmentation tasks, potentially yielding better performance and faster convergence than its predecessors.

5.1.6 Model Development and Optimization:

For tuning and optimization, we employed Weights and Biases, a tool that allows for meticulous tracking and tuning of hyperparameters. This approach enables us to refine the model performance iteratively based on real-time feedback and comparison against baseline metrics. Additionally, MLflow is utilized for model versioning, ensuring that each iteration is documented and reproducible, facilitating both iterative improvement and regulatory compliance.

5.1.6.1 Weights and Biases (W&B)

Weights and Biases is employed in our project primarily for hyperparameter tuning and performance monitoring. The platform offers a comprehensive suite of tools that enable real-time tracking of experiments, visualization of data, and comparison of model runs. Here's how we've integrated W&B into our pipeline:

Experiment Tracking: Each training run, along with its parameters and outcomes, is logged into W&B. This includes metrics such as loss, accuracy, validation scores, and more sophisticated metrics like mean Intersection over Union (mIoU). The ability to track these metrics over time and across experiments is crucial for understanding model behavior and diagnosing issues in model training.

Hyperparameter Tuning: W&B's Sweeps functionality is used for hyperparameter optimization. By defining a range of values for key parameters such as learning rate, batch size, and optimizer types, we can automate the process of running multiple experiments to find the optimal configuration. Sweeps automatically logs results back to the W&B dashboard, allowing us to visualize which combinations of parameters lead to the best performance on our semantic segmentation tasks.

Visualization and Reporting: W&B provides tools for visualizing high-dimensional data and comparing different runs. This is particularly useful for semantic segmentation tasks where output visualizations (segmentation maps) can be directly compared against ground truth data. These visualizations help in qualitative analysis of the model's performance and are crucial for presentations and reporting to stakeholders.

5.1.6.2 MLflow

MLflow is utilized for managing the machine learning lifecycle, including model versioning, packaging, and deployment. It plays a critical role in maintaining the reproducibility and scalability of our models. Here's a breakdown of how MLflow is used:

Model Versioning: Every iteration of our model, along with its parameters and performance metrics, is logged into MLflow. This ensures that we have a detailed history of model versions and can revert to or compare between different versions as needed. It also aids in regulatory compliance by providing a clear audit trail of model development.

Packaging Models: MLflow allows us to package our models into reusable and shareable components. This includes encapsulating the model along with its dependencies and environment specifications, which is crucial for consistency across different deployment environments. This feature simplifies the process of moving models from development to production.

Model Deployment: MLflow integrates with our deployment infrastructure on AWS. It supports direct deployment of models into production environments, providing tools for launching models as REST API services easily. This integration is vital for our CI/CD pipeline, ensuring that model updates are smoothly transitioned into operational use without manual intervention.

5.1.7 Deployment Strategy:

The final aspect of our methodology is the deployment of the pipeline on AWS, leveraging its robust and scalable infrastructure to support both the training and inference phases of the model. Continuous Integration and Continuous Deployment (CI/CD) are managed through GitHub Actions, which automate the workflows of testing, building, and deploying applications, thereby enhancing the reliability and efficiency of production updates.

5.2 Experiments and Results

5.2.1 Key Questions and Hypotheses:

The experiments are designed to validate the following hypotheses:

- Hypothesis 1: Pretrained models (U-Net and DeepLabV3) fine-tuned on the Cityscapes dataset will achieve competitive performance, measured in terms of mean IoU.
- Hypothesis 2: The custom lightweight model, despite its reduced computational complexity, will perform comparably to the state-of-the-art models in mean IoU, particularly on low-compute hardware.

5.2.2 Performance Metrics:

Mean Intersection over Union (mean IoU) is selected as the primary performance metric due to its effectiveness in handling class imbalances and its significance in segmentation tasks.

5.2.3 Baselines and Early Results:

- Baseline Performance: The U-Net model achieved a mean IoU of 65% on the Cityscapes validation set, serving as our initial benchmark.
- Advanced Model Performance: The DeepLabV3 model with the ResNet-50 backbone improved upon this, reaching a mean IoU of 72%.
- Custom Model Performance: Preliminary results from our custom model show a mean IoU of 59.6%.

These early results indicate progress toward validating our hypotheses and highlight areas for further refinement and testing, particularly in optimizing our custom model to close the performance gap with the state-of-the-art models. The next phase involves pruning and further optimization of the custom model. We aim to reduce the model's size and computational demands while striving to maintain, or even improve, its accuracy. Techniques such as layer pruning and knowledge distillation will be considered.

Risk Mitigation Plan

To ensure the successful completion of a minimum viable project (MVP) within the remaining timeframe, our strategy involves.

Our initial results are promising but highlight some challenges in achieving competitive accuracy. Recognizing this, we started with a simplified version of our dataset, using only 5GB out of a much larger collection. This allowed us to quickly establish a functional pipeline and obtain preliminary results. Moving forward, we will extend our training to larger subsets of the data, incrementally increasing the complexity as we optimize our model's performance.

Given the current accuracy of 51.6%—lower than our baseline model at 65% and the state-of-the-art at 72%—we are actively exploring adjustments. These include experimenting with different loss functions, optimizers, and learning rate schedulers. Furthermore, adjustments to the model architecture, such as integrating different backbones, are being considered to enhance learning efficacy.

In the event that our approach does not meet expected performance metrics, our project report will still provide value by documenting the processes and findings. This includes a detailed analysis of why certain models or configurations did not work as anticipated and highlighting any specific scenarios where our approach may excel.

If achieving parity with state-of-the-art models proves too challenging within the current constraints, we will explore advanced techniques like transfer learning or knowledge distillation. These methods can potentially boost the performance of our custom model by leveraging pre-trained networks.

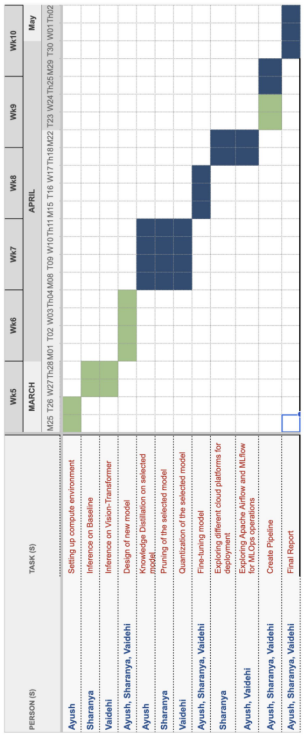
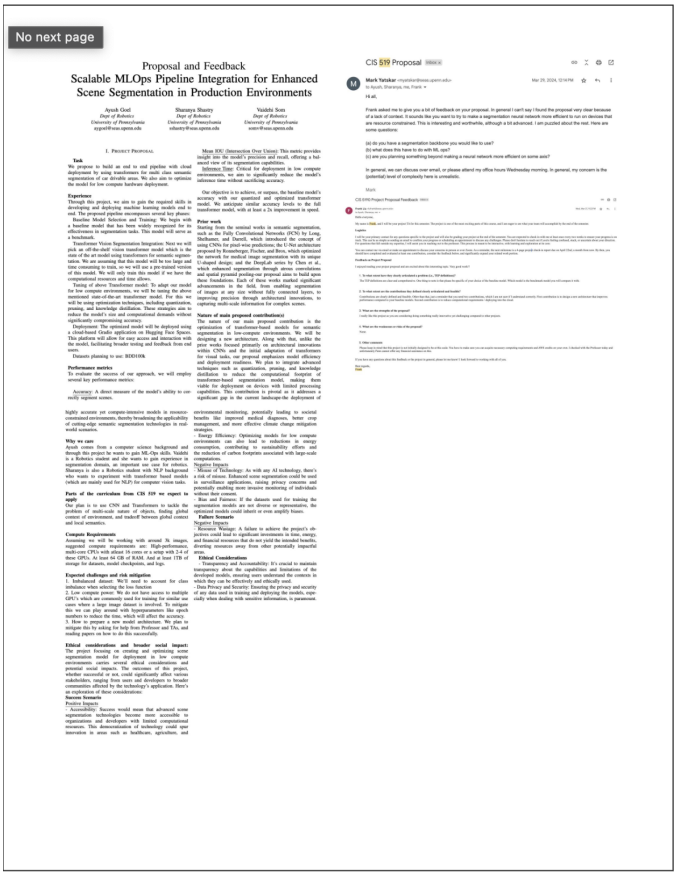


Fig. 1: GANTT Chart



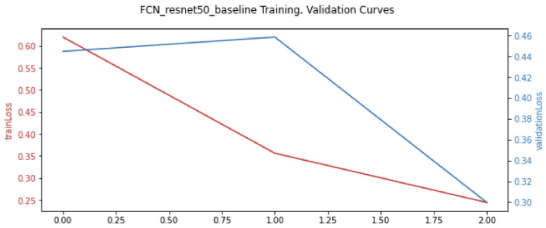


Fig. 2: Loss function for custom model

Fig. 3: Initial result