**ABSTRACT**

Semantic segmentation using RGB-D images has emerged as an important area in computer vision, with applications ranging from robotics to scene understanding. Its accuracy is especially crucial in situations where safety cannot be compromised such as in upcoming developments in the space of driverless vehicles, and the use of robotics in surgery. The initial motivation of this project was to improve semantic segmentation for robotic/wheelchair navigation in building hallways by combining depth information alongside RGB data [1]. We use depth data as it could help provide cues for object poses and possibly enhance performance in variable lighting conditions, hence enhancing scene understanding. This project will be carried using SegNet architecture. The SegNet model was originally designed only for RGB images, yet we attempt to train it with depth images as well. Training was conducted on the NYU Depth V2 dataset, comprising of 1449 RGB-D images and corresponding labels across 895 object classes.

The SegNet architecture was adapted to depth information through simple concatenation along the channel dimension. The model uses efficient parameterization through the reuse of pooling indices in decoder blocks. The data was normalized and converted into tensors for training and split into the ratio 80-10-10 for training, validation, and testing. Early stopping and checkpoints were implemented to prevent overfitting and for system robustness. We use a small batch size in order to not exceed memory limitations.

Experimental results demonstrate the performance achieved was lower than expected, possibly due to challenges with the choice of fusion method and the quality of the depth data, probably causing the model to be confused. However, when compared to independent results of SegNet trained on RGB-D data, the performance is slightly better. The performance without our method of data fusion is around 11% better.

Despite the model achieving a lower performance than expected, the results help us understand the feasibility of integrating depth information into improving semantic segmentation accuracy. The drop in performance is speculated to have stemmed from the fusion method and data quantity and quality issues. These insights emphasize the importance of further research to improve on an idea to create a more comprehensive understanding of combining depth data with RGB information without compromising performance as well as the need for the availability of more recent datasets as sensor technology has seen tremendous improvement.

Software Libraries Used: PyTorch, Matplotlib, h5py

Hardware Used: NVIDIA A100 GPU with 80GB RAM

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**CHAPTER 1**

**INTRODUCTION**

This chapter gives a brief overview of the current research limitations of semantic segmentation, objectives and motivations behind the project and how our work approaches an active research area of using depth images to enhance segmentation. It highlights the development process and the overall structure of the project report.

1.1 *General*

Traditionally, semantic segmentation in machine learning research has depended on RGB images for training. Semantic segmentation has seen its use in areas such as scene understanding, robotic navigation, autonomous vehicles, surgical precision, and more. While this approach has achieved fascinating results, it can struggle in situations where objects are partially occluded, lighting variations from shadows and glare, and small objects. We human also may find it somewhat challenging to visualize objects in our scene under such challenges. However our edge over simple vision comes from the perception of images from both eyes, that informs us the distance between us and the object through the effect of stereo vision. This project tries to use the depth images to make a more comprehensive understanding of a scene.

1.2 *Brief Present-Day Scenario*

Semantic segmentation with deep learning models has achieved astonishing accuracies coming closer to the human benchmark, with pixel accuracies reaching nearly 85% and mIOU results around 50% while also capable of high inference speeds when trained on the SUN RGBD dataset. However, there still exist challenges such as the need for large amounts of labelled data the lack of depth information being used in training models. It struggles with challenging lighting, occlusions, and small objects. Integrating depth data has the potential to enhance accuracy of object filters as well as object distances which will help the model be robust towards lighting variations.

1.3 *Motivation to Do the Project Work*

The primary motivation behind this project was to perform semantic segmentation in hospital and university hallways to perhaps be integrated in robots for autonomous navigation that would aid delivery from various ends of the building or even in wheelchair assistance.

1.3.1 *Shortcomings in Previous Work/Reference Papers*

Previous research in semantic segmentation using RGB-D images has shown promising results. However, model frameworks can suffer from limitations in fusion techniques and dataset quality causing model to be more confused and less effective than with just using RGB information. Many mechanisms have been explored to merge these modalities well including attention mechanisms that were introduced from the transformer architectures.

1.3.2 *Brief Importance of the Work*

While significant research on improving semantic segmentation by incorporating depth modality is underway we explore how simple fusion will affect the segmentation performance. By leveraging depth cues alongside RGB data, we aim to improve object delineation and semantic understanding, thereby facilitating advancements in various computer vision tasks.

1.3.3 *Uniqueness of the Methodology*

The uniqueness of our approach lies in the adaptation of the SegNet architecture to accommodate depth information. By concatenating depth images as a separate channel and training the model on the NYU Depth V2 dataset, we aim to explore combination of RGB and depth data for improved segmentation accuracy.

1.3.4 *Significance of the Possible End Result*

The potential end result of this project is a more robust and accurate semantic segmentation model capable of handling RGB-D images in diverse environments. Such a model would have applications in robotics, autonomous navigation, etc. contributing to advancements in various fields. It could provide us with more insights on how to better fuse depth information with RGB data and what is actually happening between the interactions of theses 2 modalities in a deeper level.

1.4 *Objective of the Work*

The primary objective of this project is to improve semantic segmentation performance using RGB-D images, particularly in the context of robot navigation in university hallways by training it on a set of indoor scenery datasets. The secondary objective, is to explore fusion techniques especially cross-modal attention mechanism and enhancing dataset quality as our current dataset is limited to only 1449 images and their corresponding depth images and labels.

1.5 *Target Specifications*

The end result of this project is expected to be a semantic segmentation model with good performance and robustness, particularly in indoor scenes. The importance of achieving accurate segmentation results is to compare and understand how image segmentation can be potentially improved with the involvement of depth images in the training pipeline.

1.6 *Project Work Schedule*

The project work was completed in 4 months, which involved multiple stages which can be divided as: getting up to speed with machine learning terminology and theory, finding relevant papers to our project, finalizing our work schedule that went through multiple iterations as we gained more insights, choosing a suitable model architecture and dataset with the known constraints, integrating the data and making it usable, model development, training, evaluation, and analysis.

1.7 *Organization of the Project Report*

The project report will be organized into five chapters: Introduction, Literature Review, Methodology, Result Analysis, and Conclusion and Future Scope. Each chapter will focus on specific aspects of the project, providing a comprehensive overview of the research undertaken and the findings obtained.

**CHAPTER 2**

**BACKGROUND THEORY / LITERATURE REVIEW**

In this chapter we will be giving a literature review about the topic semantic segmentation using RGB-D images. Semantic segmentation is a technique that combines color (RGB) data with depth information to improve image segmentation. The strength of this approach is that it leverages depth to enhance traditional RGB segmentation. We will discuss about the challenges faced by current methods, including cost, data sparsity, and depth measurement uncertainty. Finally, we will explore future research directions for RGB-D segmentation, focusing on improved fusion techniques, depth-aware processing, and achieving real-time performance.

According to the Changshuo Wang et al. RGB-D segmentation offers several advantages over traditional RGB-based methods which we are going to compile and discuss in this chapter. **[7]**

2.1 *Literature Review*

Let us explore the recent developments and give a brief background on semantic segmentation using RGB-D images.

2.1.2 *Present state/recent developments in the area*

Current advancements compared to traditional/previous technologies:

* Accuracy Boost: Recent methods significantly improve segmentation accuracy compared to traditional RGB-only methods. This is thanks to the extra information depth data provides about the 3D structure of a scene.
* Fusion Techniques: Recent studies have concentrated on how to effectively amalgamate RGB and depth information. This “fusion” becomes vital for the model to exploit both data’s strengths. Among these are attention-based fusion blocks, multi-modal fusion networks.
* State-of-the-Art on the Rise: New models such as GLPNet with its local and global context fusion are achieving impressive results on benchmark datasets like NYU-Depth V2. This shows that the field is constantly progressing.

The Challenges/problems being faced:

* Cost Considerations: Some RGB-D sensors can be expensive limiting the widespread adoption of this technology.
* Data Deficiencies: Training robust models requires a large amount of data so cases of parse or incomplete depth measurements may lead to hinderance in performance.
* Uncertainty in Depth: Depth sensors aren't perfect, and their measurements can be noisy or inaccurate. Models need to be robust to such uncertainties.

2.1.3 *Future scope and expectations*

Researchers are actively exploring new directions to push the boundaries of RGB-D segmentation:

* Smarter Fusion Techniques: Developing even more effective ways to combine RGB and depth data is a key area of focus.
* Convolution with Depth Perception: Integrating depth information directly into the processing steps for RGB data is another promising avenue.
* Real-Time Dreams: Achieving real-time segmentation, where results are generated instantly, would open doors for wider applications.

2.1.4 *Brief Background Theory*

When it comes to RGB-D semantic segmentation, the task is about determining the meaning of each pixel in an image using both color information from RGB cameras and depth data from sensors. This technology has been found to have a number of significant advantages over classical RGB based segmentation especially in tasks requiring perception of depth. In this rapidly growing field, we delve into recent improvements and remaining difficulties.

In order to develop and evaluate RGB-D segmentation activities, some benchmark datasets have been used. The popular ones are NYU-Depth V2, SUN RGB-D, 2D-3D-S, and COTS. By providing synchronized RGB-D images that have pixel-wise ground truth labels, these datasets help researchers to compare performances of different algorithms.

Different metrics are employed for evaluating the performance of segmentation models. Pixel Accuracy (PixAcc) indicates the percentage of pixels that were classified correctly while Mean Accuracy (mAcc) represents the average accuracy over all classes. However Mean Intersection over Union (mIoU) is a more robust metric as it calculates the average intersection over union ratio per class which shows the quality of segmentation boundaries. On the other hand Frequency Weighted Intersection over Union (f.w-IoU) further improves mIoU by considering how many times each class occurs in the dataset.

Fusion Techniques: One active area of research is how to effectively merge information from RGB and depth sources. In fact, the modalities may have different properties making it vital to find the best fusion strategies that can exploit their respective strengths.

Data Sparsity and Uncertainty: To train models that are robust, one needs large datasets. However, getting high-quality synchronized RGB-D data could be expensive as well as time consuming. Depth sensors also have limitations which might result in either sparse or noisy depth measurements thus impacting model performance.

Computational Cost: It may take a lot of computation power for complex segmentation models to process both RGB and depth data. This can prevent real-time operation and deployment on devices with limited resources.

RGB-D semantic segmentation is a field with huge prospects for different applications such as robotics, autonomous navigation and scene understanding. Some of the possible directions for future research are: Advanced fusing methods that can integrate depth information easily with RGB leading to a solid and precise segmentation, exploring other network architectures and learning paradigms that can attain real time performance while keeping high accuracy, and exploring new ways to overcome the problems of sparse data and uncertainty in depth measurements through techniques like synthetic data generation or robust learning algorithms.

Like our eyes that see the world in RGB and provide depth, RGB-D segmentation does similar things.

* Ordinary Eyesight (RGB): Traditional computer vision is based on RGB images which capture the color information in the image. This enables computers to identify objects according to how they appear.
* Introducing Depth Perception (Depth Sensor): In addition, an extra sensor for capturing depth information is used by the RGB-D segmentation. It measures how far away objects are from the sensor and creates a “distance map” of sorts.
* Comprehending the Scene (Segmentation): The problem lies in combining this color and depth data. Segmentation algorithms scrutinize both RGB and depth data to label every pixel within an image. Its aim is labeling each pixel such as “wall,” “floor,” or “chair.”

For easier understanding imagine a scene with a red ball on a blue table. RGB data might struggle to distinguish the ball from the table due to their similar colour. But depth information can tell the computer that the ball is closer, allowing accurate segmentation.

Here's a breakdown of the benefits:

* Improved Accuracy: Depth data removes ambiguities in color-based segmentation, leading to more precise results.
* 3D Understanding: By combining color and depth, the computer is able to have a more comprehensive understanding of the 3D structure of the scene.

2.1.5 *Literature Survey*

Shijie Hao et al. [8] introduces in their survey a brief review of research efforts on RGB-D semantic segmentation methods.

**Couprie et al. [9]** early work explores using depth information for indoor semantic segmentation. They likely concatenate RGB channels and the depth channel for a basic fusion approach. This method is simple to implement but might not capture the complex relationships between RGB and depth data, potentially limiting its effectiveness.

**Höft et al. [10]** This paper addresses the challenge of real-time semantic segmentation in RGB-D scenes. They propose a method using deep neural networks with GPU acceleration for faster processing. While the focus on speed is beneficial for real-time applications, the specific fusion technique within the deep neural network might not be explicitly addressed, and the impact on segmentation accuracy requires further investigation.

**Gupta et al. [11]** This work tackles the issue of extracting meaningful features from RGB-D data for object detection and segmentation tasks. The paper proposes a method for learning rich features suitable for both RGB and depth data. However, the specific details of how these features are combined for segmentation might not be explicitly addressed.

**Hazirbas et al. [12]** This paper introduces FuseNet, a Convolutional Neural Network (CNN) architecture specifically designed for RGB-D semantic segmentation. FuseNet proposes a novel CNN architecture with a dedicated depth encoding block to extract features from the depth map, which are then used to enhance the features extracted from the RGB image. This late fusion strategy has the potential to improve segmentation accuracy, but the paper might not explore alternative fusion techniques or delve deeper into the specific mechanisms within FuseNet that ensure effective feature enhancement.

**Wang et al. [13]** This work addresses the issue of learning effective features from RGB-D data for semantic segmentation. The authors propose a Deconvolutional Network architecture that focuses on learning both common and modality-specific features. The network architecture itself learns to combine these features, but the specific mechanisms for this fusion might not be explicitly addressed. Additionally, the effectiveness of the approach for different RGB-D datasets needs further evaluation.

**Qi et al. [14]** This paper introduces a novel approach using 3D Graph Neural Networks (GNNs) for RGB-D semantic segmentation. 3D GNNs can model relationships between data points in a 3D space, allowing the network to exploit the spatial information from depth data for improved segmentation. While this is a promising approach, the effectiveness of 3D GNNs for RGB-D segmentation compared to other methods needs further investigation.

**Cheng et al. [15]** The authors propose a method with gated fusion for RGB-D indoor semantic segmentation. Their approach likely utilizes a gating mechanism to control the information flow during the fusion process, potentially focusing on the most relevant features from RGB and depth data. However, more information is needed to understand the specifics of the gating mechanism and its impact on segmentation performance.

**Hu et al. [16]** This work introduces ACnet, a network that leverages an attention mechanism for RGB-D semantic segmentation. Attention mechanisms allow the model to focus on important features within the RGB and depth data, potentially leading to more accurate segmentation. It would be beneficial to explore how ACnet's attention mechanism compares to other fusion techniques in terms of effectiveness and computational cost.

**Lin et al. [17]** The authors propose a Cascaded Feature Network for semantic segmentation of RGB-D images. Their cascaded network architecture likely involves processing RGB and depth data through multiple stages, potentially refining the features at each stage. Further investigation is needed to understand the specific details of the cascaded architecture and how it contributes to improved segmentation results.

Other Papers related to our field of research include:

**Qian et al. [18]** This paper proposes a gated-residual block for semantic segmentation using RGB-D data. It addresses the limitations of capturing spatial dependencies and incorporating depth information effectively in traditional methods. The key innovation is the gated-residual block that enhances information flow and utilizes depth data. The fusion technique likely involves concatenating features from RGB channels and the depth channel before feeding them into the blocks. A potential limitation is that the approach might not explore more advanced fusion techniques.

**Seichter et al. [19]** This paper addresses the challenge of achieving real-time performance in RGB-D semantic segmentation for indoor scene analysis. The authors propose an efficient network architecture with optimizations for real-time processing. It tackles the trade-off between accuracy and speed in existing methods. While the specific fusion technique might not be explicitly mentioned, it likely employs a lightweight and efficient method for real-time processing. A potential limitation is the prioritization of real-time performance. Exploring more complex architectures or fusion methods could improve accuracy at the cost of processing speed.

**Schneider et al. [20]** This work investigates the effectiveness of multimodal neural networks for RGB-D semantic segmentation and object detection. The authors propose a network that utilizes shared features from RGB and depth data for both tasks. This addresses the limitation of traditional approaches that might rely on separate models for each task. The fusion technique likely employs feature fusion within the network architecture, potentially using concatenation or summation. A potential limitation is the lack of exploration of more advanced fusion techniques that could further improve performance on both tasks.

**Park et al.** [21] addresses the challenge of effectively combining information from RGB and depth data for improved segmentation accuracy in RGB-D semantic segmentation. They propose RDFNet, a network architecture that utilizes multi-level residual feature fusion. This approach incorporates residual connections and a multi-level fusion strategy, likely employing concatenation or summation of features extracted from RGB and depth data at different resolutions within the network. While RDFNet improves upon traditional methods, the paper might not explore more advanced fusion techniques beyond multi-level concatenation or summation.

**Jinming Cao et al.** [22] investigates a method for learning depth-weighted RGB patches for RGB-D segmentation. Traditional methods might not fully exploit the complementary information between RGB and depth data. This paper proposes a novel approach that focuses on learning depth-weighted RGB patches. This allows the network to prioritize regions in the RGB image that are more relevant for segmentation based on the corresponding depth information. While not a standard fusion technique, depth information is integrated by assigning weights to RGB patches based on depth values. This can be seen as a form of feature weighting during the processing of RGB data. The paper could benefit from exploring how this depth-weighting approach compares to more traditional fusion techniques like concatenation or summation.

**Jiang et al.** [23]- RedNet, a deep residual encoder-decoder network architecture for indoor RGB-D semantic segmentation. Residual networks have shown effectiveness in various computer vision tasks, and this work applies them to the task of RGB-D segmentation. The specific fusion technique might not be explicitly mentioned in the paper, but it likely employs a standard approach within the encoder part of the network, potentially using concatenation or summation of features from RGB and depth data streams. The paper could benefit from discussing how RedNet integrates RGB and depth information for segmentation.

**Cao et al. [24] says** Standard convolutional layers might not effectively capture geometric cues from depth information for RGB-D segmentation. Cao et al. (2021) address this limitation by proposing ShapeConv, a convolutional layer that incorporates shape information derived from depth data into the filtering process. This allows the network to learn more discriminative features that are sensitive to geometric structures. ShapeConv can be seen as a fusion technique at the layer level, combining RGB features with geometric information derived from depth data within the convolution operation itself. The paper could benefit from exploring how ShapeConv compares to other fusion techniques within the network architecture.

**Zhou et al. [25]** proposes an RGB-D Co-attention Network for semantic segmentation in their in-book chapter. Traditional methods might not fully leverage the complementary information between RGB and depth data. The authors address this challenge by introducing a co-attention mechanism. This module enables the network to learn attention weights for both RGB and depth features, highlighting informative regions in each modality that are crucial for segmentation. While not a traditional fusion like concatenation, co-attention can be seen as a form of soft fusion. The attention weights learned by the network effectively combine information from both RGB and depth features within the network architecture. The paper could benefit from exploring how the co-attention mechanism compares to other fusion techniques for RGB-D semantic segmentation.

**Hoyer et al. [26]** explores three methods for improving semantic segmentation with self-supervised depth estimation. Traditional methods for RGB-D segmentation might not fully exploit the depth information. The authors propose three techniques: leveraging depth features directly, incorporating a depth-aware loss, and using depth for data augmentation. These approaches all aim to improve the network's ability to utilize depth data for more accurate segmentation.

**Wang et al. [27]** Domain adaptation in semantic segmentation refers to adapting a model trained on one dataset to perform well on a different but related domain. Wang et al. (2021) propose a method for domain-adaptive semantic segmentation with self-supervised depth estimation. This work builds upon the idea of using self-supervised depth estimation to improve segmentation, but in the context of adapting the model to a new domain.

**Ying & Chuah [28]** introduces UCTNet, an Uncertainty-Aware Cross-Modal Transformer Network for indoor RGB-D semantic segmentation. Unlike traditional CNN-based approaches, UCTNet leverages a transformer architecture to handle the long-range dependencies between RGB and depth features. Additionally, it incorporates uncertainty estimation to focus on regions with higher prediction ambiguity, potentially leading to improved segmentation accuracy.

**Zhao et al. [29]** proposes a Cross-modal Attention Fusion Network for RGB-D semantic segmentation. This paper addresses the challenge of effectively combining information from RGB and depth data. The authors introduce a cross-modal attention mechanism that allows the network to focus on relevant regions in both modalities, leading to improved feature representation and segmentation results.

**Yang et al. [30]** Pixel Difference Convolutional Network (PDConv) is a novel approach for RGB-D semantic segmentation introduced by Yang et al. (2024). This method utilizes a PDConv layer that captures the difference between RGB and depth features, allowing the network to focus on the complementary information between these modalities. This can potentially lead to more robust segmentation performance compared to traditional methods.

**Rizzoli et al. [31]** focuses on source-free domain adaptation for RGB-D semantic segmentation using vision transformers. Domain adaptation refers to training a model on one dataset and adapting it to perform well on a different but related domain. Traditional methods might require access to the source domain data for adaptation. This paper proposes a method for RGB-D segmentation that achieves source-free domain adaptation with vision transformers, potentially improving its generalizability to unseen domains.

**Ni et al. [32]** presents an improved deep network-based method for RGB-D semantic segmentation of indoor scenes. While the specific details of the improvement might not be available from the brief citation, the paper likely proposes an enhanced deep network architecture that leverages both RGB and depth information for accurate segmentation in indoor environments.

**Tang et al. [33]** introduces a Cross-Modal Feature Fusion Model based on ConvNeXt for RGB-D semantic segmentation. ConvNeXt is a recent advancement in convolutional neural network architectures. This paper proposes a model that utilizes ConvNeXt for feature extraction from both RGB and depth data, followed by a cross-modal fusion strategy to effectively combine these features for improved segmentation performance.

2.2 *Summary*

RGB-D segmentation uses depth information to enhance traditional RGB segmentation, leading to more accurate scene understanding. Recent advancements focus on effective fusion techniques to combine RGB and depth data (e.g., attention-based fusion, multi-modal networks). Convolutional Neural Networks (CNNs) with depth-aware capabilities are showing promise. Despite progress, challenges remain: data sparsity, depth sensor limitations, and computational cost.

We hope to develop even more sophisticated fusion techniques for robust and accurate segmentation. Will be able to explore real-time capable network architectures while maintaining accuracy. Investigate methods to address data limitations and depth measurement uncertainty.

2.3 *Theoretical Discussion*

RGB-D semantic segmentation is based upon the traditional RGB-based segmentation by including depth information to achieve a more detailed understanding of the scene. Here's a breakdown of the theoretical foundation:

1. RGB vs. RGB-D Data:

RGB Images: The captured colour information using three channels (Red, Green, Blue) allows computers to identify objects based on their appearance.

Depth Information: This is obtained from depth sensors, which measures the distance between the sensor and each point in the scene, creating a "distance map."

2. Challenges in Combining Modalities:

Data Discrepancy: RGB and depth data have different characteristics. Color information might be ambiguous in certain scenarios, while depth measurements can be noisy or sparse.

Fusion Strategies: Effectively combining these modalities is crucial. Early methods might treat them as separate inputs, hindering performance.

3. Theoretical Approaches:

Feature Fusion: Aims to extract meaningful features from both RGB and depth data and then combine them for segmentation.

Recent advancements include: Attention-based Fusion: Focuses on informative features in each modality using learned weights.

Multi-modal Fusion Networks: Employ dedicated network modules to efficiently integrate RGB and depth features.

Convolutional Neural Networks (CNNs): Popular choice due to their ability to learn complex representations from image data.

Depth-aware CNNs: Incorporate depth information directly into the convolution operation, allowing for depth-sensitive feature extraction.

Recurrent Neural Networks (RNNs): Capture long-range dependencies within data, potentially useful for tasks requiring contextual information. Often combined with CNNs to exploit the strengths of both architectures.

4. Theoretical Benefits of RGB-D Segmentation:

Improved Accuracy: Depth information disambiguates color-based segmentation, leading to more precise results, especially in scenarios where color alone is insufficient.

3D Scene Understanding: By combining color and depth, the model gains a more complete understanding of the 3D structure of the scene, allowing for better scene interpretation.

2.4 *Conclusions*

RGB-D semantic segmentation offers a powerful approach to scene understanding by combining color information with depth data. This review has highlighted the significant progress made in recent years, particularly with the development of advanced fusion techniques and depth-aware convolutional neural networks. However, challenges like data limitations and computational cost still need to be addressed.

Looking ahead, research efforts will likely focus on even more sophisticated fusion strategies, exploring real-time capable architectures, and tackling data scarcity and depth measurement uncertainties. As these areas advance, RGB-D semantic segmentation holds immense potential to transform various computer vision applications, enabling machines to perceive and interact with the 3D world in a more robust and accurate way.

**CHAPTER 3**

**METHODOLOGY**

This chapter shall dictate the methodologies that will be necessary to understand our work, outline the design of the architecture we have used, and specifications of various modules. It will also go over the important tools required to run the model.

3.1 *Methodology, module specifications and justifications*

The project system can be effectively divided into stages, visualizing the NYUD V2 dataset, loading and preprocessing, implementing the SegNet model, choosing model hyperparameters and weight initialization and finally the main training loop.

3.1.1 *Visualizing the NYUD V2 dataset*

The NYUD V2 dataset contains 1449 labelled data, and contains 894 different objects for segmentation. The data was captured using the Microsoft Kinect V2 and had size (480,640). The data is contained within a MAT file. The data can be loaded using h5py library which extracts the data stored in the MAT file as NumPy lists of data. An example of image NumPy list which had the shape (number of images, width height, channels) being (1449,640,480,3). Each image and its corresponding depth image and label could be visualized side by side using matplotlib. Visualizing and getting a feel of what we were working with helped reduce the complexity of future mistakes and errors.

3.1.2 *loading and preprocessing*

Because the range of data values of RGB images is from (0,255) for each channel while depth data value has a completely different range (0-25), which is each pixel having a value of measure of distance from camera in metres. This makes the two data vary quite a bit from each other and confusing for our model weights to adapt effectively to the different modalities. Normalizing the data makes them have a consistent scale, improved convergence better generalization and reduced overfitting.

The Fusion technique we planned to use was simple concatenation of image and depth along the channel dimension. This choice was made by the fact that other possibilities of fusion like parallel pathways and attention mechanisms seemed to have more computational costs and also need much larger datasets to train and be used effectively so we avoided it and chose to focus on keeping the model simpler. This may lead to decreased accuracy in our results as simple concatenation may not be enough for the model to learn from both modalities. Because loading 1449 images and depths simultaneously and creating extra memory to concatenate them would be very memory inefficient, especially since we only had 15GB of RAM, we used the concept of Memmaps to concatenate the data in chunks.

Finally, we split the data in the ratio 80:10:10::training:validation:test sets. We use a high ratio to training as we are dealing with a small dataset. Next we save the data as tensors of the correct shape, and do so because Pytorch library is optimized to work with tensors.

3.1.3 *Implementing the SegNet model*

The SegNet model is a convolutional neural network that follows an encoder decoder structure. The novelty of this model is the saving of pooling indices after the max pooling operation at the end of each encoder block to be used for the upsampling operation in the decoder block. During the encoder convolution an input image gets regularly convolved with several filters and gradually drops in size as each region of the image gradually increases in the receptive field encoded by the model. However during this operation information gets lost when we downsample the image batch. During upsampling operation, before the compressed image gets decoded by the filters, we use the previously saved pooling indices to artificially increase the image resolution.

This approach vastly reduces the number of parameters in the SegNet encoder network from 134M to 14.7M as compared to other architectures. This memory efficiency makes it possible to train the SegNet on systems with limited RAM, hence became our model choice. However, using the depth modality in the SegNet architecture may require modifications. Also the quality of depth images from current cameras require careful post-processing to fill-in missing measurements like depth inpainting algorithms.

The output of the final decoder layer contains a tensor of the same size as the image and the same depth as the number of classes it is trained to segment, which in our case is 894. These logits can then further be processed by a SoftMax activation layer to get the probability distribution of a pixel belonging to a particular layer.

3.1.3 *Choosing model hyperparameters and weight initialization*

We use a learning rate of 0.001, for 50 epochs and batch size of 5. The reason for a small batch size is due to memory constraints encountered in initially using a small GPU. Furthermore, we decided upon using Kaiming normal to initialize the weights of the model. Initialization of model weights helps prevent vanishing and exploding gradients, and speeds up convergence.

We selected cross entropy loss as our loss function and ADAM as our optimizer.

Cross-entropy loss and the Adam optimizer are commonly used choices in deep learning, particularly for tasks like semantic segmentation. Cross-entropy loss is well-suited for multiclass classification tasks. ADAM optimizer converges quickly and efficiently, even in the presence of sparse gradients or noisy data, making it the default choice.

3.1.4 *The main training loop*

where data shuffling after each epoch, checkpointing and validation and training loss is calculated after each epoch to see overfitting and early stopping is done.

It is here where everything we have done so far comes together, we define a scheduler, a checkpoint system, calculate important time statistics, but most importantly conduct forward and backward pass of our model. This is also followed by evaluating the model based on a validation set after each epoch to understand how well the model is fitting to unseen data. Also we have implemented an early stopping detection system that stops the training as soon as the validation loss stops improving and the model has started to overfit the data.

3.2 *Assumptions Made*

We assume that the depth images once fused with RGB images using concatenation is sufficient for the network to understand and use the correlation between the data. We also assume the applicability of the SegNet architecture to semantic segmentation tasks with RGB-D images. We also assumed that the RAM available was sufficient for training and our processes

3.3 *Design & Modelling, Block Diagrams*

The design of SegNet-based semantic segmentation model, depicting the flow of information through encoder and decoder blocks. Block diagrams illustrate the hierarchical structure of the model and the processing steps involved in segmenting RGB-D images.

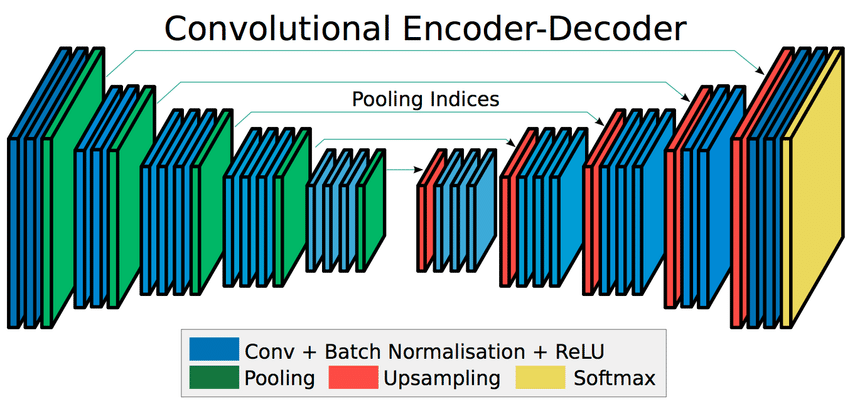


Figure 3.1 SegNet Architecture [4]

A diagram of a diagram

AI-generated content may be incorrect.

Figure 3.2 The novelty of the architecture is based on the efficient memory conumption based on the usage of pooiling indices [4]

Table 3.1 SegNet model metrics when trained on SUN RGB-D dataset [5]

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| PixAcc | mAcc | mIoU | Input | Ref. from | Published | Year |
| 72.6 | 44.8 | 31.8 | RGB | MMAF-Net-152 | TPAMI | 2017 |

Table 3.2 SegNet model metrics when trained on NYUD V2 dataset [6]

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| PixAcc | mAcc | mIoU | Input | Ref. from | Published | Year |
| 54.1 | 30.5 | 21 | RGBD | LCR | TPAMI | 2017 |

A diagram of a person

AI-generated content may be incorrect.

Figure 3.3 Project Workflow

3.4 *Tools Used*

The tools used include PyTorch and TorchVision for model development and training, along with standard libraries like h5py for data preprocessing and matplotlib for visualization. Hardware specifications include NVIDIA A100 GPU with 80GB RAM for accelerated training and inference although initially we tried to use 15GB GPU RAM offered by Google Colab.

3.5 *Preliminary Result Analysis*

It was understood from our analysis that all images have the same dimensions, we figured out using h5py and numpy the number of classes in the dataset, and visualized the labelled images against the depth and original images.

3.6 *Conclusions*

We have summarised the pipeline of the creation of our machine learning module and how each aspect of our model hierarchy looks like namely: Visualizing the NYUD V2 dataset, loading and preprocessing, implementing the SegNet model, choosing model hyperparameters and weight initialization and finally the main training loop.

**CHAPTER 4**

**RESULT ANALYSIS**

We present the analysis of results obtained from the implementation and evaluation of the model. It includes explanations for the results, and metrics.

4.1 *Result Analysis*

Results are presented in graphical and tabular formats, showcasing metrics such as mean Intersection over Union (mIoU), accuracy and dice coefficient.

**A graph with blue and orange dots

Description automatically generated**

Figure 4.1 Loss Value Graph

Table 4.1 Our SegNet model metrics when trained on NYUD V2 dataset

|  |  |  |  |
| --- | --- | --- | --- |
| Average IOU | Average Dice Coefficient | Average Pixel Accuracy | Input |
| 16.06 | 20.31 | 54.45 | RGBD |

Fig 4.3 Average Class Accuracies of SegNet predictions for 40 indoor scene classes in the

NYUD V2 dataset

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Background | Wall | Floor | Cabinet | Bed | Chair | Sofa | Table |
| 64.3 | 0.22 | 1.01 | 52.15 | 52.28 | 40.93 | 0.0 | 44.51 |
| Door | Window | Bookshelf | Picture | Counter | Blinds | Desks | Shelves |
| 0.35 | 0.0 | 0.0 | 85.42 | 13.81 | 0.61 | Nan | 2.13 |
| Curtain | Dresser | Pillow | Mirror | Floormat | Clothes | Ceiling | Books |
| 0.0 | 2.87 | 0 | 29.34 | 0 | 77.76 | 0.01 | NaN |
| Fridge | TV | Paper | Towel | Shower-  Curtain | Box | Whiteboard | Person |
| 19.77 | 0 | 23.39 | 0 | 12.67 | NaN | 0 | NaN |
| Nightstand | Toilet | Sink | Lamp | Bathtub | Bag | Other-structure | Other-furniture |
| 0 | 0 | 0 | 0 | 14.59 | 0 | 0 | 0 |
| Other-prop |
| NaN |

\*NaN values indicate that the class did not occur in the test set.

Several images of different colored objects

Description automatically generated

Figure 4.2 Some of the semantic segmentation representations from our model

A collage of images of different colors

Description automatically generated

Figure 4.3 Some of the semantic segmentation representations from our model

A collage of images of different colors

Description automatically generated

Figure 4.4 Some of the semantic segmentation representations from our model

4.2 *Explanation for the Graphical Results:*

From the trends in the graph, we see that after the 30th epoch, the validation loss starts to plateau, and we infer that the model has begun to overfit to the training set. At epoch 42 we decide to stop the training as the validation loss did not seem to improve. After saving the model weights and testing it on a different set, we got the above metrics.

4.*3 Any Deviations from the Expected Results & Its Justification*

Our experimental results demonstrated lower-than-anticipated performance in semantic segmentation accuracy. The model achieved a marginal improvement compared to another implementation of the same model and dataset. However, its overall performance fell short of expectations. This according to us could’ve been due to a multitude of reasons. The simple data concatenation for RGB and depth information might have limited the model's ability to effectively learn the relationship between these modalities. Due to the age of the NYUD V2 dataset, it might have contained low quality depth images. The size of the NYUD V2 dataset was small to begin with making the model struggle to learn important correlations and features.

4.4 *Environmental and Societal Impact of the Project*

The project solutions offer environmental and societal benefits by advancing the capabilities of computer vision systems. By enhancing the accuracy of semantic segmentation models we could improve efficiency and save energy, for instance in robot navigation where more precise movements could help save energy consumption. Also the potential for reduced wastage in the case of robots sorting recyclables that use semantic segmentation for these tasks.

4.5 *Conclusions*

Overall, the deviations from expected results provide valuable insights for future research. By addressing the identified limitations and exploring new approaches, we can effectively combine depth data with RGB information to enhance semantic segmentation accuracy. Despite challenges such as dataset quality and poor and confusing fusion mechanism, the segmentation model demonstrates competitive performance against other RGBD models, validating the efficacy of the methodology adopted.

**CHAPTER 5**

**CONCLUSION AND FUTURE SCOPE**

**5.1 *Brief Summary***

In this project we have evaluated the feasibility of improving semantic segmentation performance using RGB-D images for robot navigation in university hallways. We trained the SegNet model on the NYUD V2 dataset.

The primary objective was to enhance semantic segmentation accuracy using RGB-D data. This could potentially improve robot navigation in indoor environments by providing a more comprehensive understanding of surroundings. A secondary objective was to explore alternative fusion techniques and methods for enhancing dataset quality due to the limitations of the NYUD V2 dataset like the size and quality issues.

The project system can be effectively divided into stages, visualizing the NYUD V2 dataset, loading and preprocessing, implementing the SegNet model, choosing model hyperparameters and weight initialization and finally the main training loop.

Assumptions were made regarding dataset quality, computational resources, and model applicability, guiding the design and implementation process.

5.2 *Conclusions*

The project concludes that the proposed approach of semantic segmentation using RGB-D images yields promising results in enhancing scene understanding and object recognition. Despite challenges such as dataset quality and poor and confusing fusion mechanism, the segmentation model demonstrates competitive performance against other RGBD models, validating the efficacy of the methodology adopted.

*5.2.1 Significance of the Results Obtained*

The results obtained from the project are significant as they contribute to advancing the capabilities of computer vision systems in real-world applications. By improving semantic segmentation accuracy and robustness, the project lays the foundation for more effective robot navigation, scene analysis, and augmented reality experiences. The significance of the results lies in their potential to drive innovations and address challenges in diverse domains, ranging from robotics to healthcare.

5.3 *Contribution Summary*

In this project, I leveraged my research skills to identify relevant papers and resources in the field of semantic segmentation. I learned how to build and develop neural models from scratch using PyTorch and to use the tools for developing a neural model. My research included evaluating various datasets to find one suitable for our needs and computational limitations. Initially, we considered the SUN RGB-D dataset but switched to the NYUDv2 dataset due to memory constraints. Similarly I weighed the pros and cons of several minor adjustments that lead to the successful implementation of the model.

I implemented the model using SegNet, including the dataset loader and training mechanisms. I developed a robust training loop with checkpoints, allowing the process to be paused and resumed. I also implemented a validation loop and early stopping for improved performance.

To enhance accuracy, I explored advanced techniques for combining depth data with RGB, such as cross-modal attention. I researched methods to improve training speeds, including using pre-trained encoder models, depth-wise separable convolutions, and regularization techniques like dropout.

Overall, my contributions encompassed thorough research, coding, and optimization to ensure efficient and effective model training and validation.

5.4 *Future Scope of Work*

The project opens avenues for future research and development, offering opportunities for further exploration and refinement in several areas:

Enhanced Fusion Techniques: Future work can focus on exploring novel fusion techniques for integrating RGB and depth information more effectively. Our initial investigation into cross-modal attention showed potential for improving segmentation accuracy. By leveraging advancements in multi-modal learning and attention mechanisms, segmentation models can be enhanced to better capture spatial context and semantic features, leading to improved segmentation accuracy and robustness.

Dataset Augmentation and Diversity: Further research is warranted in augmenting existing datasets and diversifying training samples to improve model generalization across diverse environments. By incorporating additional data sources, including simulated environments and real-world scenarios which make possible to have millions of samples in a dataset, like the SceneNet dataset, segmentation models can be trained to handle variations in lighting, occlusions, and object poses, thereby enhancing their applicability in real-world settings.

Another avenue for improvement is the optimization of training processes. While we made significant research efforts with pre-trained encoder models and depth-wise separable convolutions, there is still room for enhancing training efficiency and speed. Regularization techniques like dropout have proven beneficial in our project, but additional strategies could be investigated to further improve model robustness and generalization. Research into novel regularization methods, adaptive learning rates, and other training optimizations could help in creating models that are not only more accurate but also more resilient to overfitting and capable of performing well on a wider variety of datasets and real-world scenarios.