



Bar-Ilan University

Department of Information Science.

”Digital Image Processing and Computer Vision -
VGG16 and 19 Comparison on Ariel Dataset ”

Theoretical Seminar

Maor Nave - ID 313603391

Prof. Ariel Rosenfeld

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1 Abstract

This study provides a thorough review of digital image processing (DIP) and computer vision (CV). It includes physical explanations for image acquisition, methodologies for processing and presenting basic images and algorithmic applications used to address challenges in DIP and CV technological fields. Additionally, it explores business applications and offers a detailed overview of deep learning models architectures designed for solving segmentation problems. This study investigates the performance of VGG16 and VGG19 architectures for semantic segmentation tasks using aerial imagery, focusing on metrics such as accuracy and loss. Through rigorous experimentation, including training with various learning rates, VGG19 demonstrated superior performance over VGG16, achieving a test accuracy of 83.26% compared to 82.51%. The VGG19 model's additional convolutional layers contributed to its enhanced ability to handle complex segmentation tasks, resulting in more precise and detailed visual predictions. GitHub Project: https://github.com/MaorNave/Data_science_seminar.git

2 Introduction

Digital image processing (DIP) has become a fundamental aspect of modern technology, significantly influencing various industries and research fields. At its core, digital image processing involves manipulating images through algorithms to enhance, analyze, and extract information. The foundation of this field lies in the representation of images as numerical data, specifically as arrays of pixel values in formats like RGB, HSV, or grayscale. The basic RGB encoding scheme, assigns a value to each pixel based on its intensity in the three primary colors—Red, Green, and Blue [Patin, 2003]. This method effectively represents any color visible to the human eye, making it highly applicable in digital image processing.

The process of acquiring these digital images is deeply rooted in the principles of optics and signal theory. Historically, optics has been closely linked with communication and information sciences, particularly in systems designed to receive and transmit data. Image acquisition systems are primarily concerned with capturing light intensity distributions across a spatial domain, often translating continuous optical signals into digital form [Marion, 2013]. This transformation from analogue to digital signals allows for the application of advanced computational techniques, thus broadening the scope of image processing.

Computer vision (CV), a subfield of artificial intelligence, extends digital image processing

by enabling machines to interpret and understand visual data. Computer vision encompasses various tasks such as image segmentation, object detection, image classification, reconstruction, and registration [Szeliski, 2022]. These tasks involve extracting meaningful information from images, often mimicking the perceptual abilities of human vision. The development of computer vision algorithms has led to significant technological advancements, allowing machines to recognize patterns, identify objects, and even reconstruct three-dimensional environments from two-dimensional images.

The practical applications of computer vision are vast and diverse, impacting industries from medical imaging to autonomous vehicles. Medical imaging, for instance, relies heavily on computer vision for tasks such as tumor detection, image-guided surgery, and diagnostic analysis. In the automotive industry, computer vision is a key component in the development of autonomous vehicles, enabling them to navigate, recognize obstacles, and make decisions in real-time [Păvăloaia and Necula, 2023]. Similarly, in fields like surveillance, security, agriculture, and augmented reality (AR)/virtual reality (VR), computer vision systems provide critical capabilities that drive innovation and efficiency. The versatility of computer vision, lies in its ability to adapt to different domains and the nature of the data being analyzed, making it a crucial tool across various sectors [Wiley and Lucas, 2018].

Within the realm of computer vision, Convolutional Neural Networks (CNNs) have emerged as powerful architectures for processing visual data. The VGG family of models, specifically VGG16 and VGG19, has gained prominence for its deep network structure, which enhances the ability to capture intricate features in images. These models represent a significant advancement in artificial intelligence, particularly in their application to tasks like image segmentation. The VGG16 and VGG19 models, both characterized by their layered architecture, differ primarily in the number of convolutional layers, with VGG19 incorporating three additional layers [Mascarenhas and Agarwal, 2021]. This structural difference allows VGG19 to achieve higher accuracy in tasks requiring fine-grained analysis, such as the segmentation of aerial datasets.

This paper will compare the performance of VGG16 and VGG19 models in segmenting aerial images using a dataset processed on a Google Colab environment with A100 GPU resources. The comparison will focus on metrics such as accuracy and loss, highlighting how the additional layers in VGG19 contribute to improved performance in specific segmentation tasks.

3 Background and Literature Review

The literature review will focus on several key areas central to the field of computer vision and digital image processing. It will begin by exploring the fundamentals of digital image processing and representation, along with the physical principles underlying image acquisition and the various digital image formats such as RGB, HSV, and grayscale. This will be followed by an examination of computer vision, its technological advancements, and applications across multiple industries, including a detailed review of technological applications of computer vision such as : image segmentation, object detection, image classification, reconstruction, and registration. Finally, the review will delve into the business applications of computer vision, with a particular focus on medical imaging, autonomous vehicles, surveillance, agriculture, and augmented and virtual reality, before concluding with a comparison of general CNN architectures and a specific analysis of the VGG16 and VGG19 models.

3.1 Digital Image Processing

Digital image processing is a crucial aspect of computer vision, involving the analysis and manipulation of images to extract meaningful information or enhance their quality. Digital image is represented as matrices of pixels, where each pixel's intensity or color value contributes to the overall image. This field, used by computer vision, encompasses a variety of tasks, such as segmentation, classification, and reconstruction, aimed at interpreting and improving these pixel matrices. The complexity of image processing highlights its importance in applications ranging from medical imaging to autonomous vehicles, underscoring its role in advancing modern technology [Dixit, 2024] [Wiley and Lucas, 2018].

3.1.1 Physical Explanations

Image acquisition is the foundational process in digital imaging, involving capturing and converting visual information into a digital format Figure 1. The process begins with the interaction of light with a scene, which is then collected by an imaging sensor such as a camera's CCD or CMOS chip [Dixit, 2024]. These sensors convert light into electrical signals, creating a digital representation of the image through sampling and quantization Figure [Wiley and Lucas, 2018].

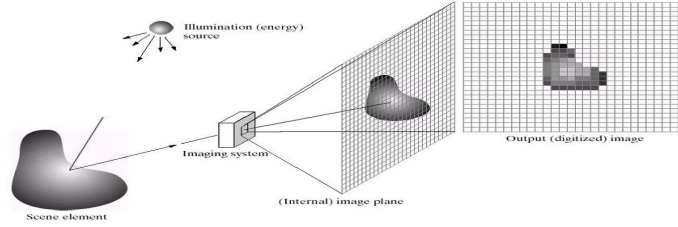


Figure 1: Image acquisition graphic model

3.1.2 Different ways of Image Representations

Digital image representations such as RGB, grayscale, and HSV play a crucial role in image processing and computer vision. The RGB model, comprising red, green, and blue channels, captures a wide range of colors but can be computationally intensive [2](#). In contrast, grayscale images simplify processing by using a single intensity channel, which is effective for tasks where color differentiation is unnecessary. The HSV model, which separates hue, saturation, and value, is particularly useful for tasks involving color manipulation and segmentation, as it allows for intuitive adjustments of color properties. Each of these representations offers distinct advantages depending on the specific requirements of the image processing task [\[Patin, 2003\]](#) [\[Marion, 2013\]](#) [\[Dixit, 2024\]](#) [\[Zhang et al., 2022\]](#).

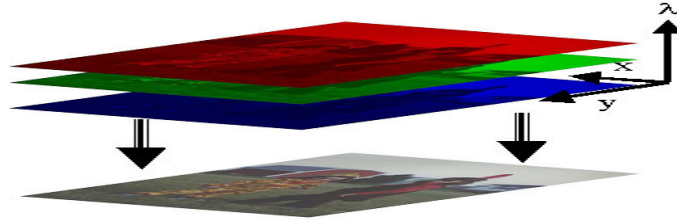


Figure 2: RGB frame graphic representation

3.1.3 Computer Vision

Computer vision is a multidisciplinary field that enables machines to interpret and understand visual information from the world. It encompasses various tasks such as image segmentation, which involves dividing an image into meaningful regions; object detection, which identifies and locates objects within an image; and image classification, which categorizes an image into predefined classes. Advanced computer vision tasks also include image reconstruction and image registration, which aim to improve image quality and align multiple images, respectively. By leveraging algorithms and deep learning techniques, computer vision systems can extract valuable insights from visual data, transforming industries from healthcare to autonomous vehicles [\[Păvăloaia and Necula, 2023\]](#) [\[Rosenfeld, 1988\]](#).

3.2 DIP and CV Technological Applications

DIP and CV have revolutionized numerous technological applications by enhancing the ability to analyze and interpret visual data. Key tasks in these fields include image segmentation, which partitions an image into distinct regions for further analysis; object detection, which identifies and locates objects within an image; and image classification, which categorizes images into predefined classes. Additionally, image reconstruction aims to restore or enhance images to improve their quality, while image registration aligns multiple images to create a unified view. These technologies have broad applications across various industries, driving advancements in areas such as medical imaging, autonomous vehicles, and surveillance [Szeliski, 2022] [Wiley and Lucas, 2018], [Marion, 2013].

3.2.1 Algorithms Applications

- Image Segmentation - This task involves partitioning an image into multiple segments or regions, each representing a different object or area. It is crucial for understanding the structure of objects in an image and is widely used in medical imaging, autonomous vehicles, and object recognition [Minaee et al., 2021].
- Object Detection - involves identifying and localizing objects within an image. It detects and classifies objects, drawing bounding boxes around them. Applications include facial recognition, video surveillance, and automated inspection systems [Zou et al., 2023].
- Image Classification - This task involves categorizing an entire image into one of several predefined classes. It forms the basis for many other computer vision tasks and is essential in applications like image search engines, photo organization, and medical diagnostics [Lu and Weng, 2007].
- Image Reconstruction - Image reconstruction aims to restore or reconstruct images from incomplete or corrupted data. This task is essential in fields like medical imaging (e.g., MRI, CT scans) and astronomy, where high-quality images are needed despite imperfections in data acquisition [Gull and Daniell, 1978].
- Image Registration - Image registration aligns two or more images of the same scene, often taken at different times, from different viewpoints, or by different sensors. It is vital in medical imaging, remote sensing, and computer vision, enabling accurate comparisons and integrations of data from multiple sources [Wyawahare et al., 2009].

3.2.2 Business Fields Applications

- **Medical Imaging** - This field leverages image processing techniques to analyze medical images from MRI, CT scans, X-rays, and more. It is crucial for diagnosing diseases, planning treatments, and conducting research, leading to advancements in early detection and personalized medicine.
- **Autonomous Vehicles** - Computer vision plays a pivotal role in enabling self-driving cars to perceive and navigate their environment. This includes tasks like object detection, lane detection, and image segmentation, which are essential for safe and efficient autonomous driving.
- **Surveillance and Security** - Image processing and computer vision are fundamental to modern surveillance systems, enhancing capabilities in real-time monitoring, facial recognition, and anomaly detection. These technologies are widely used in public safety, military applications, and private security.
- **Agriculture** - Computer vision in agriculture is used for tasks such as crop monitoring, yield estimation, and automated harvesting. These technologies help optimize farming practices, increase productivity, and reduce costs by enabling precision agriculture.
- **Augmented Reality (AR) and Virtual Reality (VR)** - These fields use image processing and computer vision to create immersive digital environments by overlaying digital content onto the real world (AR) or creating entirely virtual experiences (VR). They are widely used in gaming, training simulations, real estate, and marketing, driving innovation and customer engagement.

[[Girasa and Girasa, 2020](#)] [[Păvăloaia and Necula, 2023](#)]

3.3 CNN, UNET and VGG models Architectures

Convolutional Neural Networks (CNNs) are essential in the field of computer vision, providing a robust framework for tasks such as image recognition, classification and segmentation. CNNs operate by applying convolutional filters to images, allowing them to detect and extract features like edges and textures through a series of layers. This layered approach enables CNNs to process visual data efficiently, identifying patterns and making sense of complex images. U-Net, a specialized CNN architecture, is designed specifically for image segmentation. Unlike traditional CNNs, U-Net has a unique architecture with an encoder-decoder structure that allows it to capture both spatial context and fine details, making it

highly effective in applications like medical imaging where precise segmentation is crucial. Finally, the VGG models, particularly VGG16 and VGG19, represent a significant advancement in CNN architecture. Developed by Simonyan and Zisserman, these models are known for their deep networks composed of small 3x3 convolutional filters stacked in multiple layers [Simonyan, 2014]. VGG16 and VGG19 excel in image classification and segmentation tasks, with VGG16 featuring 16 weight layers and VGG19 featuring 19 backbones (encoders), both designed to process and recognize images with high accuracy by progressively capturing more complex features through their deep architectures Figure 3.

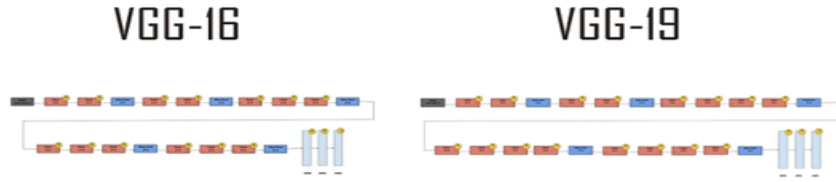


Figure 3: VGG 16 and 19 backbones architectures

4 Research Questions

The proposed study will address two research questions by conducting a comprehensive analysis of the literature, with particular emphasis on the evolving processes within an information-driven technological society. Additionally, this study aims to validate and refine these research questions by analyzing the experimental results. This will be achieved through the development of an engineering methodology that compares two model architectures within the same computing environment and using the same dataset.

- Can the VGG16 and VGG19 architectures achieve a reasonable performance metric (accuracy above 70 percent) on a state-of-the-art aerial dataset?
- Do the different but similar architectures improve model performance metrics? Specifically, are the three convolutional layers in VGG19 beneficial for enhancing the model's metrics (Accuracy and Loss)?

5 Methodology and Implementation

The methodology and implementation of the experiment represented in this research involve several critical steps, beginning with the use of the "Semantic Segmentation of Aerial Imagery" dataset, sourced from the Kaggle platform. This dataset contains aerial images of Dubai, captured by MBRSC satellites, and annotated for pixel-wise semantic segmentation

across six classes. With a total of 72 images organized into six larger tiles, the dataset provides a robust foundation for the experiment. Data preprocessing, including the development of custom data generator modules to effectively turns the input data to augmented big data images, which is a key step to ensure the models can efficiently process and learn from the images. Following data preparation, the methodology covers the fine-tuning of models from external libraries in Python, specifically focusing on programming a new head (classifier) for the VGG16 and VGG19 architectures using torchvision models. Both of models architectures have been trained, validate and tested generically on the same data, with the same number of epochs and on the same hardware using Google Colab (A100 GPU with 40GB memory) Finally, the results and metrics presentation will provide a comprehensive evaluation of the model performances, highlighting the effectiveness of the implemented techniques. GitHub Project: https://github.com/MaorNave/Data_science_seminar.git

5.1 Data Preprocess

In this research, the development of data preprocessing modules was essential for preparing the model to perform segmentation on aerial images. Using the "Semantic Segmentation of Aerial Images" dataset from Kaggle, which features 72 annotated images of Dubai captured by MBRSC satellites, the data was organized into six larger tiles. To ensure consistency across all input images, a series of augmentation processes were applied, generating generic and relevant data for the model. This led to the creation of a custom module named Data Generator, which handled multiple tasks: cropping images to a standard resolution, saving relevant images and masks, extracting and saving patches (sized 224×224), performing augmentations like rotations and flips (8 per each image and mask), and organizing the processed data into folders for training, validation, and testing. Additionally, the Data Generator module converted masks into one-hot encoded vectors, simplifying the model's architecture during the training phase. The module also redistributed a percentage of data across these folders to maintain diversity in the training set, ultimately resulting in 4622 test images and masks, 16776 training images, and 5444 validation images. This preprocessing pipeline was crucial for ensuring that the model could generalize well across different tiles and image resolutions, providing a robust foundation for the segmentation task. By systematically managing data distribution and format conversion, the module enhanced the model's ability to handle variations within the dataset, leading to more accurate segmentation results.

5.2 Models Architectures Fine Tune and Predictions

To effectively train and fine-tune model architectures for the segmentation task, the research represents implementation process called fine-tuning. This involves adapting existing model weights using new data generated by the Data Generator module (from last section). To ensure a uniform classifier across models and isolate differences based on architecture, a SegmentationModel module was developed. This module allows for the selection of pre-trained or untrained weights for each model and integrates a new classifier (net head) that performs an upsampling process. This process involves convolution and factorization of data with intermediate ReLU layers (5 additional layers in total), resulting in tensor-type data structures divided into segments representing class probabilities for segmentation (higher probability in a pixel in a specific dimension number will have a better confidence level to be the relevant segmentation class). With that, in this research two additional modules were programmed: TrainValModels and PredictModels. The TrainValModels module offers functionality for generic training and validation phases of VGG16 and VGG19 architectures, utilizing TensorBoard to extract metrics and statistics (Loss and Accuracy). Training was performed across various learning rates (0.00003, 0.0001, 0.0003, 0.001, 0.003) and batch sizes (64 for training and 32 for validation), with each session conducted for 10 epochs. This module tracks accuracy and loss metrics, saving the best weights for each model. Furthermore, TrainValModels module performs a test session on test data by batching 16 images and masks per each batch iteration resulting each model best params accuracy and loss values. The PredictModels module, on the other hand, loads the most relevant weights for each model architecture, bypassing existing weights as needed, and performs predictions on data from the test set. This ensures that predictions are made with the optimal model weights, based on data prepared from the test folder.

5.3 Results

The models were evaluated based on loss and accuracy metrics, with training conducted across various learning rates to identify the optimal configuration. As shown in Tables 1 and 2, each model, VGG16 and VGG19, was trained and validated with different learning rates, ranging from 0.00003 to 0.003. The best-performing learning rate, determined by the lowest validation loss and highest accuracy, was selected for each model. For VGG16, the optimal learning rate resulted in a validation loss of 0.0059 and an accuracy of 85.33%, while

VGG19 achieved slightly better results with a validation loss of 0.0054 and an accuracy of 85.97% at its best learning rate. Consequently, the final test results, presented in Table 3 and Figure 4, demonstrate that VGG19 outperforms VGG16 in both loss and accuracy metrics, achieving a test accuracy of 83.26% compared to 82.51% for VGG16. These results address the first research question, showing that both models achieve over 70% accuracy on the test data. Additionally, visual predictions provided in Tables 4 and 5 indicate that VGG19 offers superior segmentation performance, particularly in differentiating pixel-wise data, thus answering the second research question effectively.

LR	Validation Loss	Validation Acc
0.00003	0.0097	81.36
0.0001	0.0067	84.55
0.0003	0.0059	85.33
0.001	0.0109	79.99
0.003	0.0145	77.45

Table 1: VGG 16 validation results

LR	Validation Loss	Validation Acc
0.00003	0.0091	81.83
0.0001	0.0066	84.57
0.0003	0.0054	85.97
0.001	0.0128	78.78
0.003	0.0158	75.58

Table 2: VGG 19 validation results

Model	Test Acc
VGG 16	82.51
VGG 19	83.26

Table 3: VGG models test results

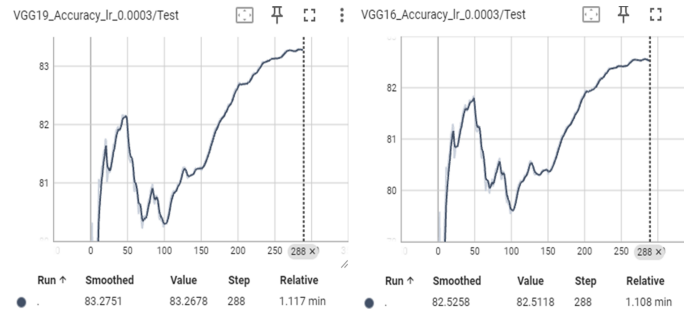


Figure 4: VGG models test results - Tensor Board

Input	GT Mask	Net Pred

Table 4: VGG 16 predictions



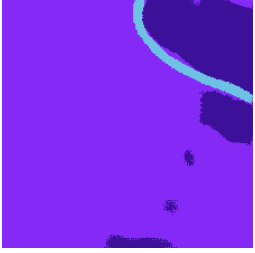



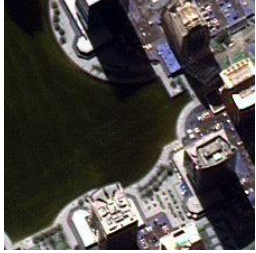
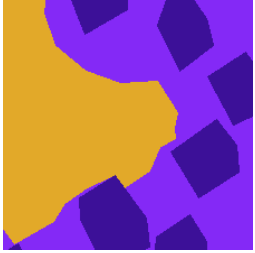




Input	GT Mask	Net Pred
		
		
		
		

Table 5: VGG 19 predictions

6 Discussion and Conclusion

This research have presented comprehensive exploration and understanding of digital image processing and computer vision, focusing specifically on the practical and business applications of this subject. Furthermore, a performance evaluation of two state-of-the-art models, VGG16 and VGG19, for segmentation tasks using an aerial imagery dataset was presented in this research. The experimental approach was grounded in rigorous methodology, encompassing dataset preprocessing, model fine-tuning, and detailed performance evaluation. The experiment include a preprocessing pipeline involved a custom-developed Data Generator module, which ensured data consistency and quality by performing tasks such as cropping, patch extraction, augmentation, and data redistribution. This process resulted in a robust dataset prepared for training, validation, and testing, with a total of 46,622 images across various splits. The Data Generator also converted segmentation masks into hot vector val-

ues, simplifying the model training phase and enhancing the accuracy of segmentation tasks. In the model fine-tuning phase, both VGG16 and VGG19 architectures were employed, with training conducted across various learning rates. The performance metrics for each model were meticulously recorded, revealing that both models achieved accuracies exceeding 70% on the test dataset and by that answering the first RQ. Notably, VGG19 demonstrated superior performance compared to VGG16, with a test accuracy of 83.26% versus 82.51%, respectively. This improvement in accuracy is consistent with the validation results, where VGG19 outperformed VGG16 across all learning rates tested. The VGG19 model exhibited lower validation loss and higher accuracy, suggesting its enhanced capability to handle complex segmentation tasks. The findings confirm that the VGG19 model provides better performance in segmentation tasks, as it effectively leverages its deeper architecture with additional convolutional layers to capture finer details in aerial imagery. This advantage is evident in the visual predictions, where VGG19 produced more accurate and detailed segmentations compared to VGG16. The results validate the second RQ demonstrating its efficacy in visualizing and differentiating pixel-wise data. In conclusion, this research underscores the significance of model architecture in improving segmentation performance or any relevant task in the field of DIP and CV. The study’s comprehensive approach, from thorough explanation and literature review about the fields of DIP and CV, data preparation, Models train and validation phases to model inference, provides valuable insights into the practical application of deep learning models in computer vision, contributing to the broader understanding of model performance in complex image processing tasks. Future research could explore additional model architectures and techniques in various imaging contexts.

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