# Comparing Models of Medical Image Classification with Segmentation

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## Introduction

Image segmentation provides a vital method for image analysis in various fields and applications, and different models have been designed over time to optimize this process. General testing measures along with specific image segmentation statistic tests are applied to different architectures and classifiers to gauge similarities and differences. In this poster, we compare models of image segmentation (UNet and FCN) and classifiers (SVM and Naïve Bayes') to measure the statistical significance of each model. The goal is to analyze the resulting statistical data to find which model provides the best application of image segmentation in the medical field. Finding this result will help improve the accuracy of medical diagnosis through image segmentation.

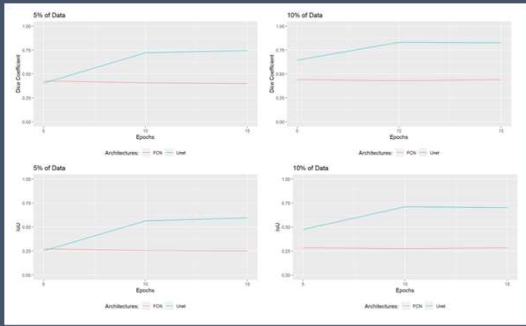
## The Dataset

Released by the Medical University of Vienna, the HAM1000 data is an open source that is public for use in medical image segmentation. [13] The dataset has 10015 dermatoscopic images of pigmented skin lesions to serve as a training set for machine learning. The collection of data for the ground truth was confirmed by histopathology, follow up examinations, expert consensus, and confirmation by in-vivo-confocal microscopy. Many of the images were taken from different populations to increase the diversity of ethnicities, race, and gender represented in the dataset.

## Methodology

Statistical tests were applied to UNet and FCN with classifiers SVM and Naïve Bayes'. (Example: UNet – SVM and UNet – Naïve Bayes') However, aspects of input like changing the percentage of total data used and switching the total number of iterations for training in one cycle (epoch) helped evaluate the capabilities of each model. Therefore, testing measures were measured when there was 5% and 10% of data with varying epochs: 5, 10, and 15. Changing these distinctive features allowed for more testing measures on whether or not different factors affected efficiency for each model and classifier.

## Results




| 5% | Accuracy | F-1 Score | Recall | Precision |
|---|---|---|---|---|
| UNet: SVM | 0.703 | 0.693 | 0.703 | 0.685 |
| UNet: NB | 0.756 | 0.724 | 0.756 | 0.705 |
| FCN: SVM | 0.719 | 0.686 | 0.719 | 0.658 |
| FCN: NB | 0.693 | 0.682 | 0.693 | 0.677 |

| 10% | Accuracy | F-1 Score | Recall | Precision |
|---|---|---|---|---|
| UNet: SVM | 0.777 | 0.723 | 0.777 | 0.709 |
| UNet: NB | 0.765 | 0.708 | 0.765 | 0.672 |
| FCN: SVM | 0.777 | 0.718 | 0.777 | 0.682 |
| FCN: NB | 0.772 | 0.716 | 0.772 | 0.678 |

The Dice Coefficient and IoU are testing measures that are specific to image segmentation shown on the left. On the right are the average for all epochs for broad testing measures: accuracy, F-1 score, recall, and precision for all architectures and specific classifiers.

## Conclusion

Using a medical dataset for skin lesions for the models UNet and FCN has shown that ten percent of data has better results for statistical testing than when five percent of data is used. This may be because using more data allows the model to train more images and then successfully identify cancerous skins lesions. The added data allows for more exposure for scenarios to the model which helps the model interact with different types of cases. Another aspect found in the study is that FCN has less fluctuation in the results from the testing measures and more of a consistent model, whereas UNet has a greater range for resulting testing values. However, the exception to this concept is in UNET study with Naïve Bayes' Classifier. The model shows FCN with greater variance over the two types of data percentages in comparison to the other model.

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