Automating the Segmentation of X-ray Images with Deep Neural Networks

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Introduction

- Increasing importance of analyzing tomographic X-ray datasets in scientific, medical, and industrial applications.
- Manual segmentation of raw data is time-consuming, error-prone, and limits the pace of technological development.
- Automation using deep neural networks addresses errors, accelerates the process, and supports ongoing technological advancements.
- Automation ensures alignment with the rapid development of X-ray technology, supporting scientific discoveries and industrial insights.[1]
- Automation removes subjectivity introduced by human intervention, ensuring accuracy and consistency in the analysis.

U-Net Architecture

- Utilization of U-Net architecture, renowned for image segmentation effectiveness.[2]
- Implementation involves a symmetric encoder-decoder structure with skip connections, ideal for handling spatial relationships and capturing contextual information.
- Real-world X-ray datasets utilized for training and evaluation, with benchmarking against manually labeled datasets.
- Implemented with RELU and ADAM
  - ▷ RELU:
  - ▷ ADAM:

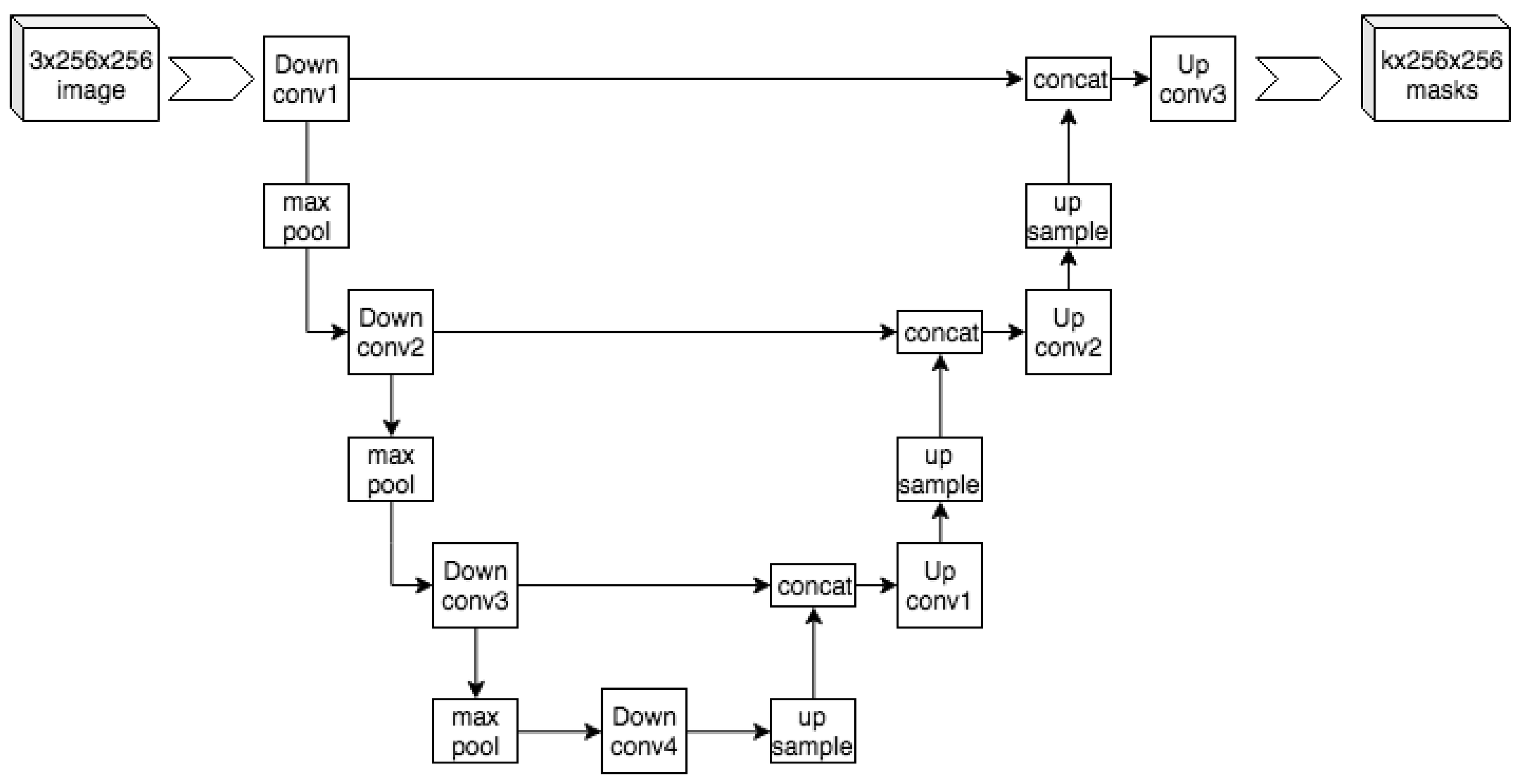


Figure 1: U-Net architecture representation.

Visualization of performance

Learning rate	Batch size	epochs
0.001	16	10

Table 1: Table for learning rate, batch size and epochs

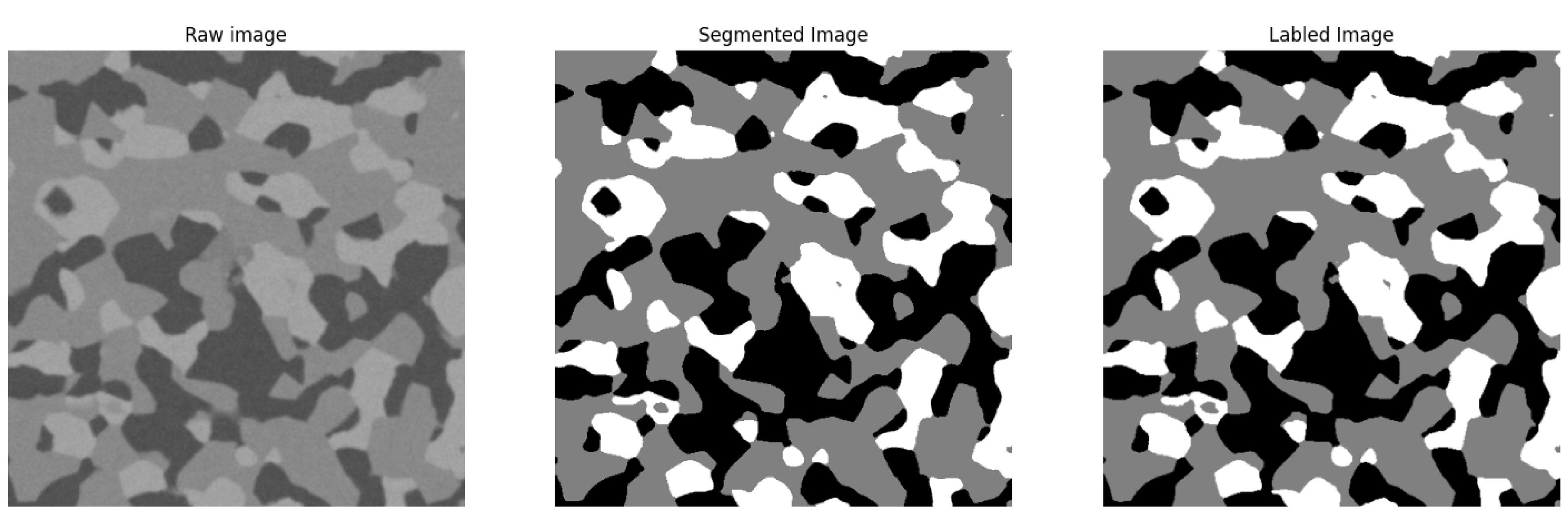
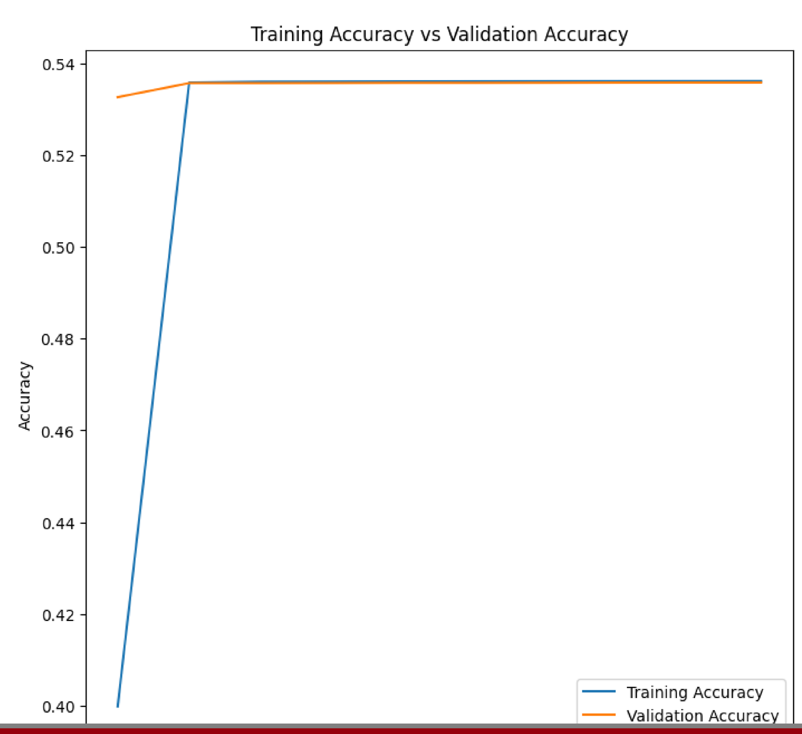
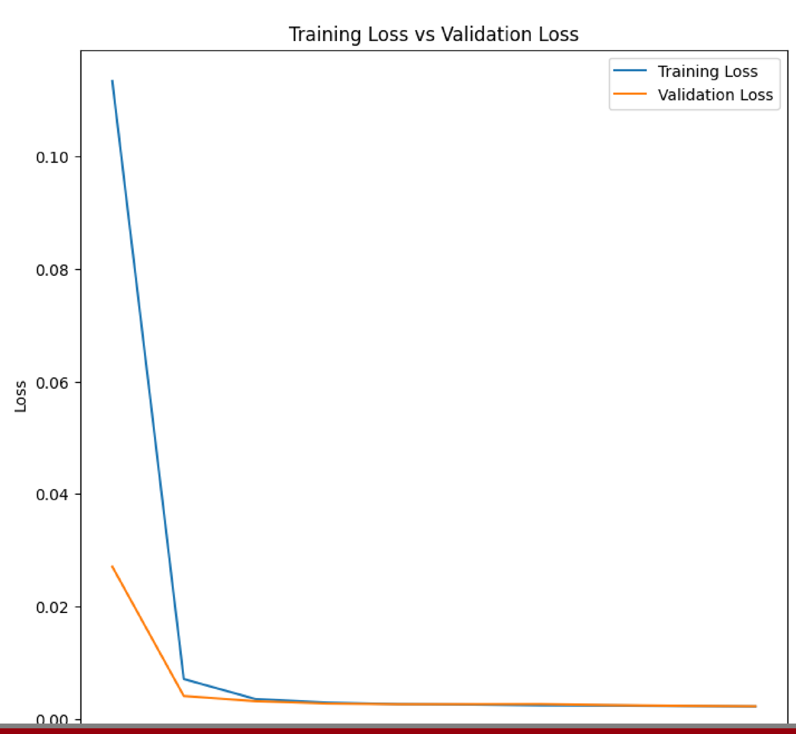


Figure 2: comparing for the raw image, segmented and the labeled image

Accuracy and Loss for the model





Model performance

- U-Net demonstrates high accuracy and precision in automating X-ray image segmentation.
- Performance metrics, including accuracy, precision, recall, and F1 score, affirm the model's proficiency.
- Visual analysis through image collages showcases the model's ability to identify and segment diverse regions of interest effectively.

Metric	Score	In percent
Accuracy	0.8539	85.39
Precision	0.9969	99.69
Recall	0.7912	79.12
F1 Score	0.8822	88.22

Table 2: Performance score for the U-Net model

Visualization of the segmentation

hows a collage of nine images arranged in a 3x3 grid, each column depicting different stages of the image analysis process. The first column is the original image, the raw input data the model is processing. This is then followed by the middle column, which is the predicted mask that is the output after analysing the original image. The model has attempted to identify and segment different regions of interest in the image. The last column is the overlay predicted mask, the true mask, a composite image that overlays the model's predictions with the actual true mask. This is done to have a direct visual comparison between the model predictions and the actual true image. Red is the predicted colour, and blue is the true colour. This visualisation provides a comprehensive understanding of the U-Net model's performance. By comparing the predicted mask with the true mask, areas of strength and weakness in the model's ability to segment the original image can be identified. The model appears to perform well in certain areas and lacks in others.

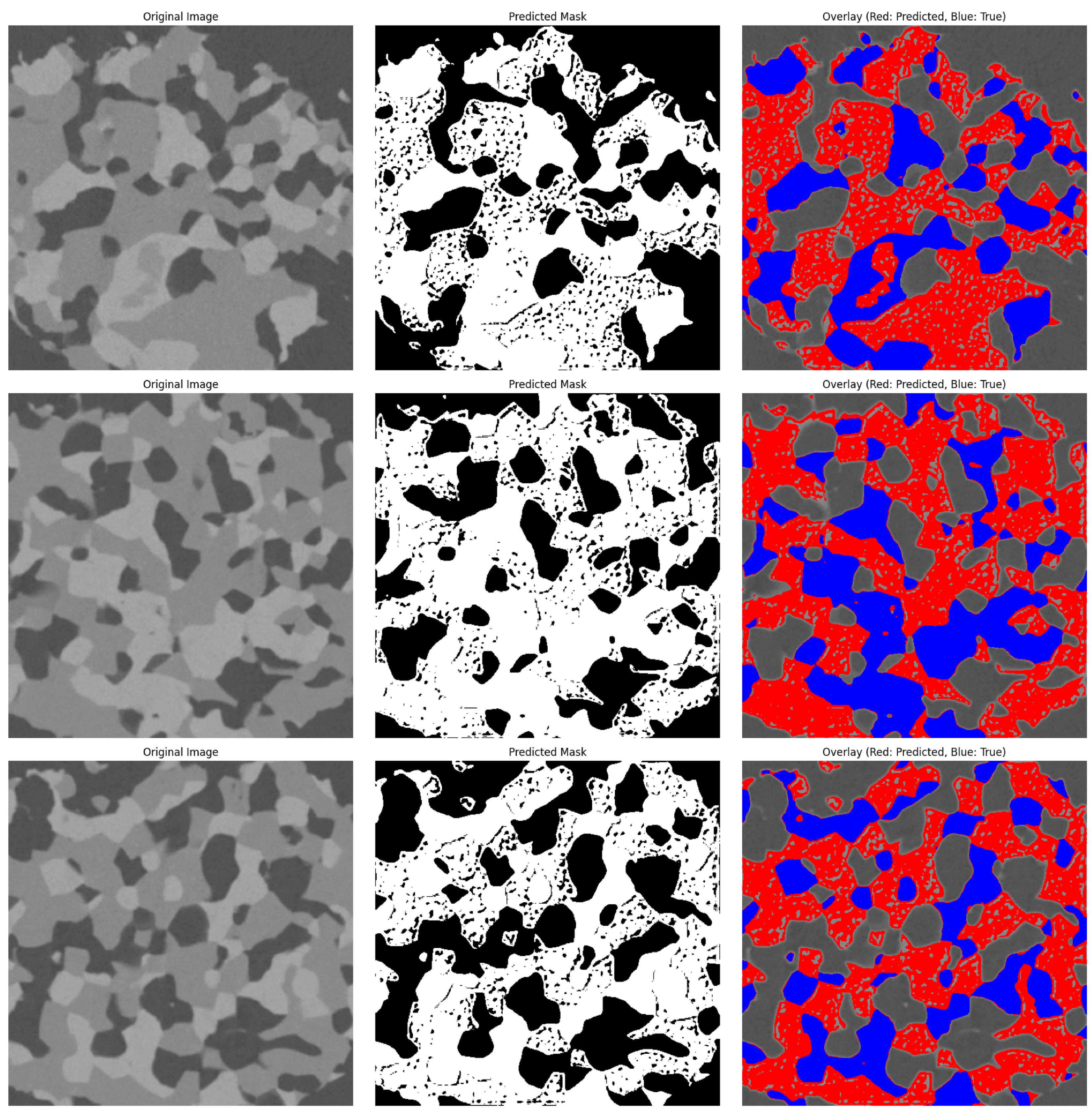


Figure 4: Visualization of three images in different images

Key Takeaways

- Successful application of U-Net architecture in automating the segmentation process for X-ray images.
- Metrics and visual analysis confirm the model's accuracy, precision, and ability to handle different regions of interest.
- The project highlights the potential of deep neural networks, specifically U-Net, in advancing and automating manual, time-consuming tasks in medical image analysis.

References

[1] R. D. R. B. S. S. S. B. S. O. J. S. . T. V. Hari McGrath, Peichao Li. Manual segmentation versus semi-automated segmentation for quantifying vestibular schwannoma volume on mri, 2020. URL https://theaisummer.com/unet-architectures/https://medium.com/analytics-vidhya/what-is-unet-157314c87634.

[2] t. f. e. Wikipedia. U-net, 2018. URL https://en.wikipedia.org/wiki/U-Net.

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