

CELL SEGMENTATION

INNOVATORS

ML+CV COMBINED



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Spot Nuclei. Speed Cures.

The challenge: Create an algorithm to automate nucleus detection

40%

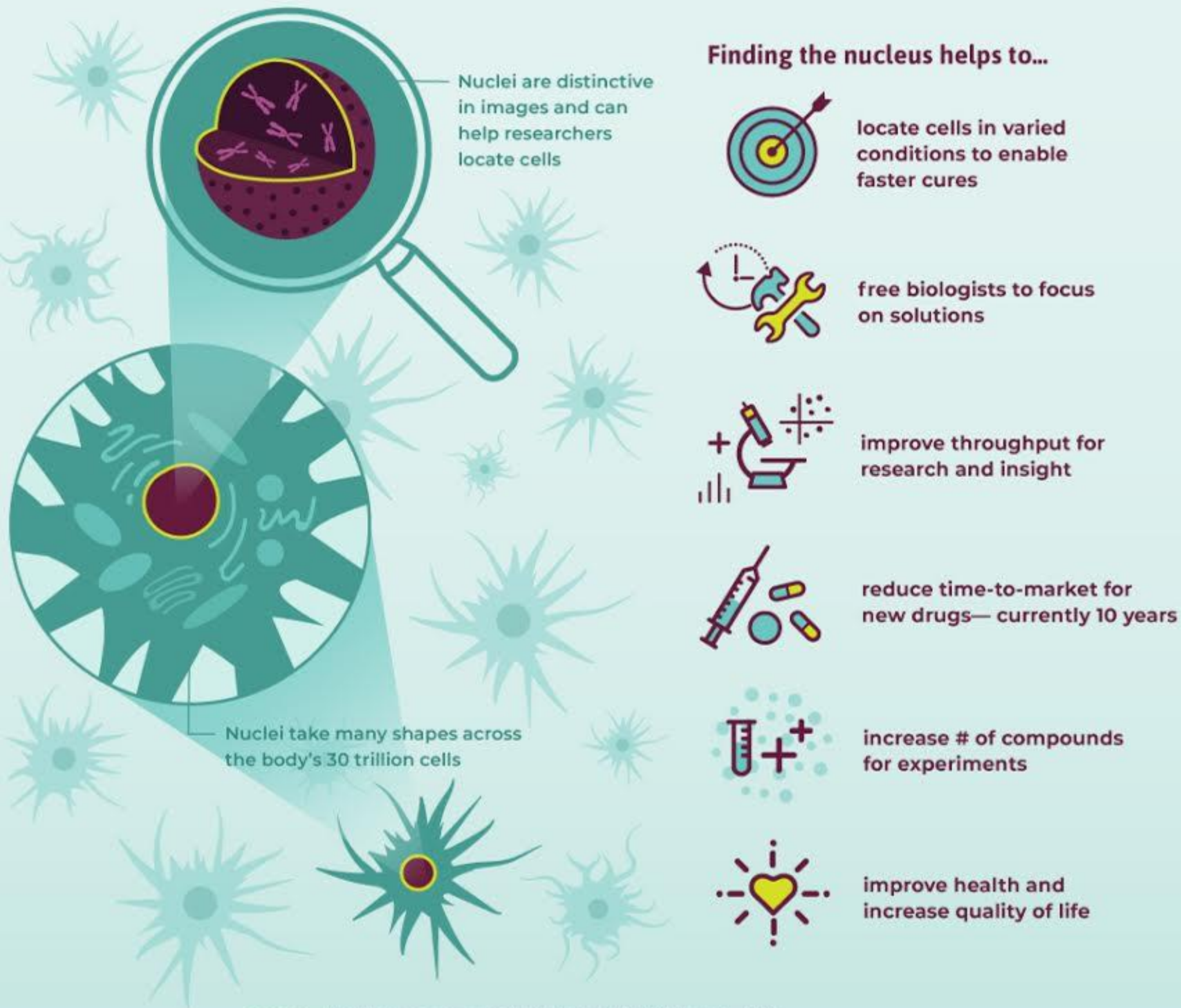
of all deaths are caused by illnesses like heart disease and cancer¹

75%

of rare diseases affect children²

30%

of affected children with rare diseases die before age 5²



SOURCES: ¹Heart disease and cancer causing 40% of all deaths – World Health Organization (WHO). 2015 – 56.4 million deaths. <http://www.who.int/mediacentre/factsheets/fs310/en/>
2015 – 17.7 deaths from cardiovascular diseases (CVDs). <http://www.who.int/mediacentre/factsheets/fs317/en/>
2015 – 8.8 million deaths from cancer. <http://www.who.int/mediacentre/factsheets/fs297/en/>

²Childhood diseases – 75% of rare diseases affect children; 30% die before age 5 – European Society of Paediatric Oncology (SIOPe). <http://www.siope.eu/SIOPE-EU/English/SIOPE-EU/Advocacy-Activities/Rare-Diseases/page.aspx/248>

INTRODUCTION

- Cell segmentation is a crucial task in biological image analysis, which involves identifying and separating individual cells from a digital image of a biological sample.
- With the increasing volume and complexity of biological data, automated cell segmentation has become essential in various fields such as cell biology, pathology, and drug discovery.

DATASET

2018 Data Science Bowl

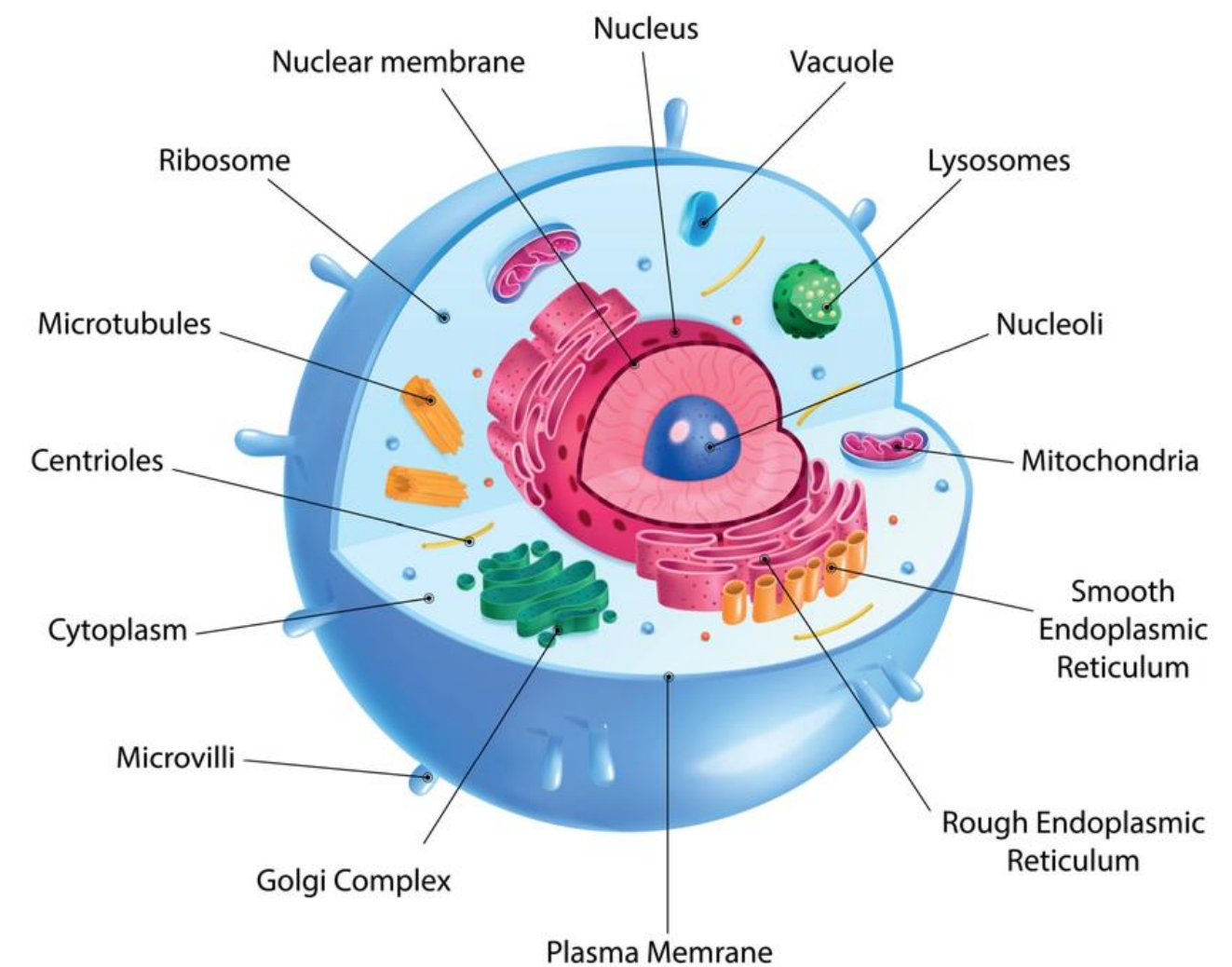
<https://www.kaggle.com/competitions/data-science-bowl-2018/overview>

- This dataset contains a large number of segmented human nuclei images.
- It contains 670 training images
- The images were acquired under a variety of conditions and vary in the cell type, magnification, and imaging modality (brightfield vs. fluorescence).

PROBLEM STATEMENT

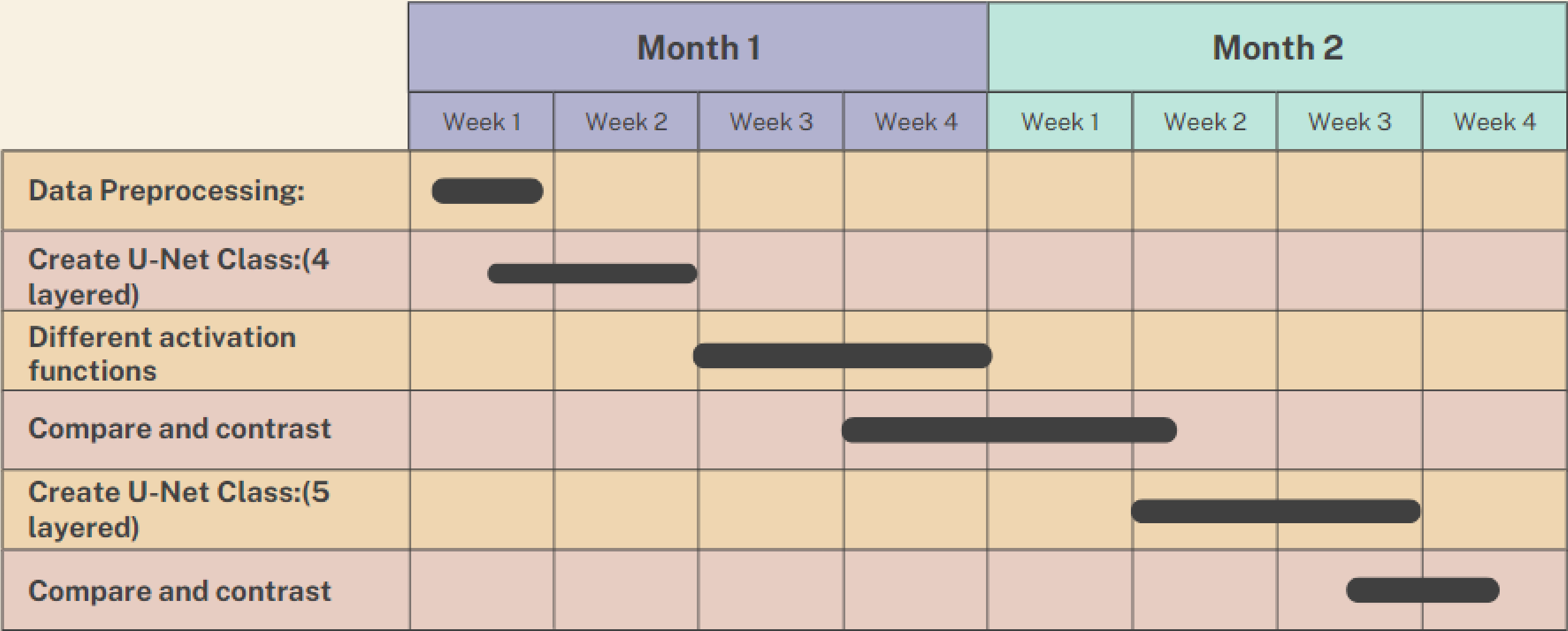
The goal of this project is to create a cell segmentation model based on deep learning using the UNet architecture and several activation functions in an effort to determine the most effective method for precisely and effectively segmenting individual cells in microscope images.

HUMAN CELL ANATOMY



GANTT chart showing the project progress

Project Timeline

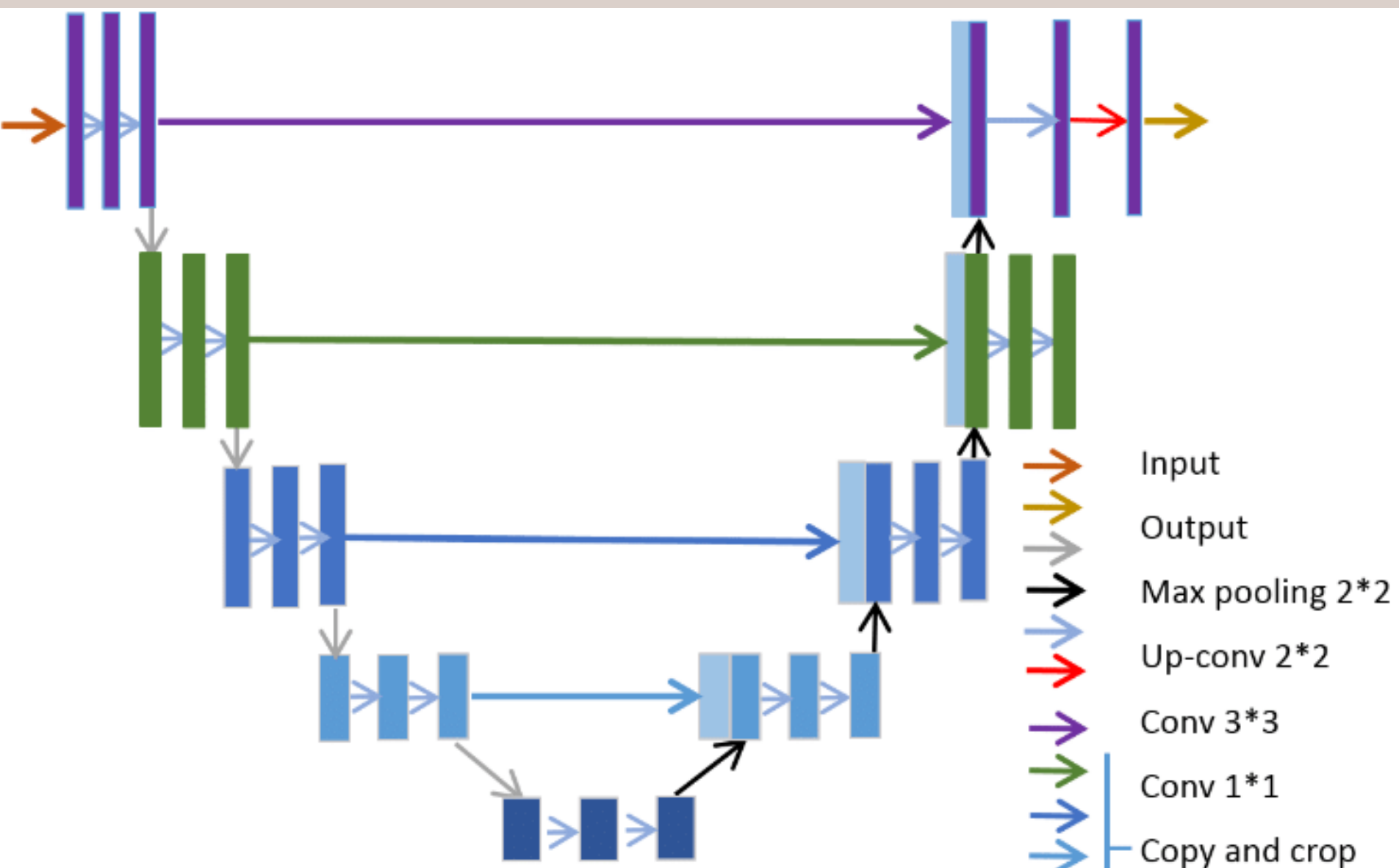


THE EXISTING BODY OF WORK

01

U-Net: Convolutional Networks for Biomedical Image Segmentation

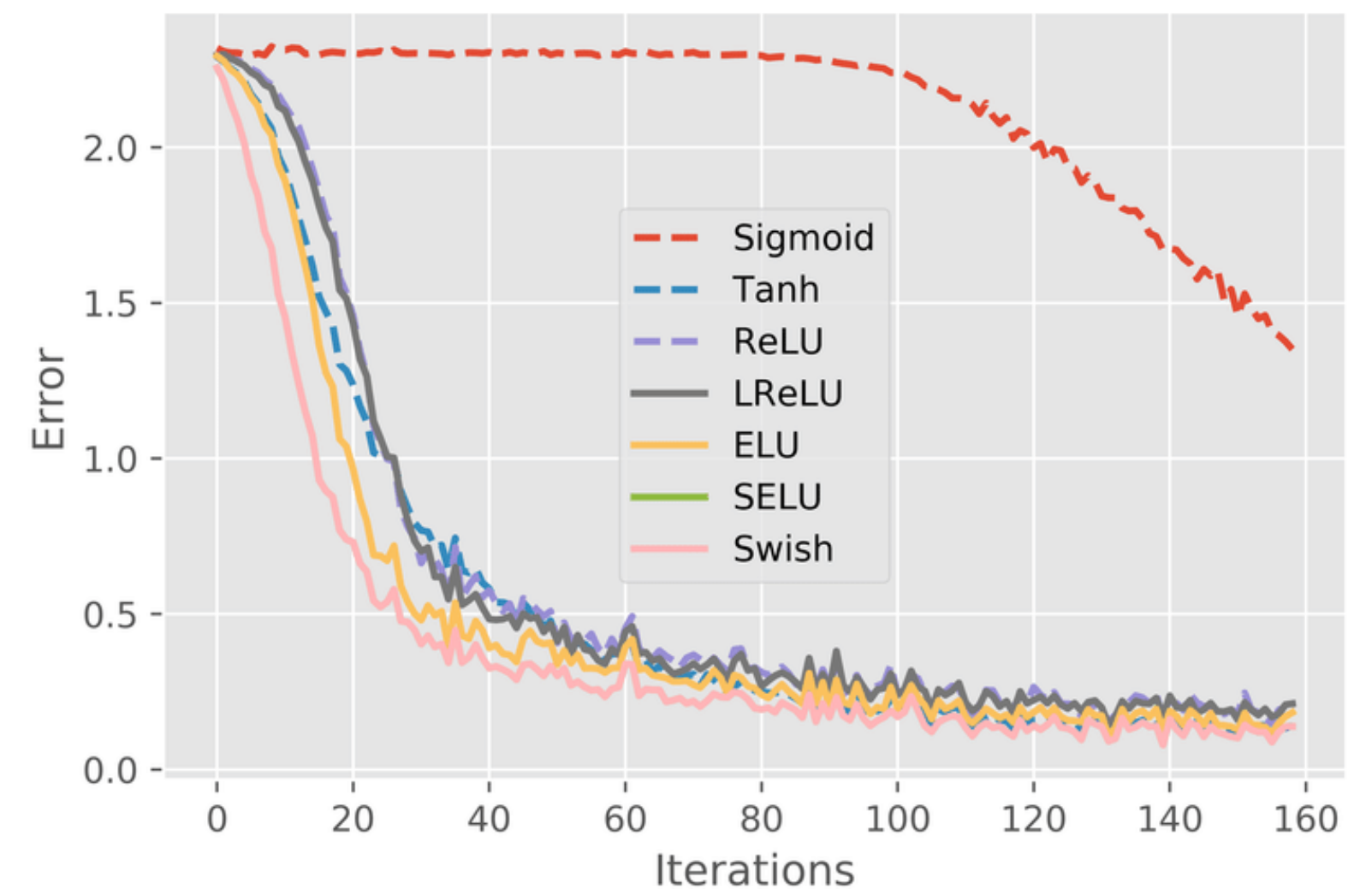
<https://arxiv.org/abs/2103.15898>



02

Comparison of different convolutional neural network activation functions.

<https://arxiv.org/abs/2103.15898>



YOUR APPROACH

We trained our model using ReLu activation function utilising the UNet architecture, and then we tried some more different activation functions. We utilised the following activation functions:

- MexicanRelu
- Swish
- TrainableLeakyReLU
- ISRU
- Mish



- Gated_Swish
- LearnableSwish
- h
- SRS
- TanELU

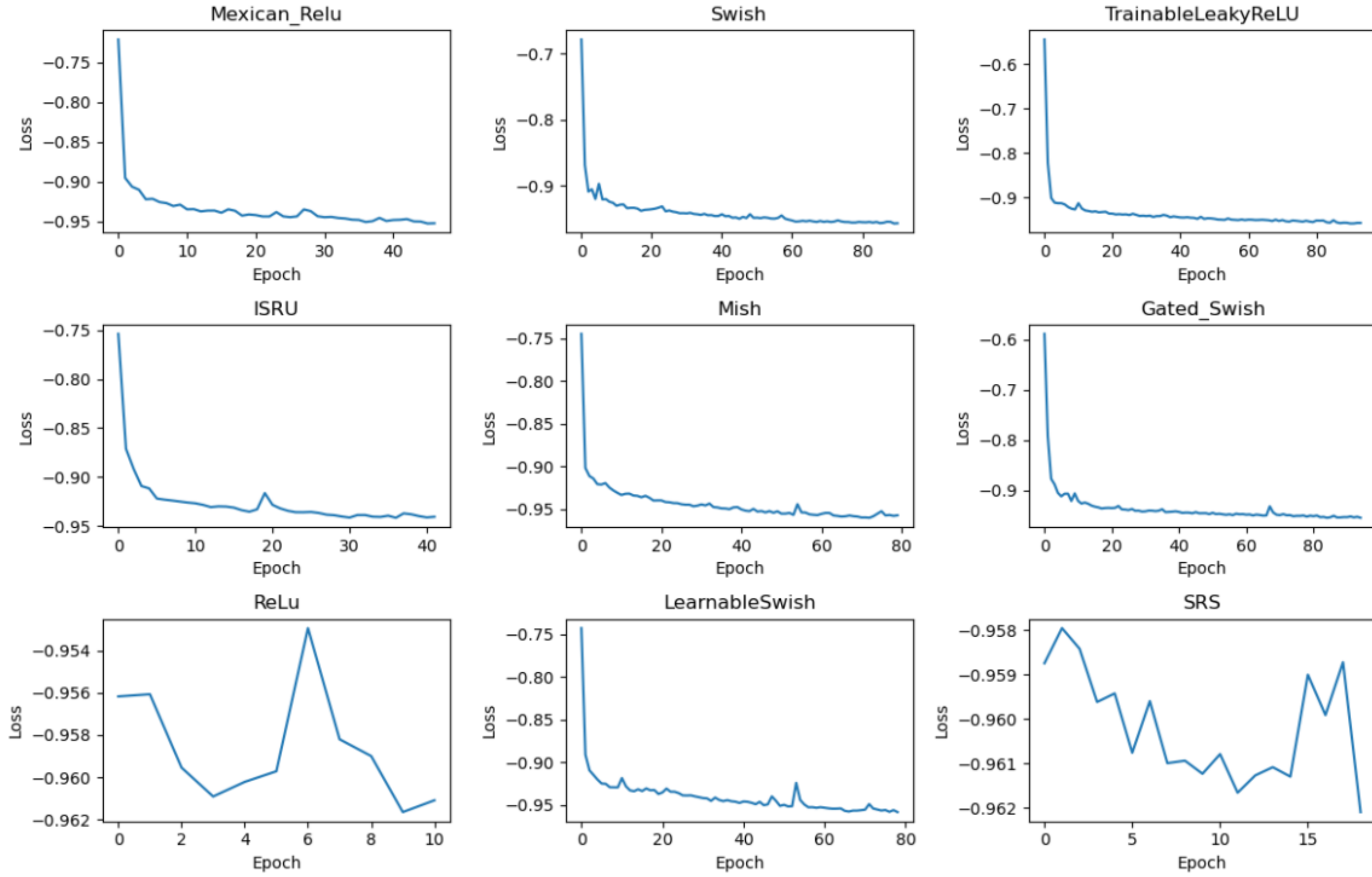
YOUR APPROACH

- We used optimizer as Adam ,Loss function as dice loss and metric as IOU
- We monitored the activation functions using callbacks which monitored the validation loss with patience equal to 10 epochs
- We compared the loss ,iou,validation_loss,training time corresponding to every activation function
- We tried different architectures and found that 4 layered and 5 layered gave us best accuracy
- We added one layer in encoding as well as decoding part and carried out the whole process

FINAL RESULTS

4 layered

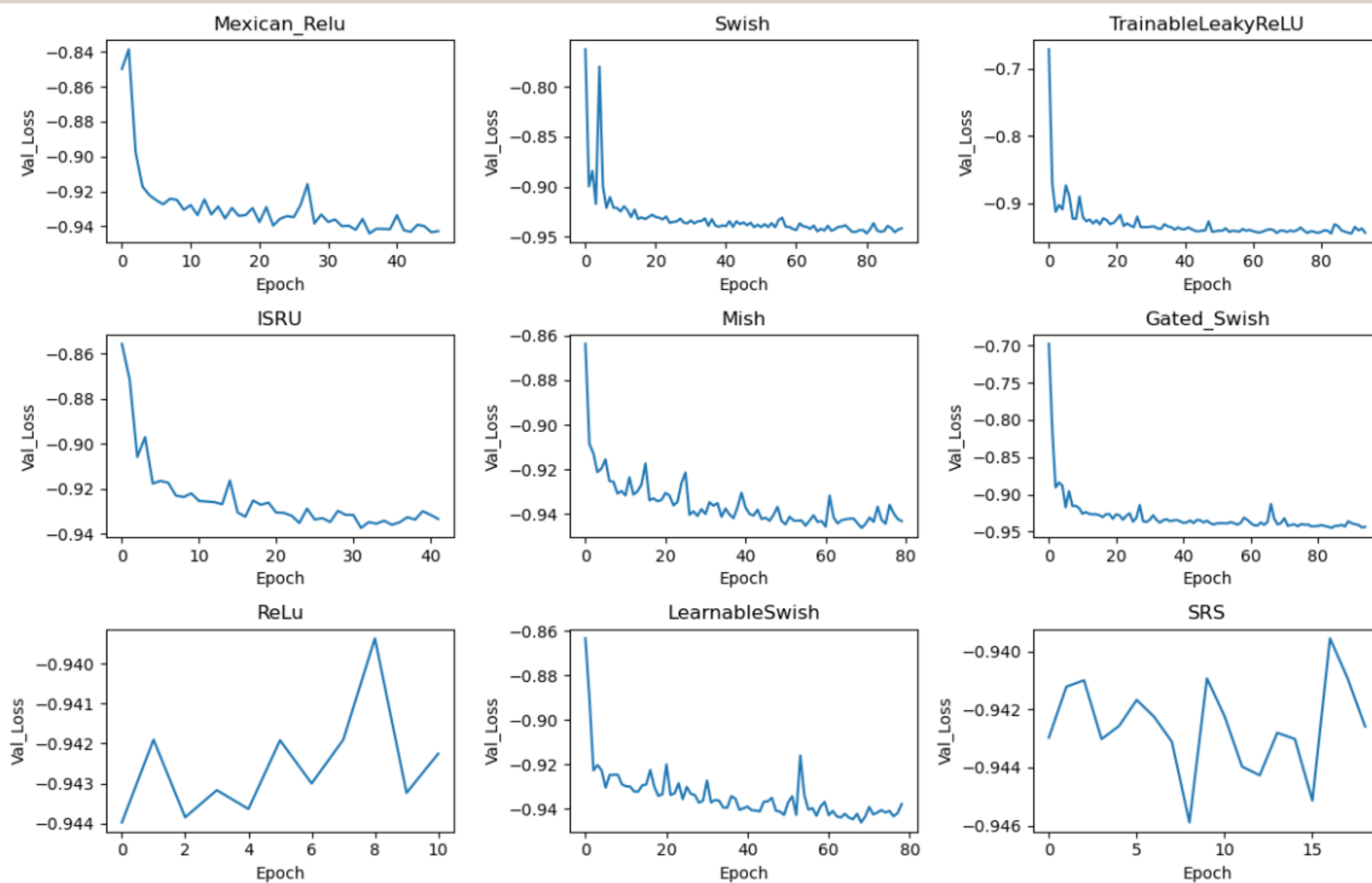
UNet
Loss



FINAL RESULTS

4 layered

UNet
Val_Loss

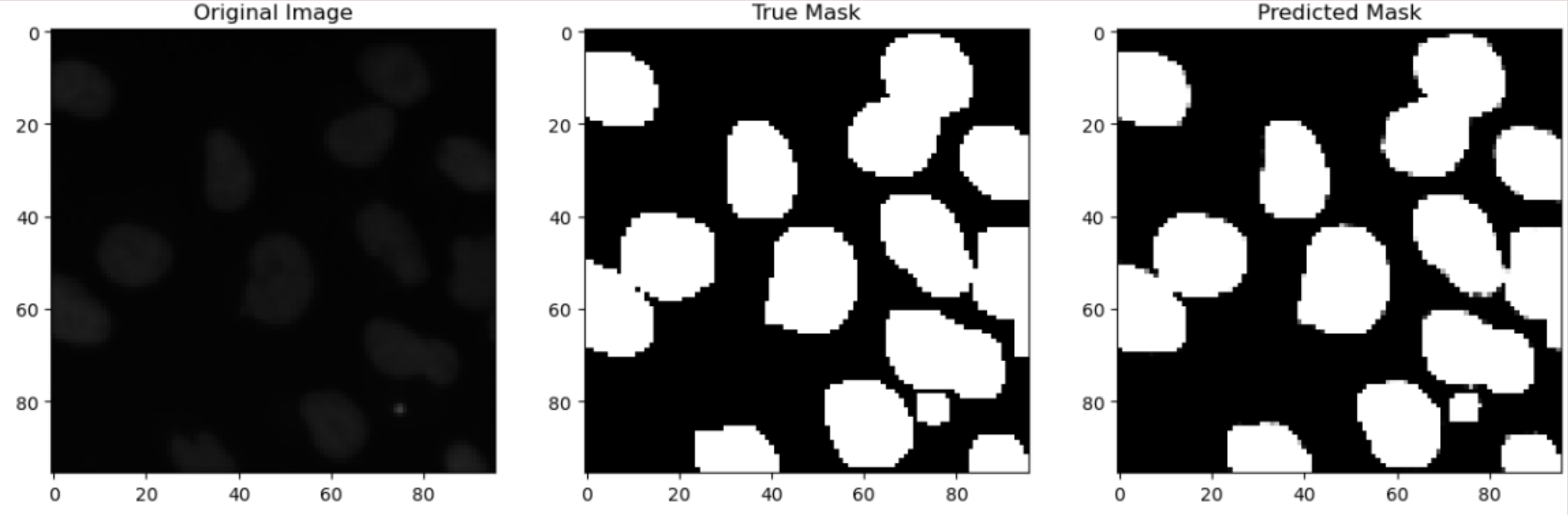


FINAL RESULTS

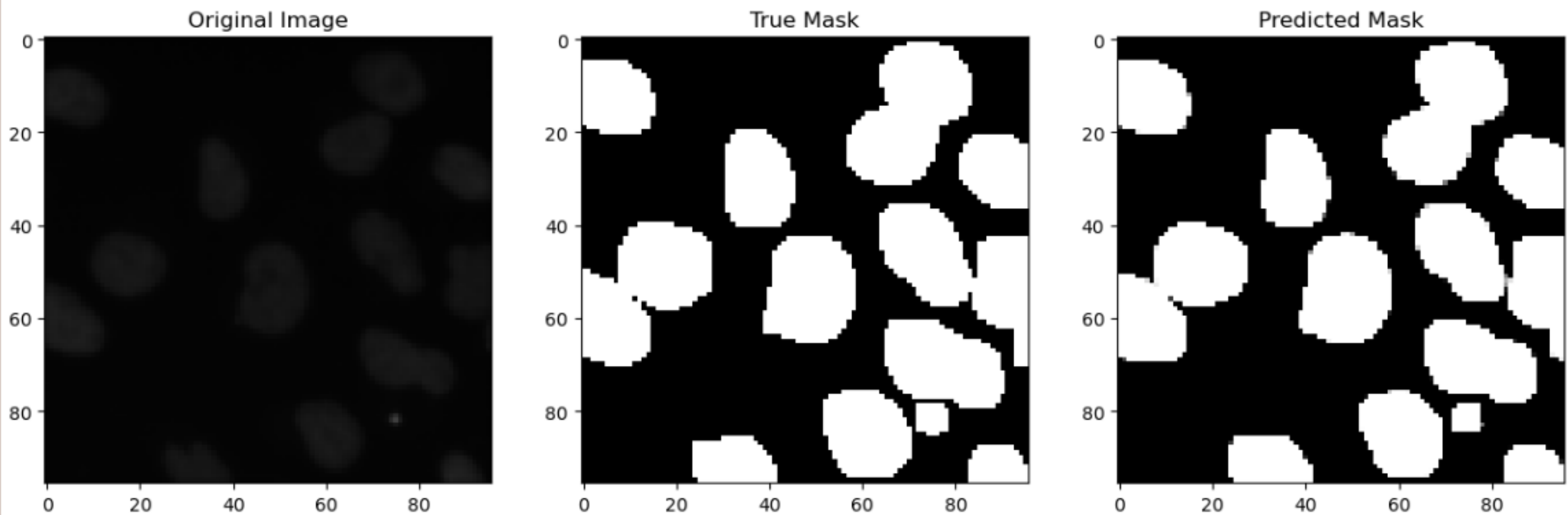
4 layered
UNet

<i>Activations</i>	<i>Top-1 Accuracy</i>	<i>Epochs till Convergence</i>	<i>Training time (s)</i>
Mexican ReLU	90.08	71	125.46
Swish	89.88	79	82.74
Trainable LeakyReLU	87.59	27	32.94
InverseSquareRootUnit	89.11	61	79.65
Mish	89.93	60	65.71
GatedSwish	90.01	67	78.63
ReLU (Baseline)	89.81	21	22.24
Learnable Swish	90.11	63	75.78
SigmoidReLUShifted (SRS)	90.15	24	27.584

Prediction using MexicanRelu



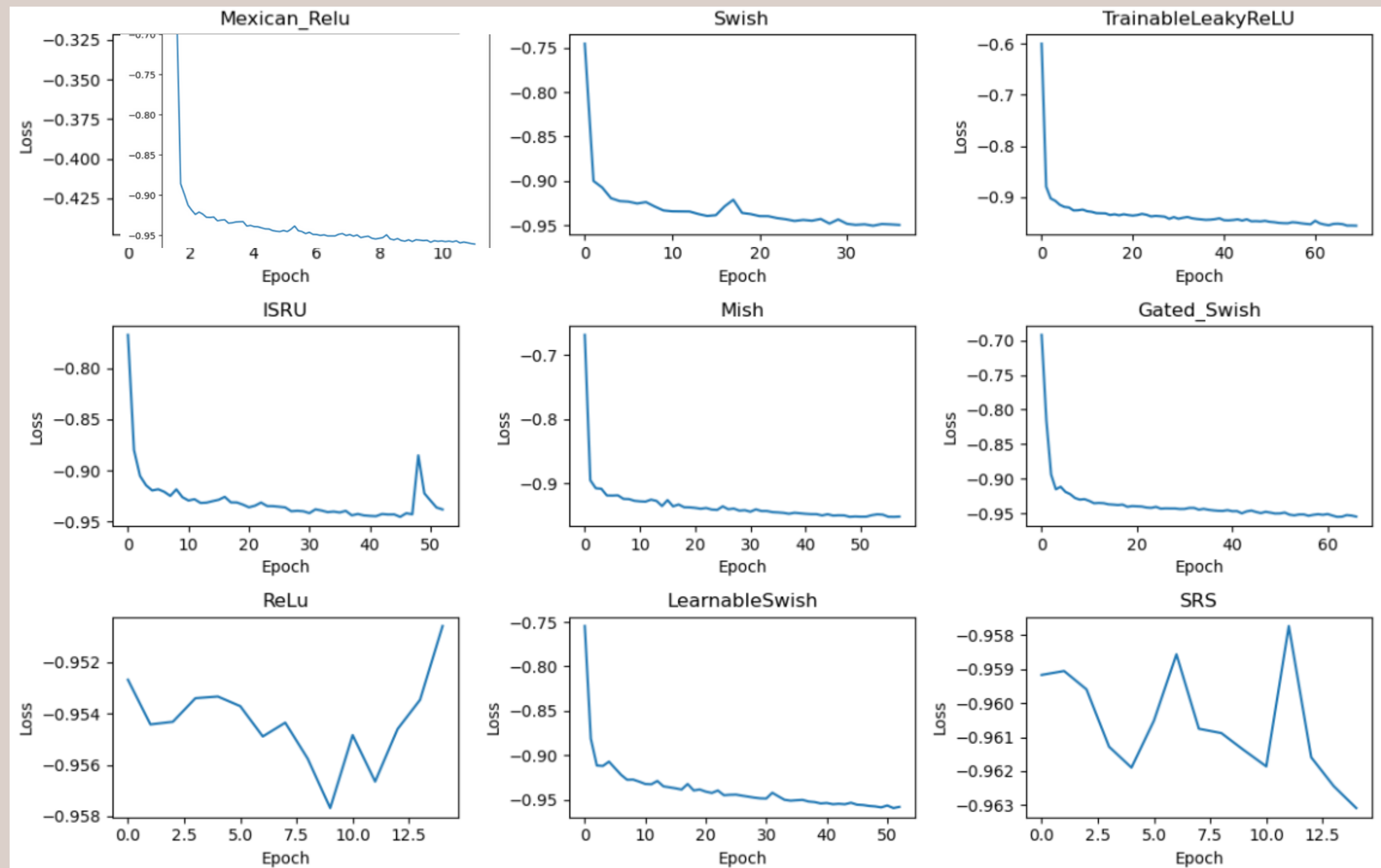
Prediction using Swish



FINAL RESULTS

UNet with an extra layer

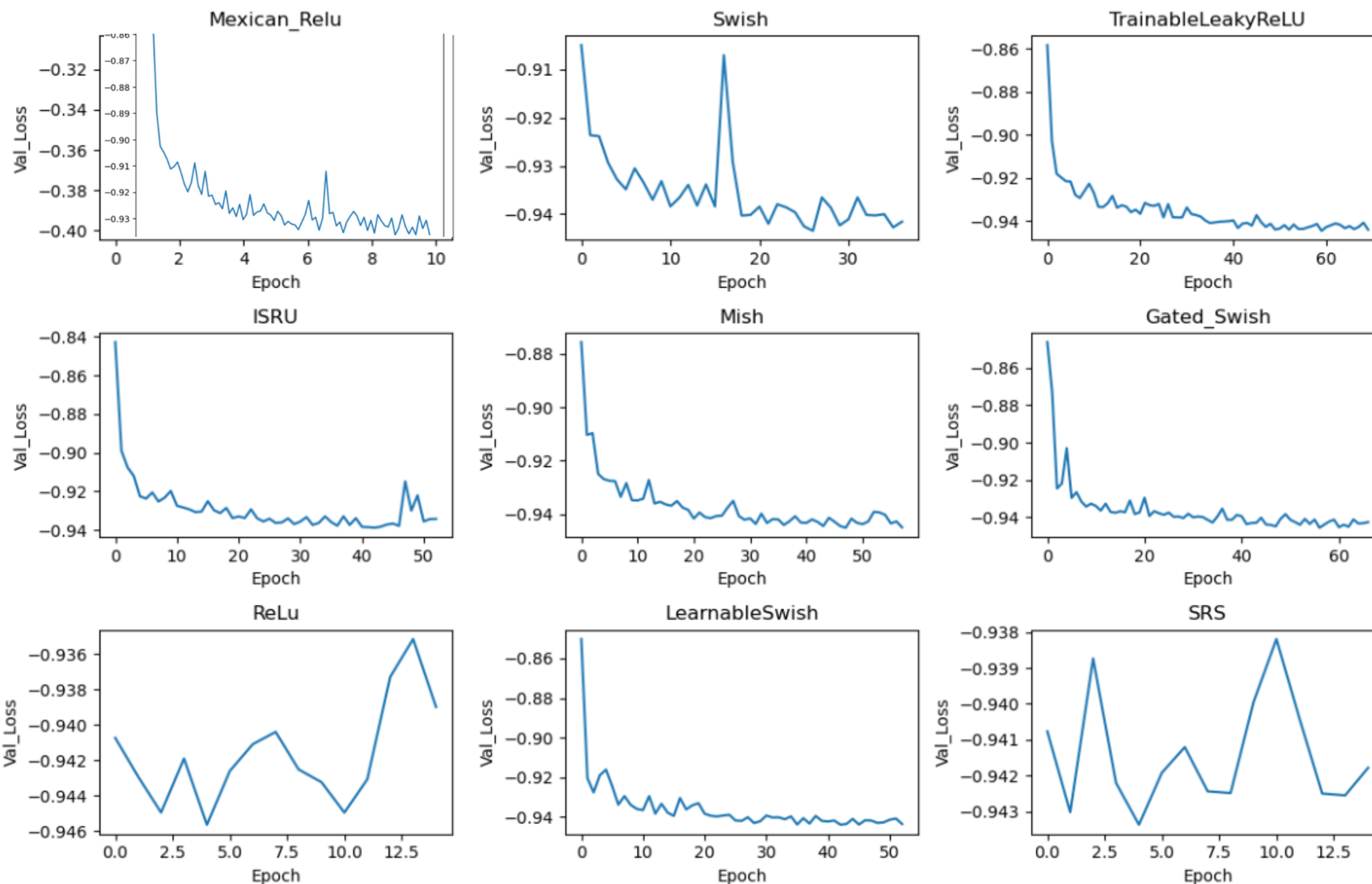
Loss



FINAL RESULTS

UNet with an extra layer

Val_Loss



FINAL RESULTS

UNet with an extra layer

Activation Function	Top-1 Accuracy	Epochs Till Convergence	Training Time(s)
Mexican Functions	0.8819	80	230.67
Swish	0.8834	64	116.92
TrainableLeakyRelu	0.8751	35	86.49
InverseSquareUnit	0.8648	37	83.85
Mish	0.674	20	66.68
GatedSwish	0.8808	47	121.32
Relu(BaseLine)	0.8688	14	40.159
LearnableSwish	0.8799	43	118.818
SigmoidReluShifted	0.8819	5	29.54

ROLE OF EACH GROUP MEMBER IN THE PROJECT

Aadya Chinubhai

- 4 layered UNet
- Implementing Mexican Relu,Swish,Trainable_leaky Relu ,Report

Razin Karimi

- 5 layered UNet
- Implementing ISRU,Mish, Gated_swish
- PPt

Abhishu Oza

- 4 Layered UNet
- Implementing Learnable Swish,SRS,Relu
- Report

Nihar Jani

- 5 layered UNet
- Weekly Reports, Dataset Analysis,PPt, Report,ReLu

CONCLUSIONS

- Four layered U-Net was giving best results
- There are little differences between every activation function.
- Some of them converge better because simple activation function converges faster. ReLU converges faster because it is a non-saturating activation function
- Some activation function are better in terms of training time. Here also ReLU has the faster training time this is because ReLU is a non-saturating activation function that does not have a maximum output value
- Accuracy is best given by SRS

REFERENCES

- Nanni, L. (2021, March 29). Comparison of different convolutional neural network activation functions and methods for building ensembles. arXiv.org.
<https://arxiv.org/abs/2103.15898>
- Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. Lecture Notes in Computer Science, 234–241.
https://doi.org/10.1007/978-3-319-24574-4_28
- Team, T. A., & Team, T. A. (2023, January 7). Medical Image Segmentation: 2018 Data Science Bowl. Towards AI. *<https://towardsai.net/p/l/medical-image-segmentation-2018-data-science-bowl>*
- Ronneberger, O. (2015, May 18). U-Net: Convolutional Networks for Biomedical Image Segmentation. arXiv.org. *<https://arxiv.org/abs/1505.04597>*

THANK YOU

