IISER PUNE

*NGN 2023 Conference*

# Evaluating U-Nets for Skull Stripping of Augmented T1-weighted MRI Scans


**Anway Pimpalkar**[1] **Dr. Rashmika Patole**[1] **Dr. Ketaki Kamble**[2] **Dr. Mahesh Shindikar**[2]

COEP Technological University, Pune IN

[1]*Department of Electronics and Telecommunication,* [2]*Department of Applied Sciences*


COEP Tech

# Neuroimaging Techniques

- Computed Tomography
- Diffusion Tensor Imaging
- Magnetic Resonance Spectroscopy
- Magnetization Transfer Imaging
- Cerebral Perfusion Imaging
- Single Photon Emission Computed Tomography
- Magnetic Resonance Imaging
- Positron Emission Tomography
- Electroencephalogram
- Ultrasound Imaging
- Functional Near-Infrared Spectroscopy

# Neuroimaging Techniques

Computed Tomography

Diffusion Tensor Imaging

Magnetic Resonance Spectroscopy

Magnetization Transfer Imaging

Cerebral Perfusion Imaging

Single Photon Emission Computed Tomography

Magnetic Resonance Imaging

Positron Emission Tomography

Electroencephalogram

Ultrasound Imaging

Functional Near-Infrared Spectroscopy

# MRIs and Skull Stripping

- Information of both **brain and non-brain tissues**.
- **Only brain** tissue required for most studies of neuroanatomy, neurophysiology, and internal functions such as cognition and control.

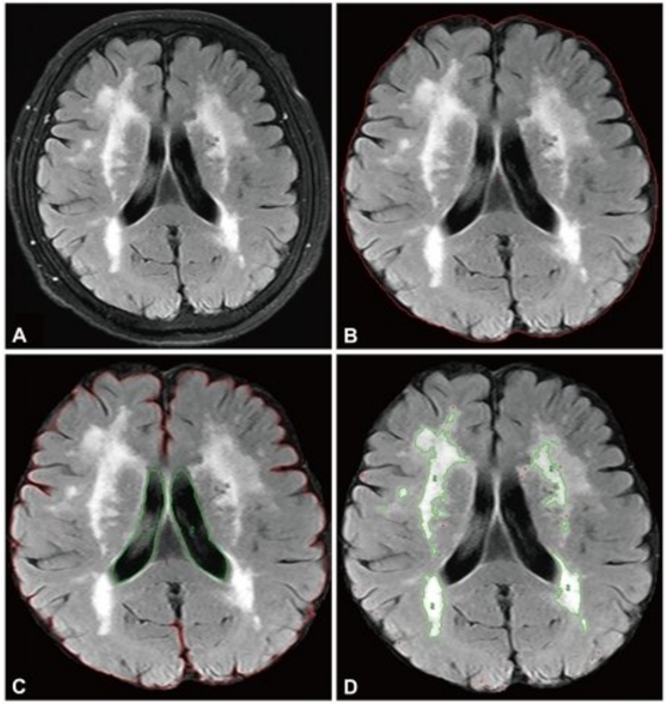


**Fig 1.** Adapted from the work by Lee et al. (2011).

Hahn et al. (2000).

# MRIs and Skull Stripping

- Information of both **brain and non-brain tissues**.

- **Only brain** tissue required for most studies of neuroanatomy, neurophysiology, and internal functions such as cognition and control.

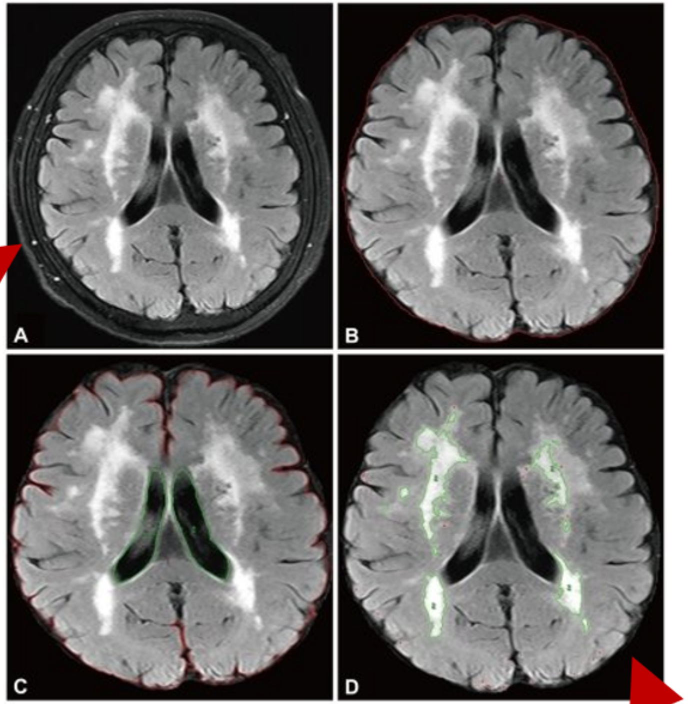



**Fig 1.** Adapted from the work by Lee et al. (2011).

Hahn et al. (2000).

# MRIs and Skull Stripping

- Information of both **brain and non-brain tissues**.

- **Only brain** tissue required for most studies of neuroanatomy, neurophysiology, and internal functions such as cognition and control.

- **Skull Stripping** is the separation of brain tissue, including grey and white matter from non-brain voxels such as the skull, scalp, and dura mater.

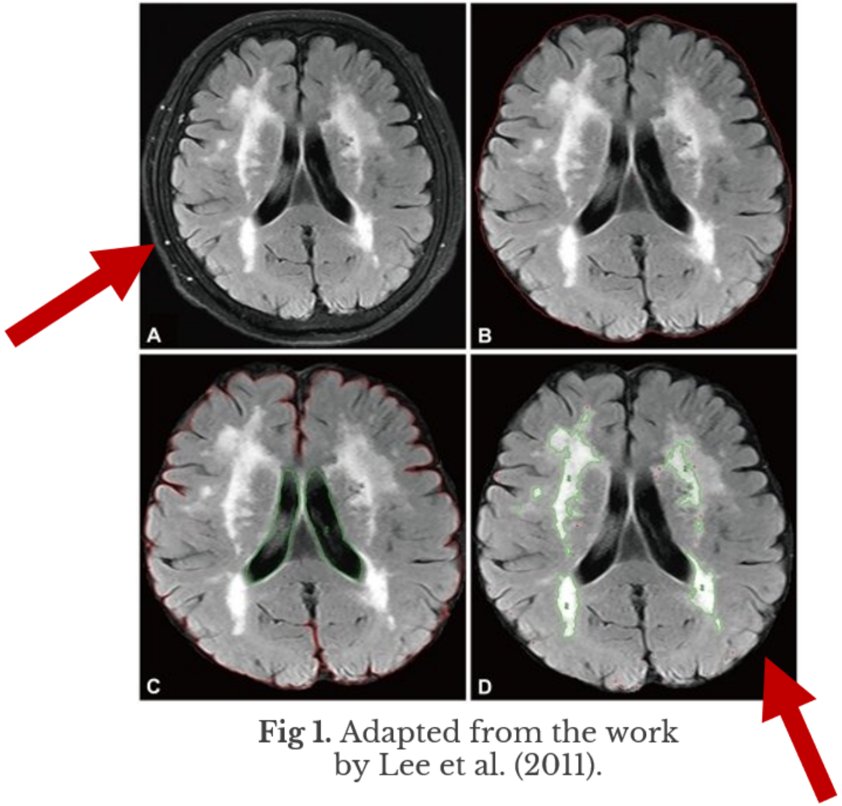



**Fig 1.** Adapted from the work by Lee et al. (2011).

Hahn et al. (2000).

# Conventional Skull Stripping Methods

- Conventional Methods
  - Manual Skull Stripping
  - Morphology Based
  - Deformable Surface Based
  - Intensity Based
  - Template and Atlas Based
  - Hybrid

Kalavathi et al. (2015).

# Conventional Skull Stripping Methods

**Conventional Methods**

- Manual Skull Stripping
  - Gold standard
  - Requires expertise
  - Cannot be integrated
- Morphology Based
- Deformable Surface Based
- Intensity Based
- Template and Atlas Based
- Hybrid

Kalavathi et al. (2015).

# Conventional Skull Stripping Methods

## Conventional Methods

### Manual Skull Stripping
- Gold standard
- Requires expertise
- Cannot be integrated

### Morphology Based
- Mathematical morphological operations
- Thresholding techniques

### Deformable Surface Based
- Fit curve to the brain contour
- Energy function driven
- Used in BET

### Intensity Based
- Pixel-by-pixel intensities
- Sensitive to bias.

### Template and Atlas Based
- Region matching to a pre-defined atlas/map

### Hybrid
- Combination of others

Semi-automated

Kalavathi et al. (2015).

# Conventional Skull Stripping Methods

**Conventional Methods**

- **Manual Skull Stripping**
  - Gold standard
  - Requires expertise
  - Cannot be integrated
- **Morphology Based**
  - Mathematical morphological operations
  - Thresholding techniques
- **Deformable Surface Based**
  - Fit curve to the brain contour
  - Energy function driven
  - Used in BET
- **Intensity Based**
  - Pixel-by-pixel intensities
  - Sensitive to bias.
- **Template and Atlas Based**
  - Region matching to a pre-defined atlas/map
- **Hybrid**
  - Combination of others

Semi-automated

**Disadvantages:**

- Require many user-dependent parameters.
- Susceptible to multi-scanner variability.

Kalavathi et al. (2015).

# Advances in Skull Stripping

**Modern Methods**

**Machine Learning Based**
- Fuzzy Active Surface Model
- ROBEX

**Deep Learning Based**
- 3D-CNN
- VoxResNet
- U-Nets

Kobashi S. et al. (2007). Iglesias JE. et al. (2011), Kleesiek et al. (2016), Chen et al. (2018), Ronneberger et al. (2015)

# Advances in Skull Stripping

Modern Methods

Machine Learning Based

- Fuzzy Active Surface Model
- ROBEX

Deep Learning Based

- 3D-CNN
- VoxResNet
- U-Nets

- **U-Net architectures** are encoder-decoder networks for semantic segmentation.

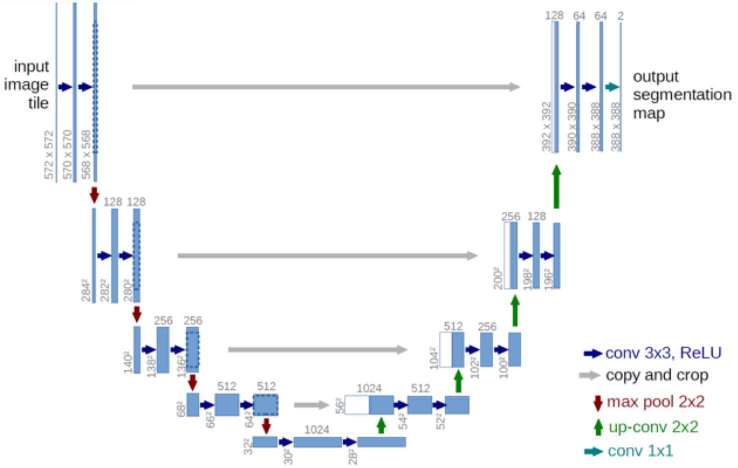



**Fig 2.** U-Net architecture representation. (Ronneberger et al., 2015)

Kobashi S. et al. (2007). Iglesias JE. et al. (2011), Kleesiek et al. (2016), Chen et al. (2018), Ronneberger et al. (2015)

# Advances in Skull Stripping

- **U-Net architectures** are encoder-decoder networks for semantic segmentation.

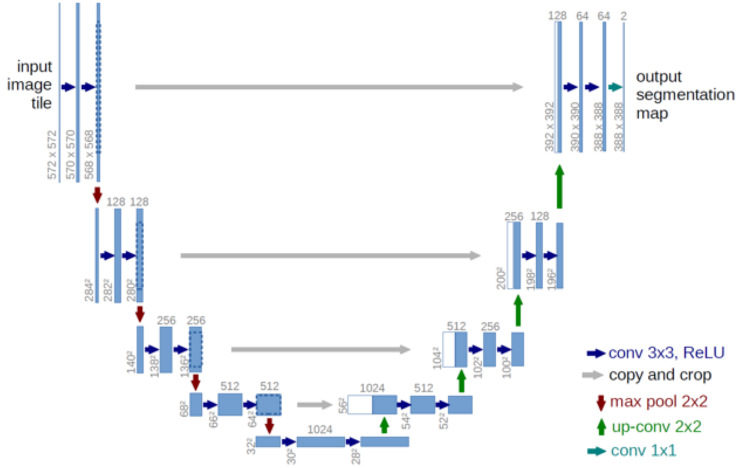



**Fig 2.** U-Net architecture representation.
(Ronneberger et al., 2015)

# Project Objective

- To evaluate the performance of three flavors of 2D U-Net architectures for Skull Stripping:
  - (a) Vanilla
  - (b) Residual
  - (c) Dense
- Robustness to multi-scanner variance.

Kobashi S. et al. (2007). Iglesias JE. et al. (2011), Kleesiek et al. (2016), Chen et al. (2018), Ronneberger et al. (2015)

# U-Net Architectures

- Encoder-decoder
- Two paths:
  - **Contractive**: Downsampling image to feature representation.
  - **Expansive**: Upsampling representation to segmentation map.
- 2D or 3D convolutions
- Skip connections

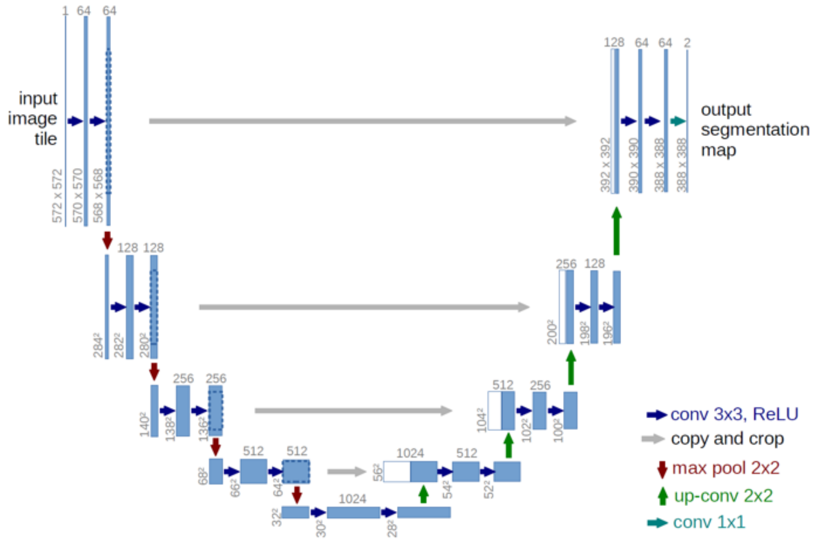



**Fig 2.** U-Net architecture representation. (Ronneberger et al., 2015)

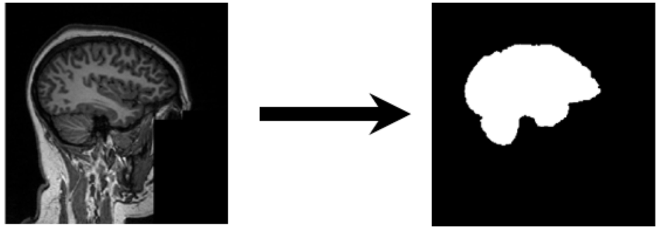


**Fig 3.** U-Net input and output.

# U-Net Architectures

- Encoder-decoder
- Two paths:
  - **Contractive**: Downsampling image to feature representation.
  - **Expansive**: Upsampling representation to segmentation map.
- 2D or 3D convolutions
- Skip connections

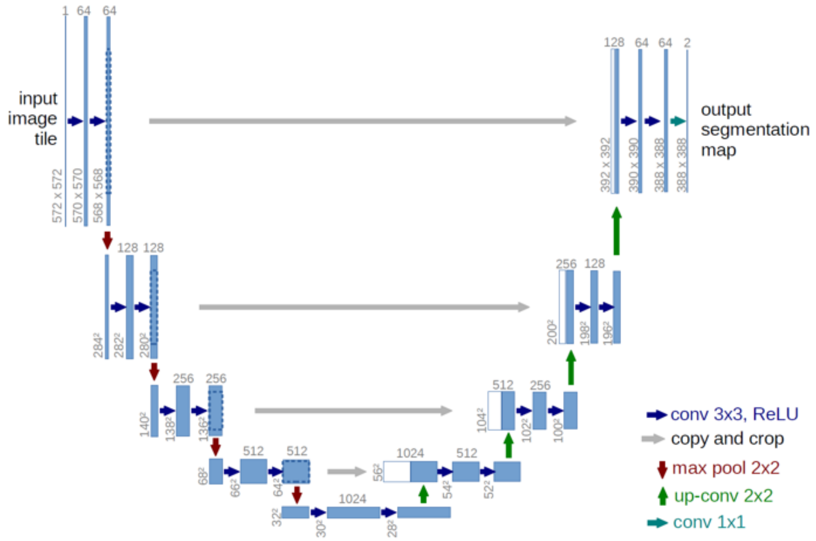



**Fig 2.** U-Net architecture representation. (Ronneberger et al., 2015)

- Based on connection density, we divide them into:
  - Vanilla U-Net
  - Residual U-Net
  - Dense U-Net

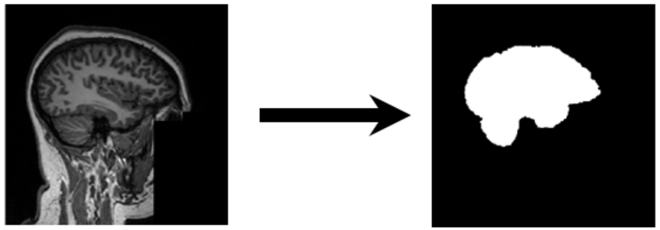


**Fig 3.** U-Net input and output.

Ronneberger et al. (2015).

# U-Net Architectures for Skull Stripping

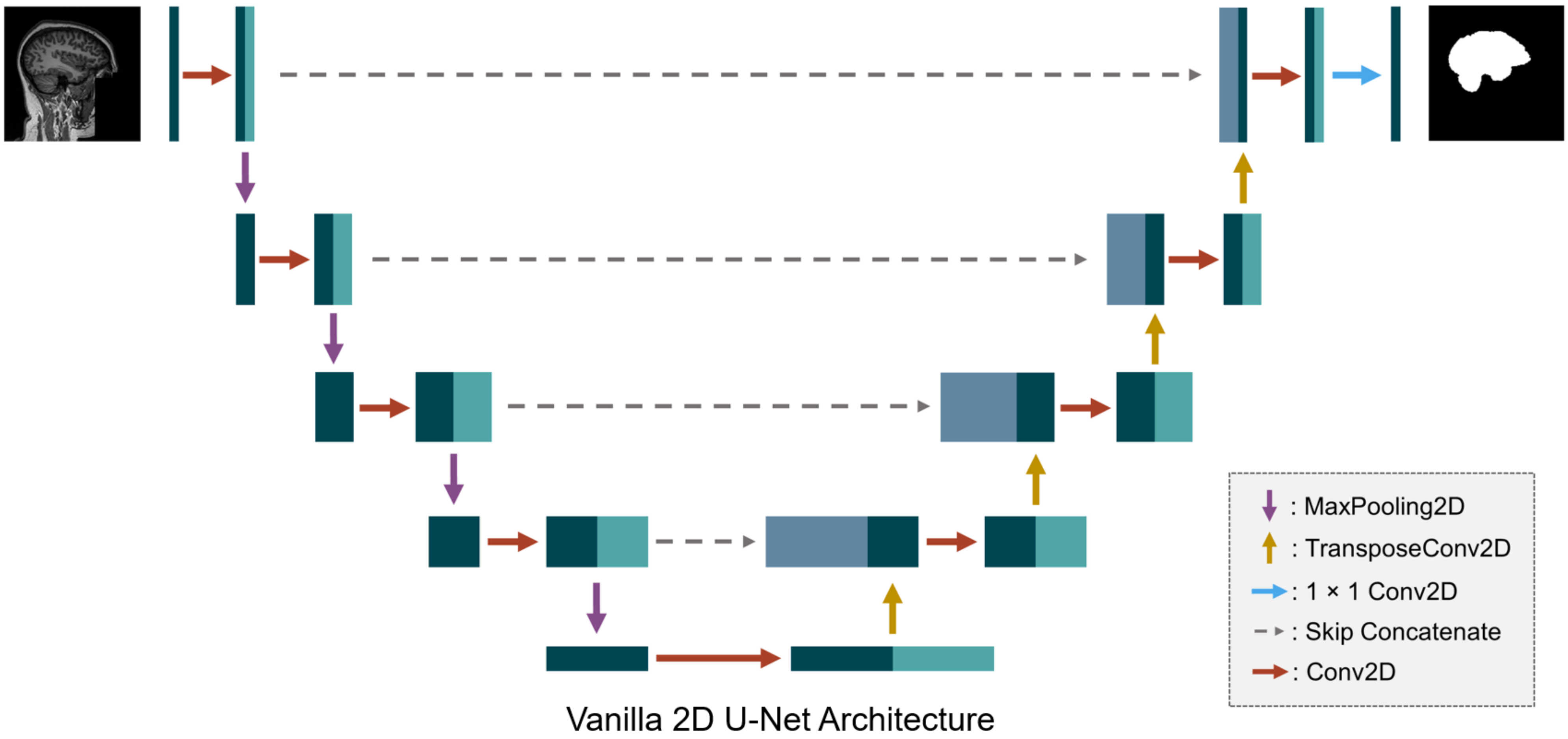
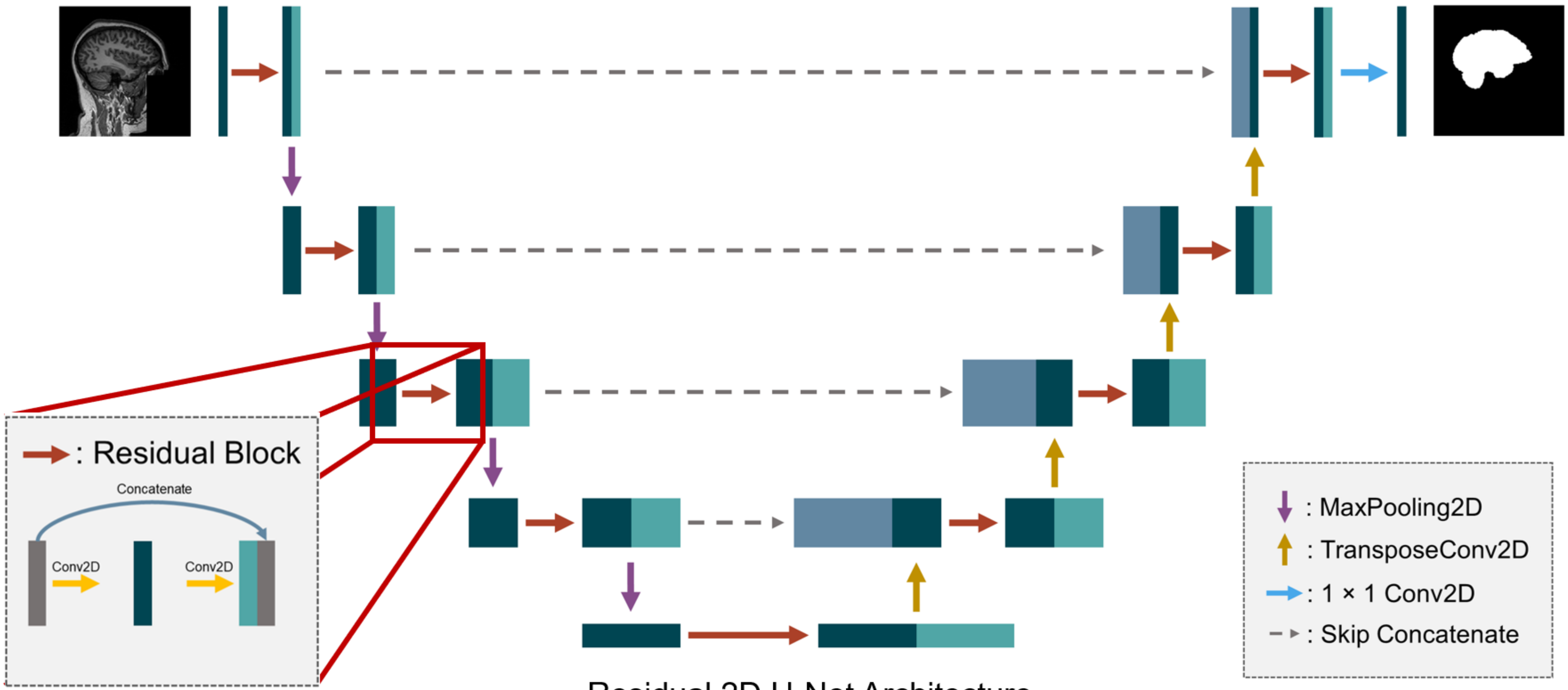



Fig. 4

Pimpalkar et al. (2022).

# U-Net Architectures for Skull Stripping




Residual 2D U-Net Architecture

Fig. 5

# U-Net Architectures for Skull Stripping

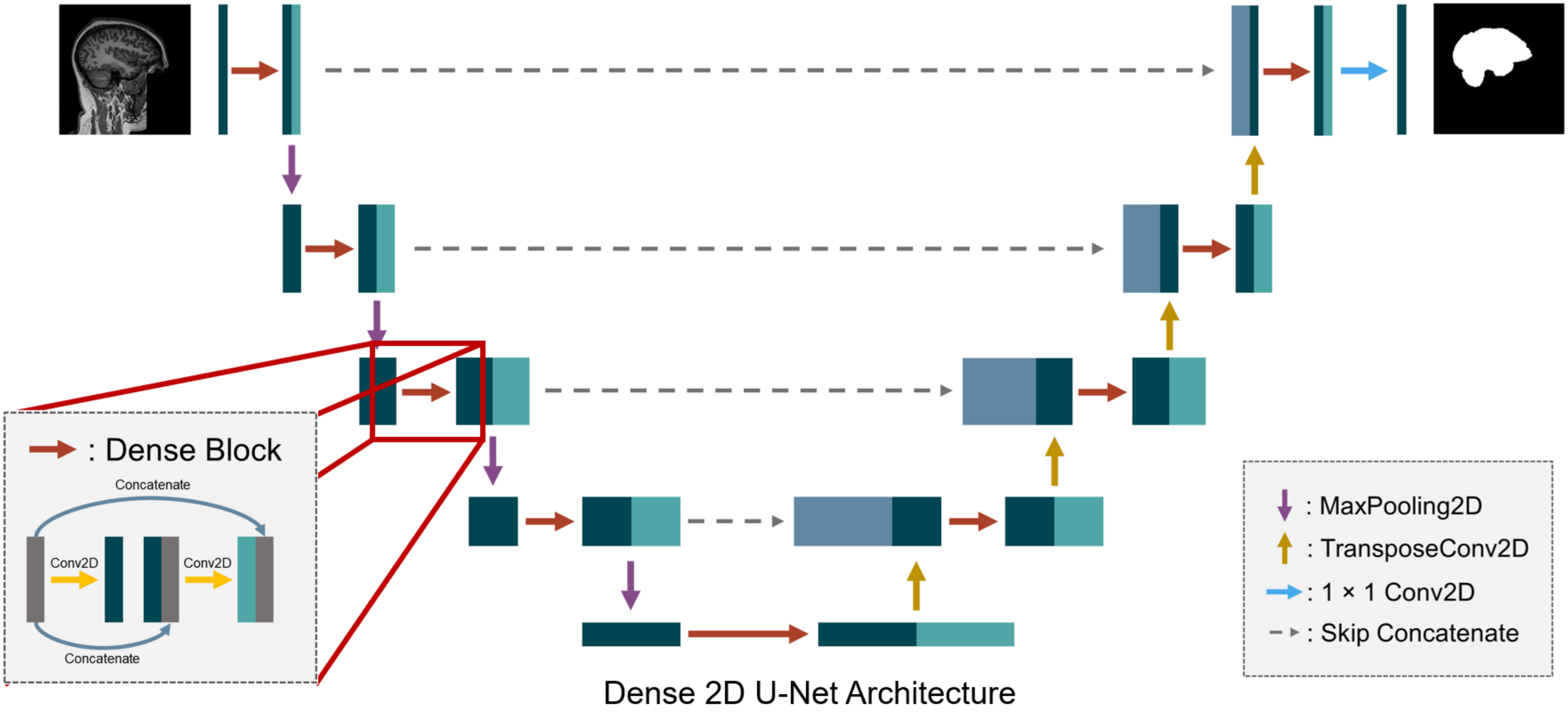



Fig. 6

Pimpalkar et al. (2022).

# U-Net Architectures for Skull Stripping

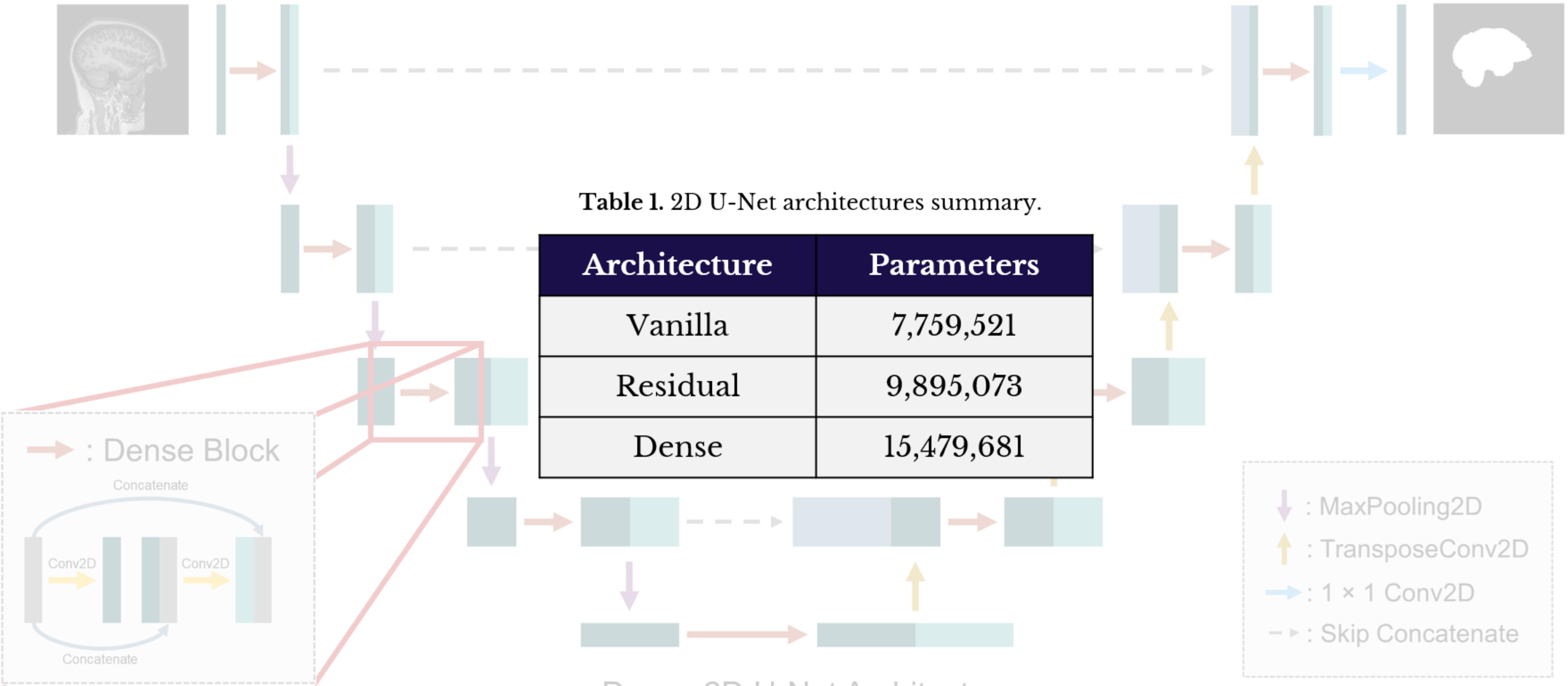



**Table 1.** 2D U-Net architectures summary.

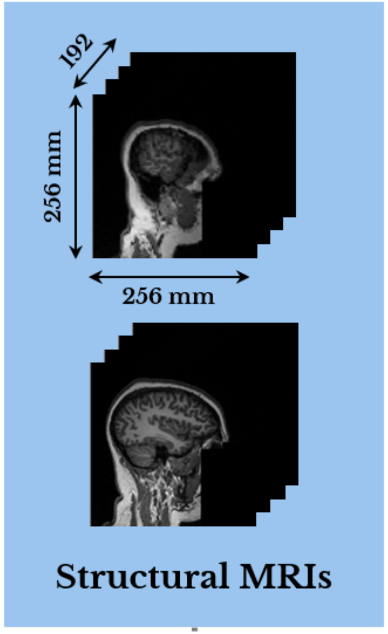
| Architecture | Parameters |
|---|---|
| Vanilla | 7,759,521 |
| Residual | 9,895,073 |
| Dense | 15,479,681 |

Dense 2D U-Net Architecture

Fig. 6

Pimpalkar et al. (2022).

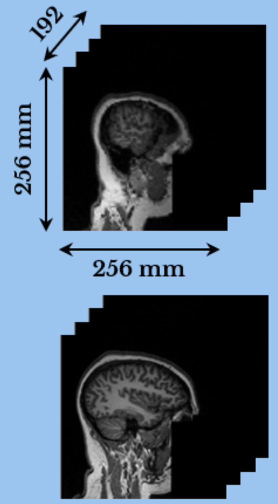
# Training Methodology




- Source: NFBS Repository
- Manually Skull Stripped assisted by BEaST
- Total 125 scans, 110 used for training, 15 for test

Puccio et al. (2016), Pimpalkar et al. (2022).

# Training Methodology




**Structural MRIs**

- Source: NFBS Repository
- Manually Skull Stripped assisted by BEaST
- Total 125 scans, 110 used for training, 15 for test

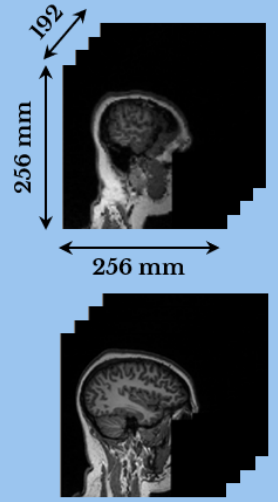
**Pre-processing**

- Intensity z - normalization

$$I_{z-norm}(x) = \frac{I(x) - \mu_{brain}}{\sigma_{brain}}$$

Puccio et al. (2016), Pimpalkar et al. (2022).

# Training Methodology




**Structural MRIs**

- Source: NFBS Repository
- Manually Skull Stripped assisted by BEaST
- Total 125 scans, 110 used for training, 15 for test

**Pre-processing**

- Intensity z - normalization

$$I_{Z-norm}(x) = \frac{I(x) - \mu_{brain}}{\sigma_{brain}}$$

**Data Augmentation**

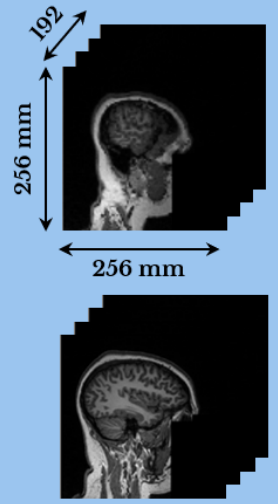
- Intensity transforms
- Spatial transforms
- Training dataset grown fivefold, i.e. 550 scans

**Hyperparameters**

- Optimizer = Adam
- $\beta_1 = 0.9$
- $\beta_2 = 0.999$
- $\varepsilon = 10^{-8}$
- $\alpha = 10^{-5}$
- $\alpha$ = Decay = $1.99 \times 10^{-8}$

Puccio et al. (2016), Pimpalkar et al. (2022).

# Training Methodology




**Structural MRIs**

- Source: NFBS Repository
- Manually Skull Stripped assisted by BEaST
- Total 125 scans, 110 used for training, 15 for test

**Pre-processing**

- Intensity z - normalization

$$I_{z-norm}(x) = \frac{I(x) \; - \; \mu_{brain}}{\sigma_{brain}}$$

**Data Augmentation**

- Intensity transforms
- Spatial transforms
- Training dataset grown fivefold, i.e. 550 scans

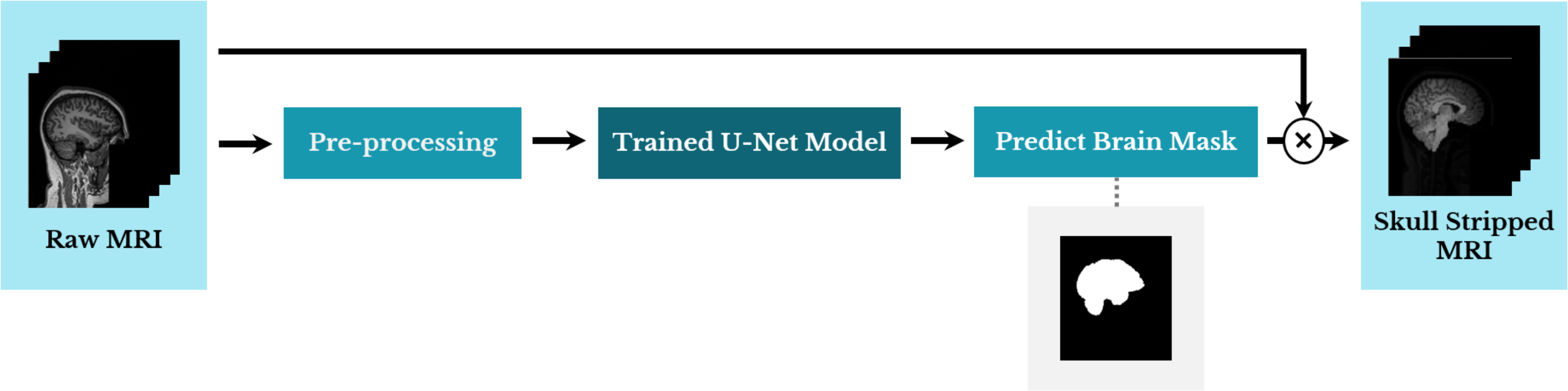
**Hyperparameters**

- Optimizer = Adam
- $\beta_1 = 0.9$
- $\beta_2 = 0.999$
- $\varepsilon = 10^{-8}$
- $\alpha = 10^{-5}$
- $\alpha$ = Decay = $1.99 \times 10^{-8}$

**Trained U-Net Model**

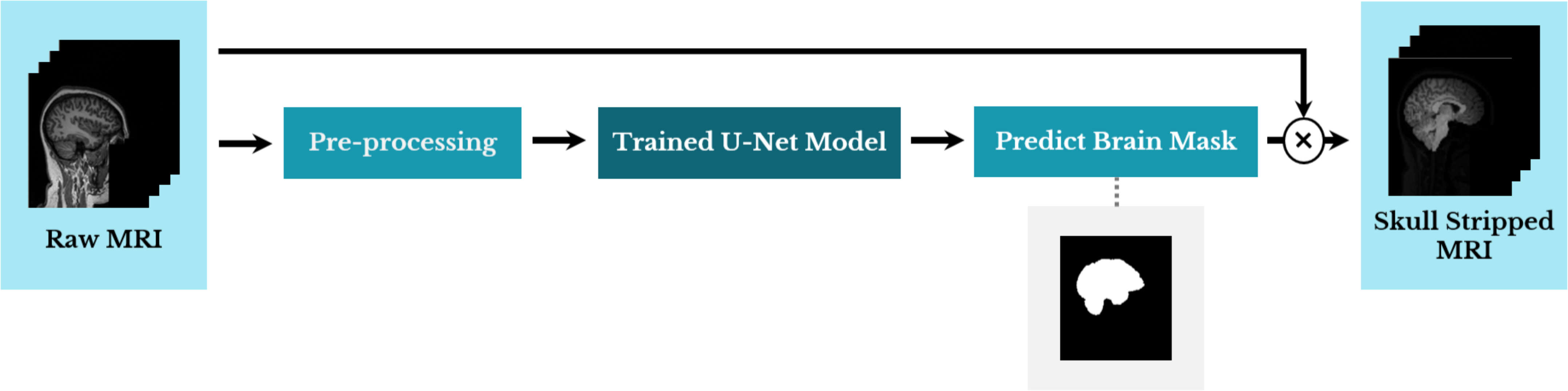
Puccio et al. (2016), Pimpalkar et al. (2022).

# Skull Stripping using U-Nets




Puccio et al. (2016), Pimpalkar et al. (2022).

# Skull Stripping using U-Nets



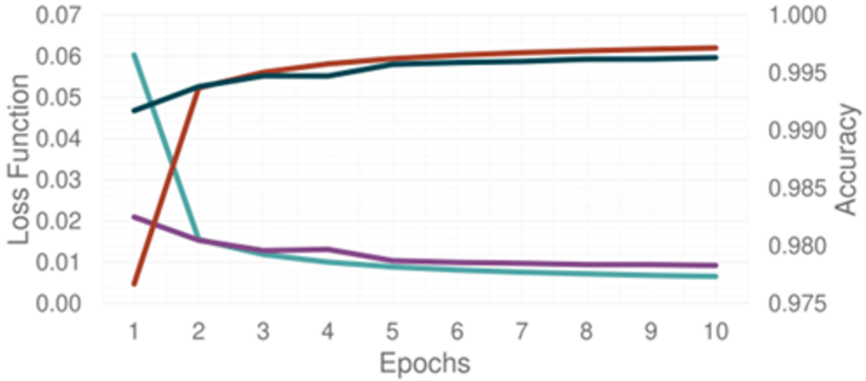

**Implementation:**

- Train/Validation split: 90/10 (Repeated Holdout).
- EarlyStopping callback to prevent overfitting.
- TensorFlow in Python.
- NVIDIA A100 Tensor Core GPU (40GB) Hardware Accelerator.

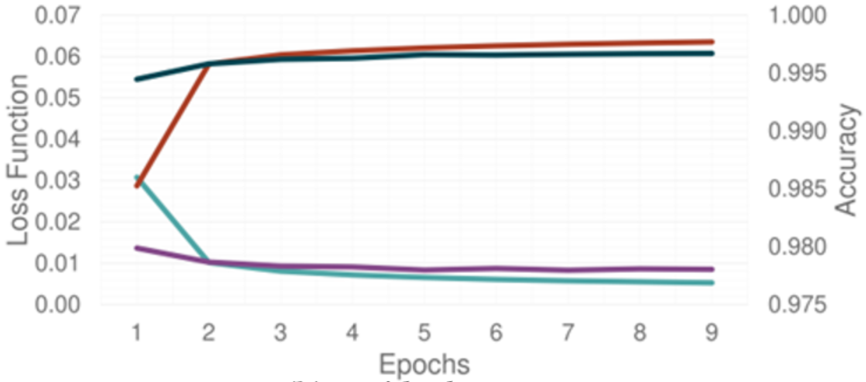
Puccio et al. (2016), Pimpalkar et al. (2022).

# Results

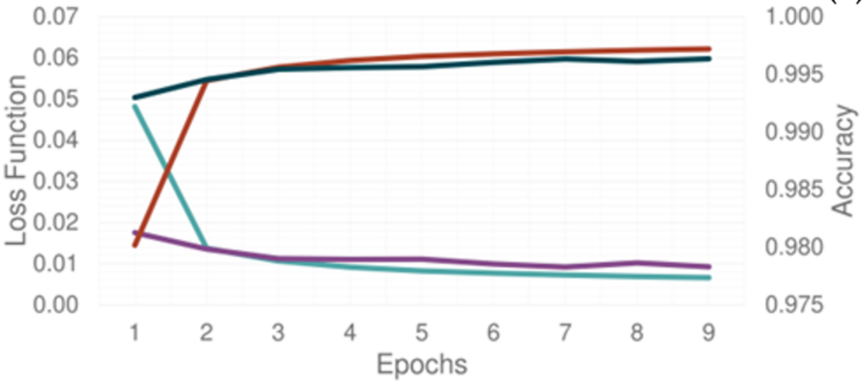
- **Loss Function:** Binary Cross Entropy Loss Function
- **Metric:** Accuracy




**(a)** Vanilla U-Net




**(b)** Residual U-Net




**(c)** Dense U-Net

**Fig 7.** Training results.

# Results

- **Loss Function:** Binary Cross Entropy Loss Function
- **Metric:** Accuracy

**Table 2.** 2D U-Net architecture training results.

| Architecture | Epochs | Batch Size | Training | | Validation | | Testing | |
|---|---|---|---|---|---|---|---|---|
| | | | Loss | Accuracy | Loss | Accuracy | Loss | Accuracy |
| Vanilla | 10 | 32 | 0.0066 | 99.72% | 0.0093 | 99.63% | 0.0065 | 99.73% |
| Residual | 9 | 32 | 0.0066 | 99.72% | 0.0092 | 99.63% | 0.0067 | 99.72% |
| Dense | 9 | 16 | 0.0053 | 99.77% | 0.0085 | 99.67% | 0.0062 | 99.75% |

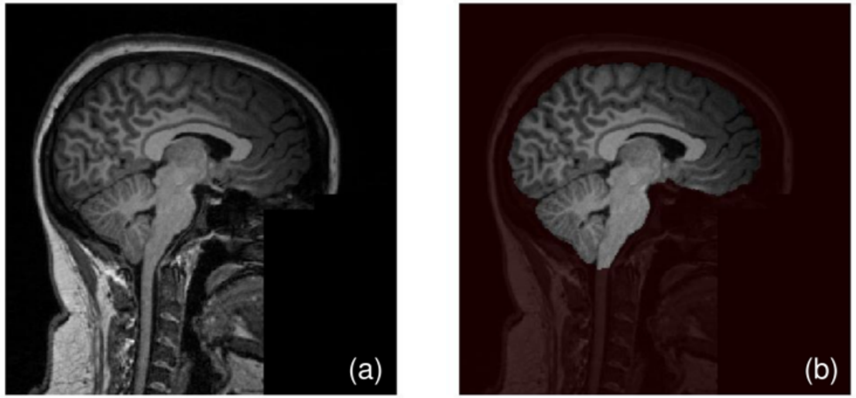



**Fig 8.** (a) A sagittal 3D T1-w MRI slice from the NFBS repository and (b) corresponding Skull Stripped mask superimposed on the MRI scan.

Puccio et al. (2016), Pimpalkar et al. (2022).

# Results

- **Loss Function:** Binary Cross Entropy Loss Function
- **Metric:** Accuracy

**Table 2.** 2D U-Net architecture training results.

| Architecture | Epochs | Batch Size | Training | | Validation | | Testing | |
|---|---|---|---|---|---|---|---|---|
| | | | Loss | Accuracy | Loss | Accuracy | Loss | Accuracy |
| Vanilla | 10 | 32 | 0.0066 | 99.72% | 0.0093 | 99.63% | 0.0065 | 99.73% |
| Residual | 9 | 32 | 0.0066 | 99.72% | 0.0092 | 99.63% | 0.0067 | 99.72% |
| Dense | 9 | 16 | 0.0053 | 99.77% | 0.0085 | 99.67% | 0.0062 | 99.75% |

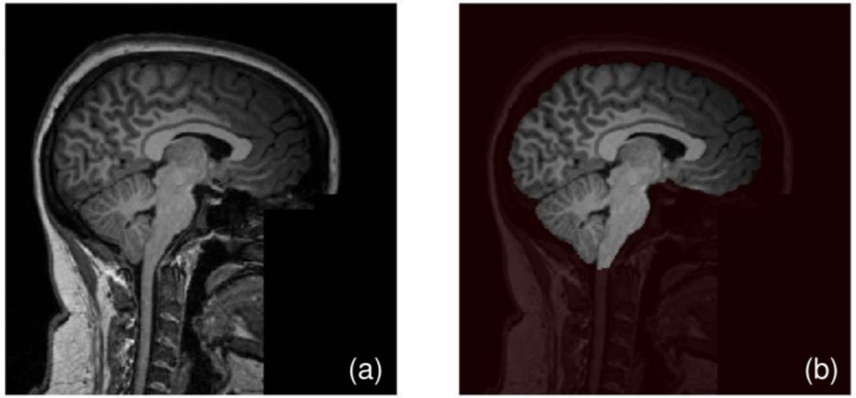



**Fig 8.** (a) A sagittal 3D T1-w MRI slice from the NFBS repository and (b) corresponding Skull Stripped mask superimposed on the MRI scan.

Puccio et al. (2016), Pimpalkar et al. (2022).

# Conclusion and Ongoing Work

- Dense 2D U-Net Architectures:
  - Better performance with same network depth.
  - Strengthen shallower models.
- Almost same output accuracies for all, need to dive deeper.
- Current work:
  - Test multi-variate scanning.
  - Expand number of architectures.

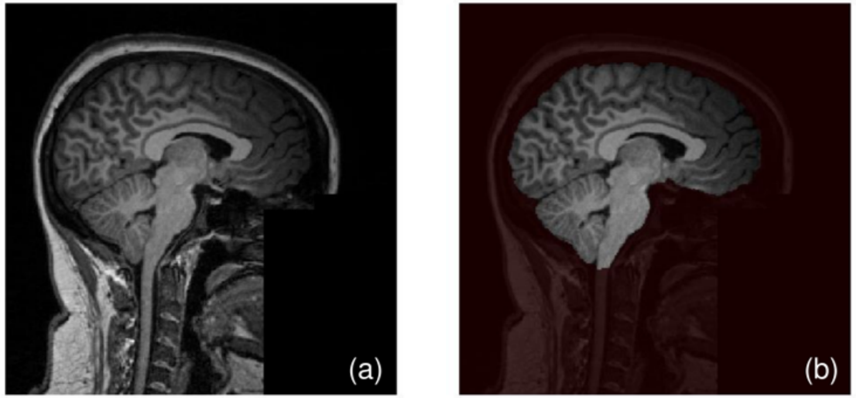



**Fig 8.** (a) A sagittal 3D T1-w MRI slice from the NFBS repository and (b) corresponding Skull Stripped mask superimposed on the MRI scan.

Puccio et al. (2016), Pimpalkar et al. (2022).

# Acknowledgements


**Dr. Rashmika Patole, Dr. Ketaki Kamble, and Dr. Mahesh Shindikar**

Supervisors

**Center of Excellence in Signal and Image Processing**

Department of Electronics and Telecommunication
COEP Technological University



**Reach out!**
pimpalkaras19.extc@coep.ac.in