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NGN 2023 Conference

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

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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

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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.

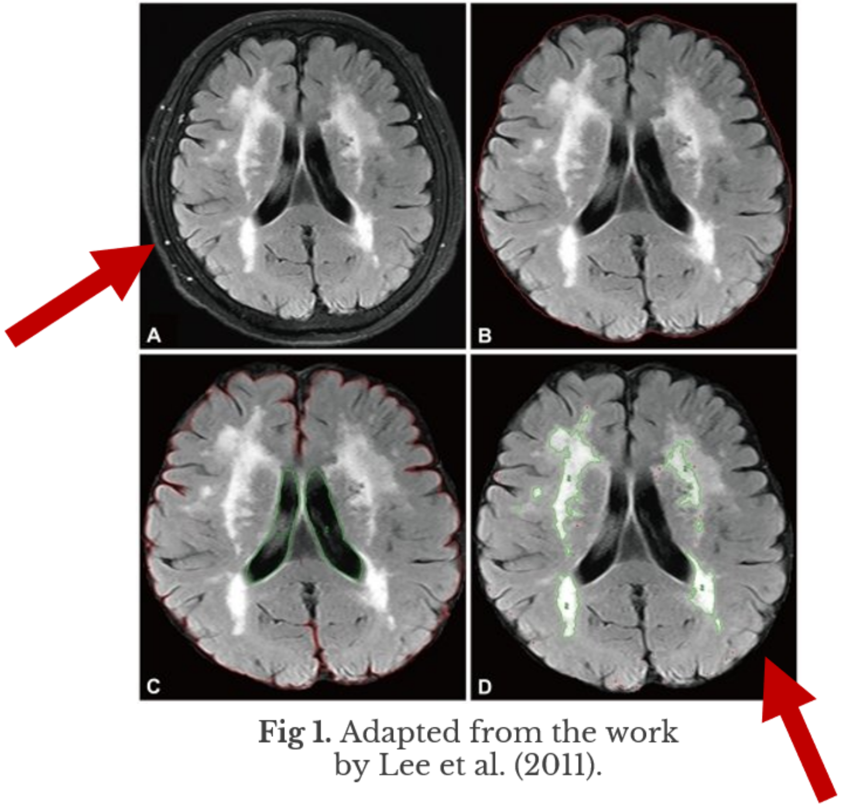

Fig 1. Adapted from the work by Lee et al. (2011).

Hahn et al. (2000).

Conventional Skull Stripping Methods

Conventional Methods

Manual Skull Stripping
- 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)

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

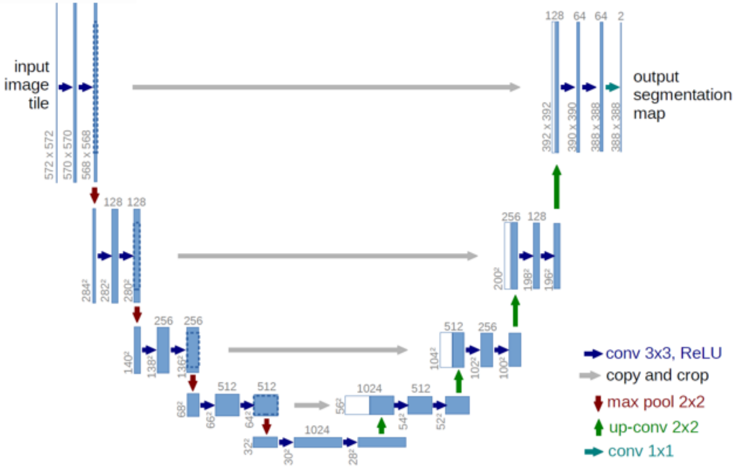

Fig 2. U-Net architecture representation. (Ronneberger et al., 2015)

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

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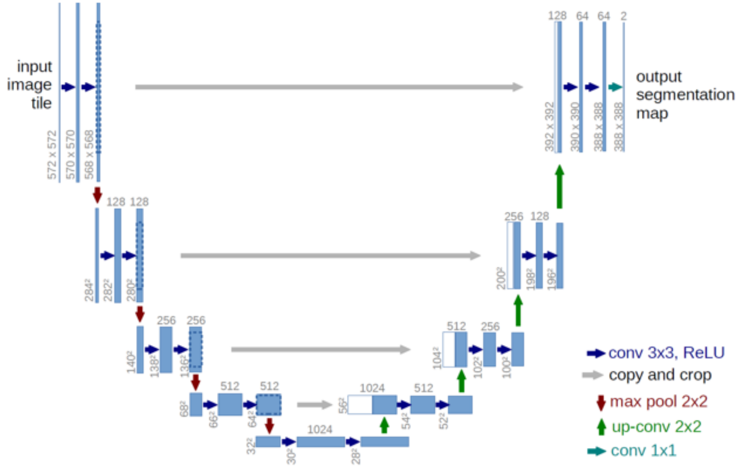

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Project Objective

- 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

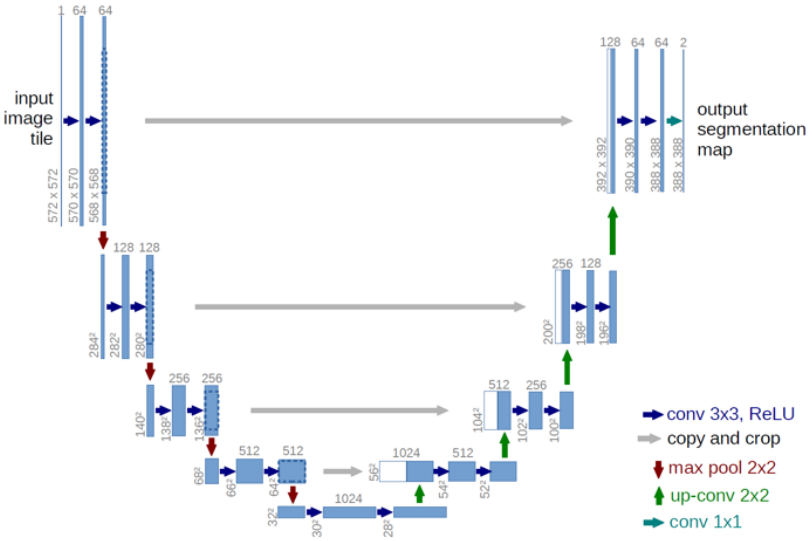


Fig 2. U-Net architecture representation. (Ronneberger et al., 2015)

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

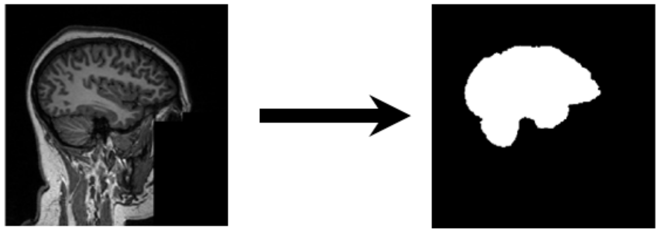


Fig 3. U-Net input and output.

U-Net Architectures for Skull Stripping

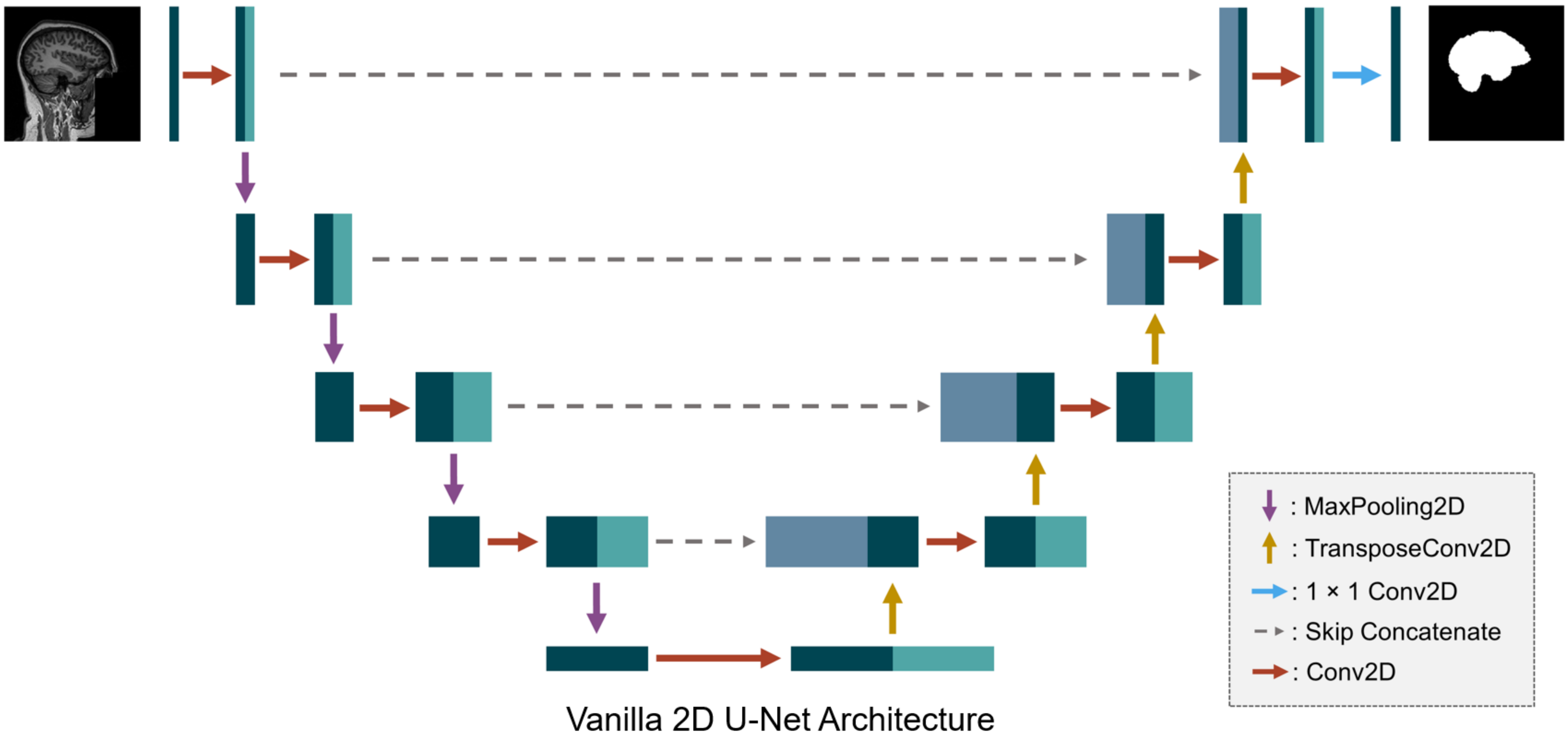
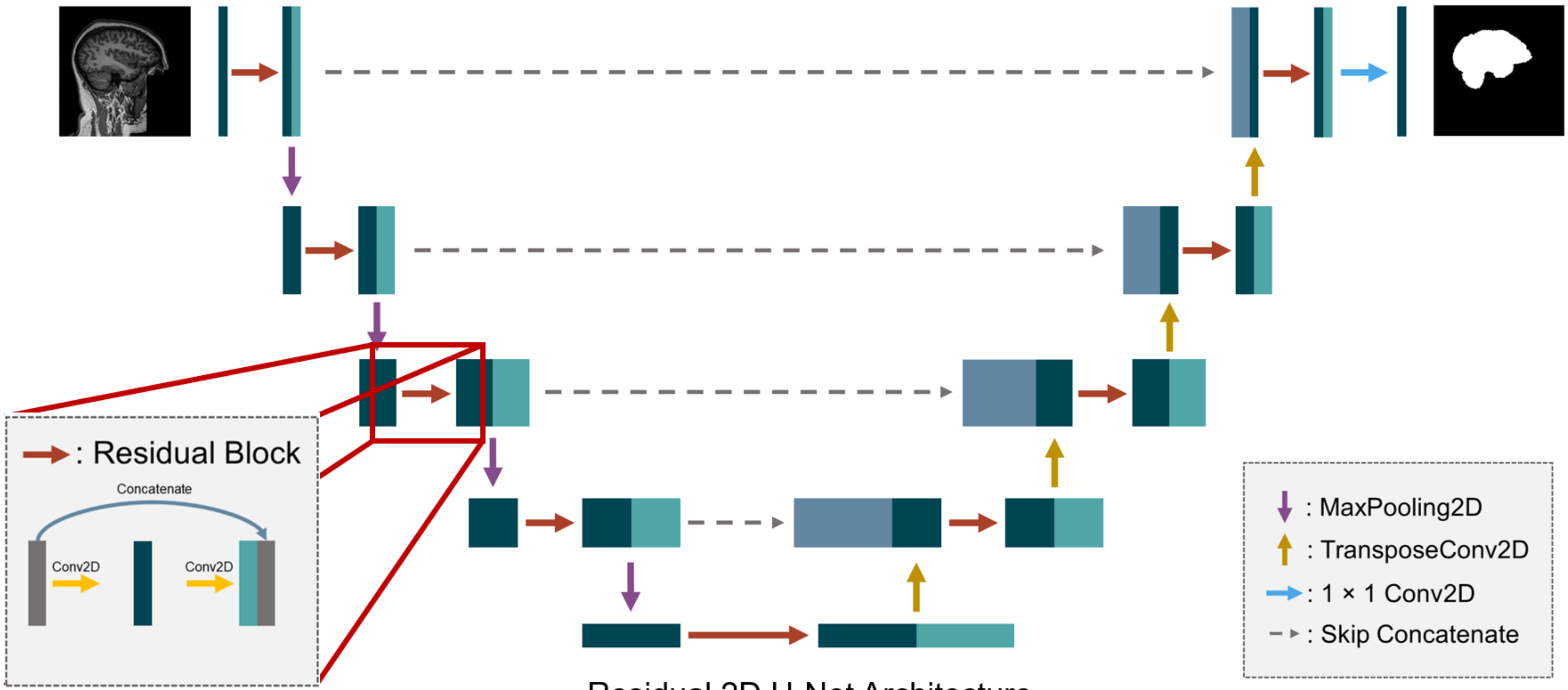


Fig. 4

Pimpalkar et al. (2022).

U-Net Architectures for Skull Stripping



Residual 2D U-Net Architecture

Fig. 5

Pimpalkar et al. (2022).

U-Net Architectures for Skull Stripping

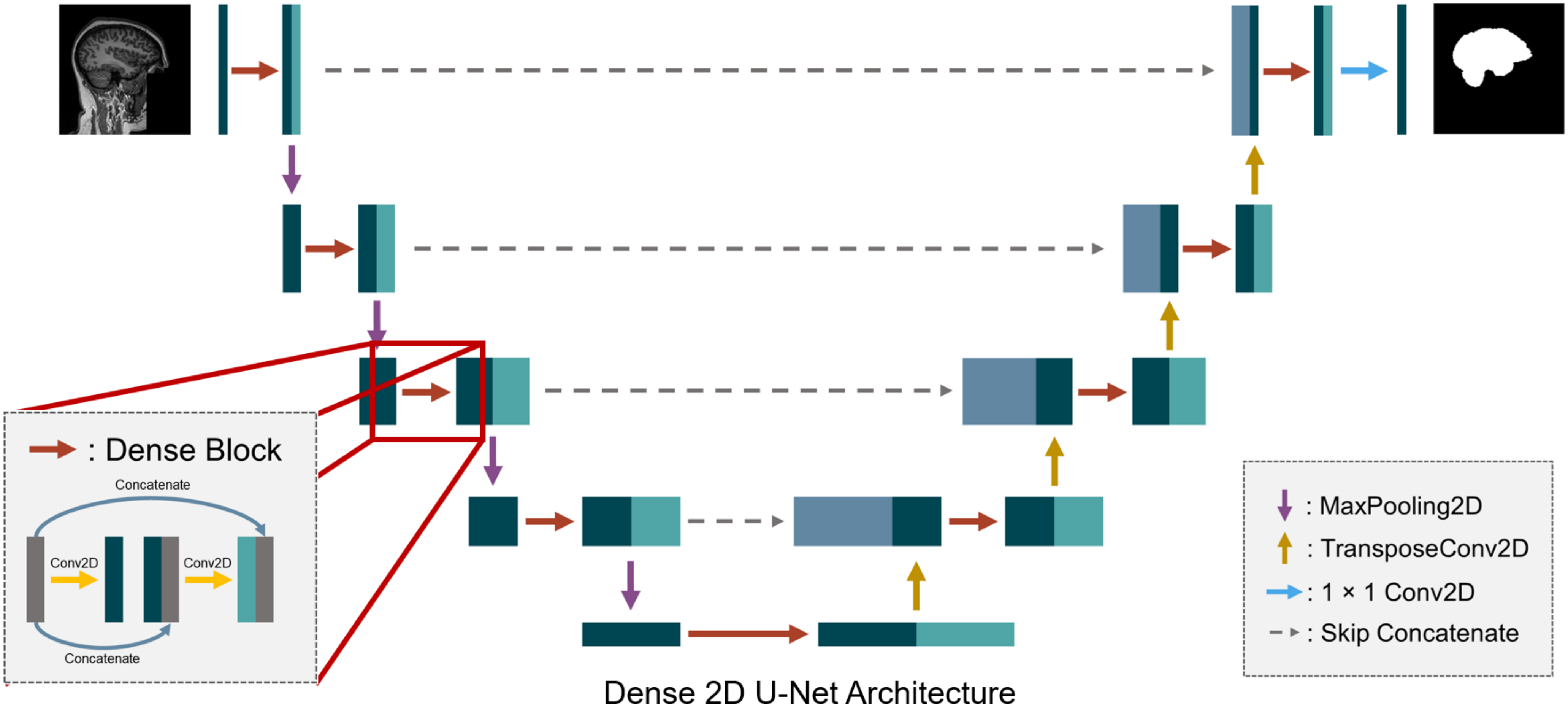


Fig. 6

Pimpalkar et al. (2022).

U-Net Architectures for Skull Stripping

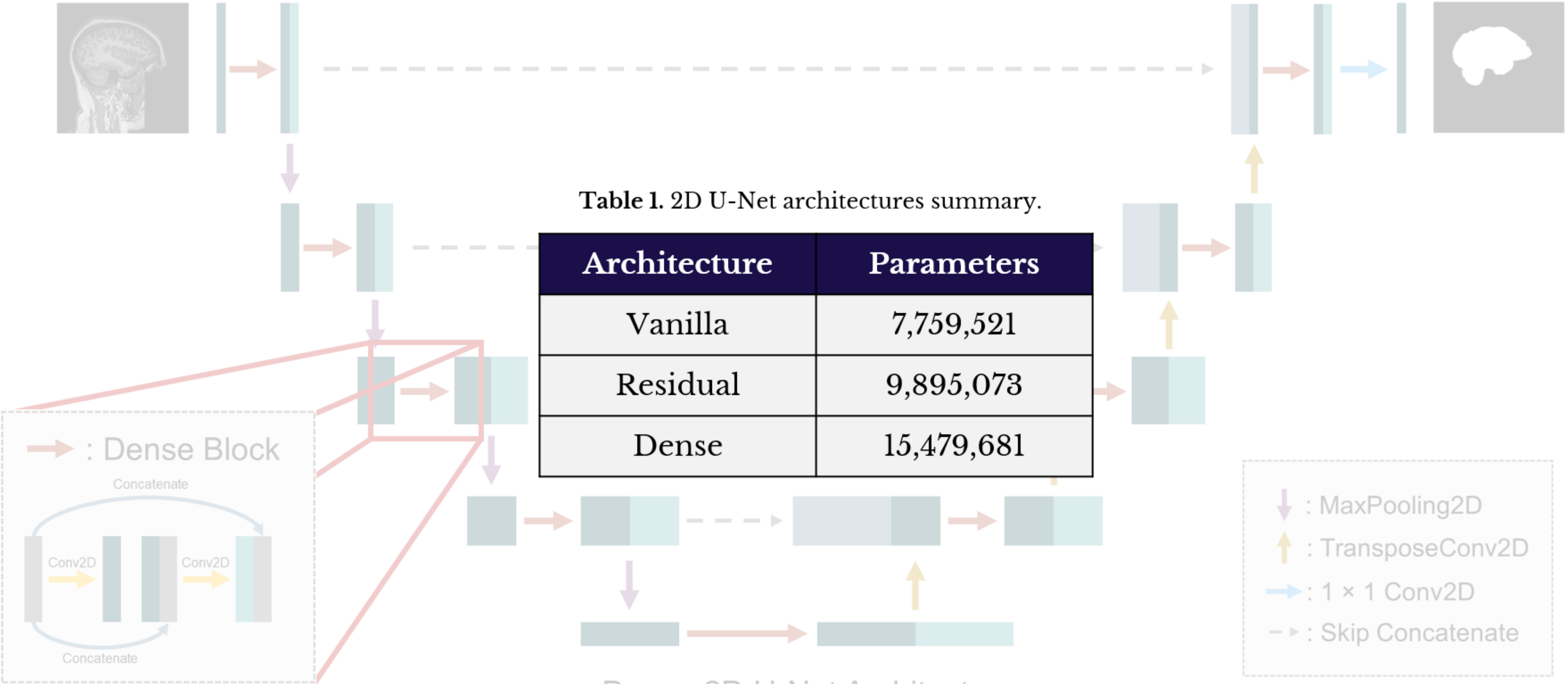


Table 1. 2D U-Net architectures summary.

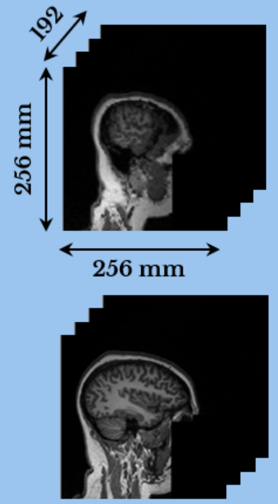
Architecture	Parameters
Vanilla	7,759,521
Residual	9,895,073
Dense	15,479,681

Dense 2D U-Net Architecture

Fig. 6

Pimpalkar et al. (2022).

Training Methodology



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

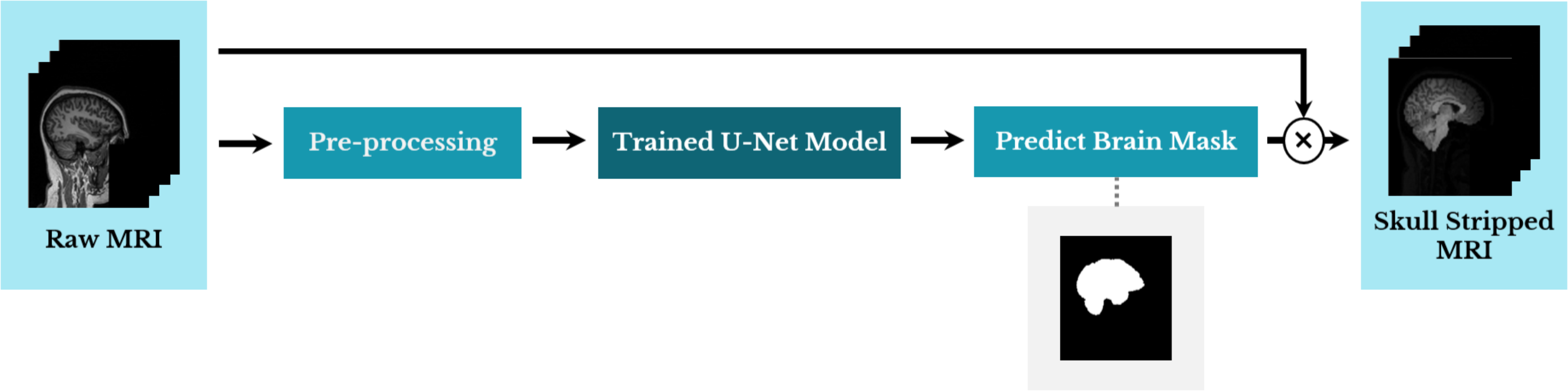
- Intensity transforms
- Spatial transforms
- Training dataset grown fivefold, i.e. 550 scans

Hyperparameters

- Optimizer = Adam
- β_1 = 0.9
- β_2 = 0.999
- $\varepsilon = 10^{-8}$
- $\alpha = 10^{-5}$
- α = Decay = 1.99×10^{-8}

Trained U-Net Model

Skull Stripping using U-Nets



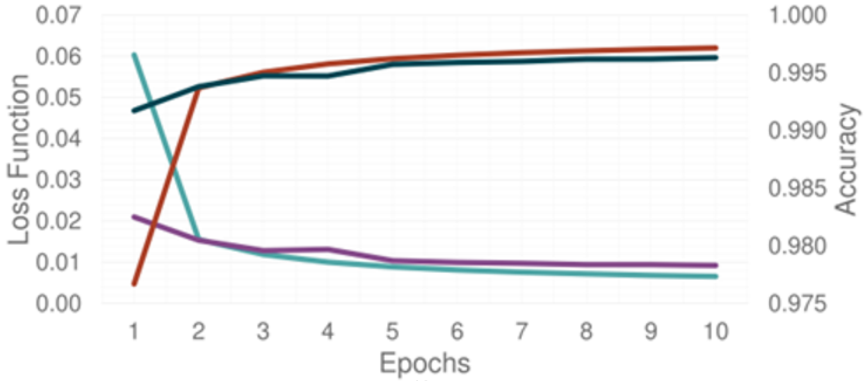
Implementation:

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

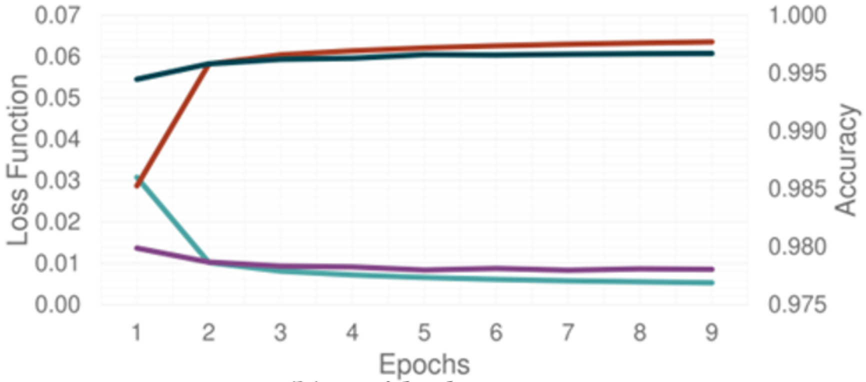
Puccio et al. (2016), Pimpalkar et al. (2022).

Results

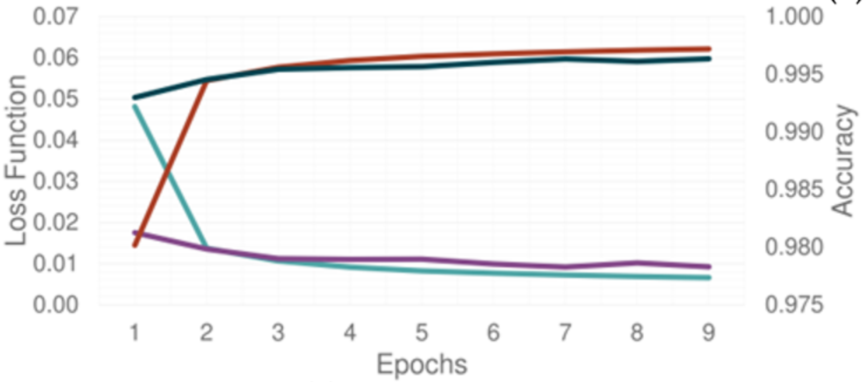
- **Loss Function:** Binary Cross Entropy Loss Function
- **Metric:** Accuracy



(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%

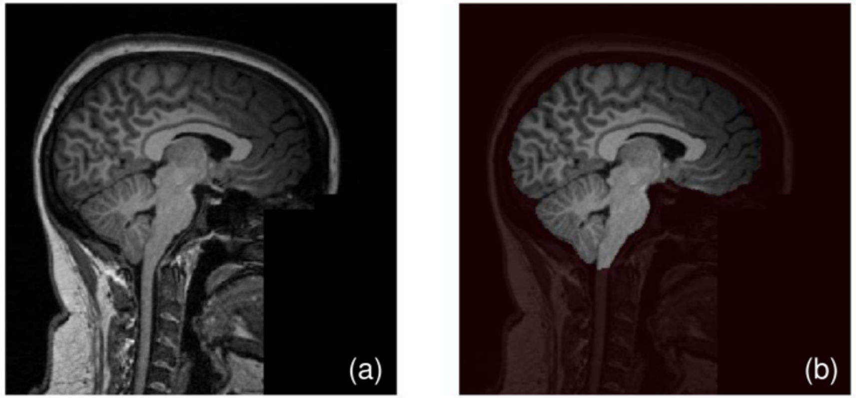
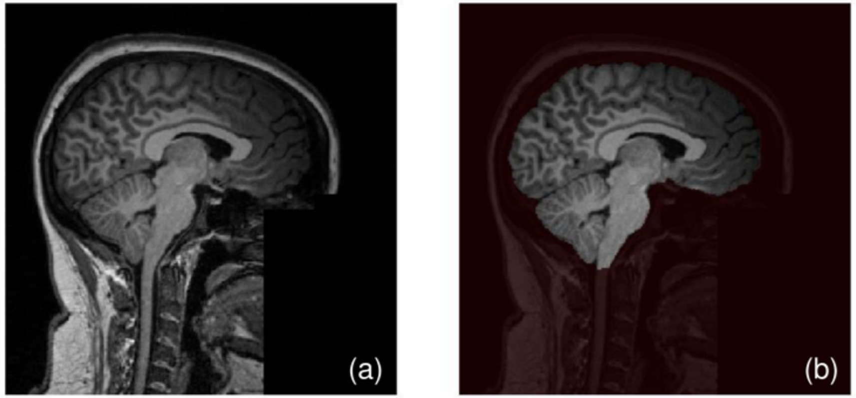


Fig 8. (a) A sagittal 3D T1-w MRI slice from the NFBS repository
and (b) corresponding Skull Stripped mask superimposed on the MRI scan.

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

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.



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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
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Reach out!
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