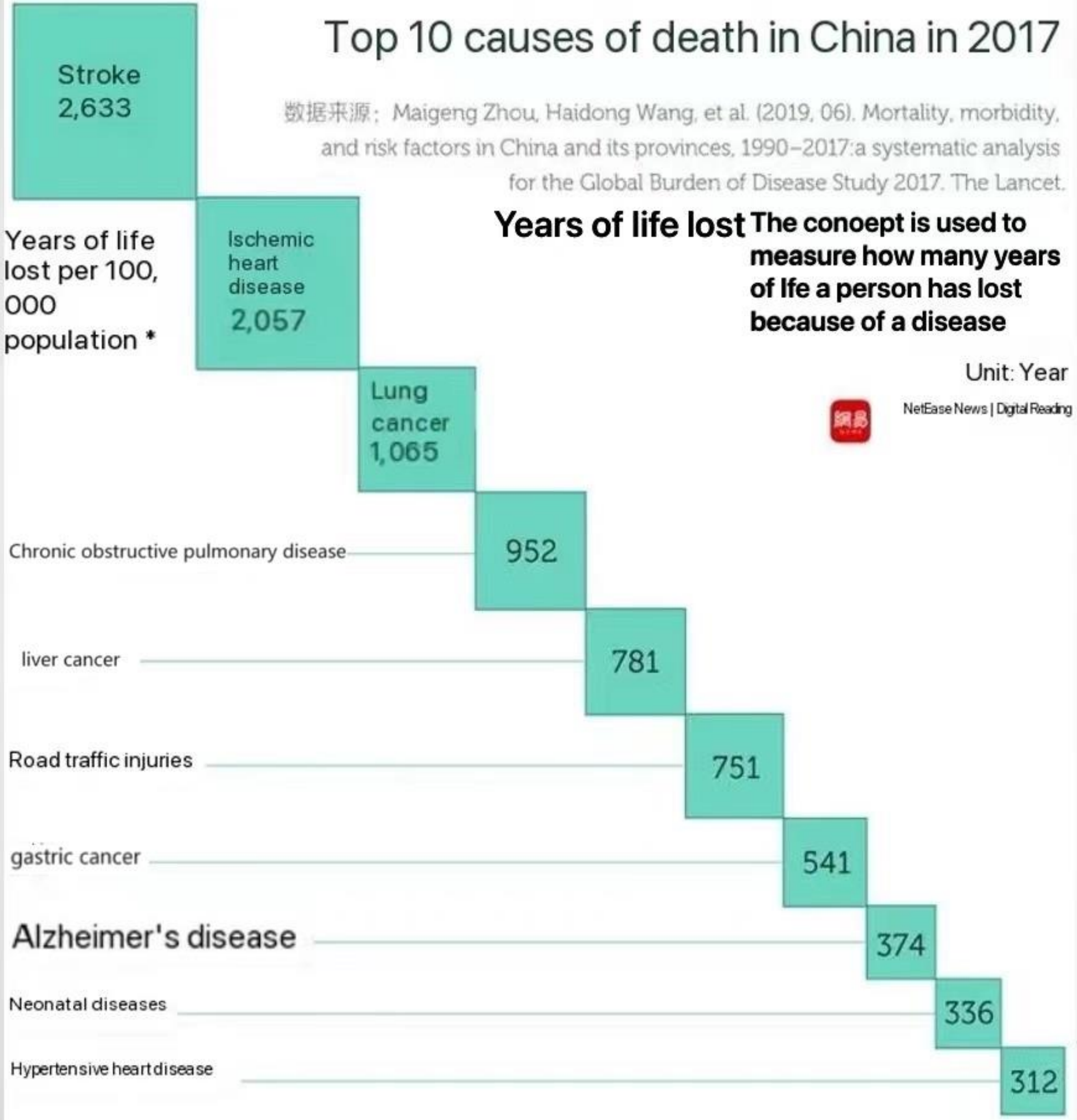
Research Paper Presentation

Stroke detection by image segmentation with Residual U-Net

Presenter

Presentation Date

Background



Global Stroke Burden

Stroke: 2nd Leading Cause of Death, 3rd Leading Cause of Disability Worldwide

Importance of Early Detection

- Early Detection Saves Lives
- Improves Survival Rates
- Enhances Quality of Life
- Reduces Long-term Disability Risks

Existing Challenges

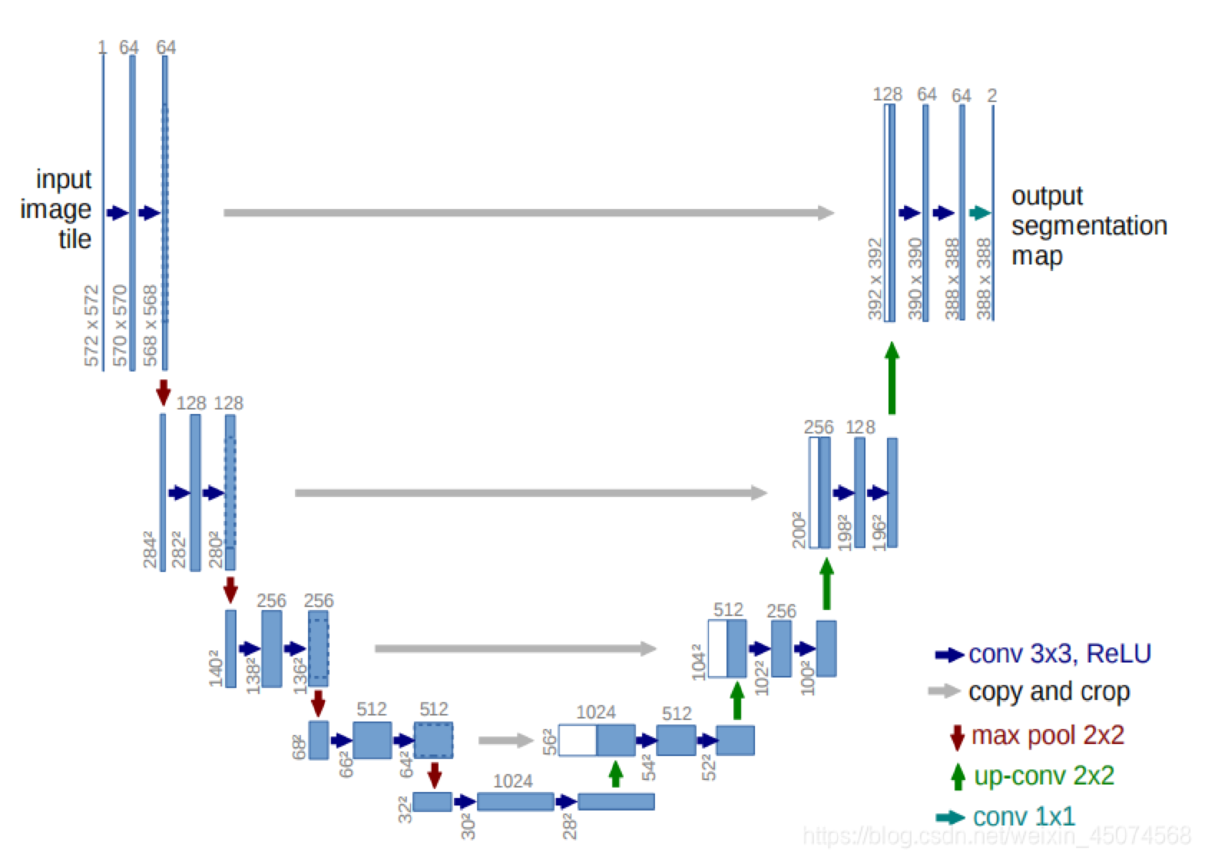
- Dependence on Professional Diagnosis
- Need for Rapid, Accurate Automated Detection Methods
- Complexity in Medical Imaging

Background

Robust performance even with limited training data

Efficient utilization of computational resources

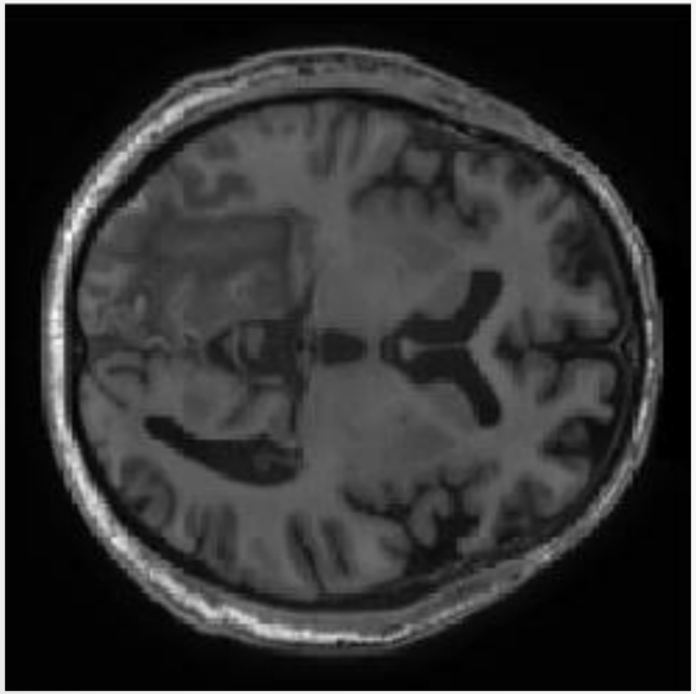
Adaptability to various medical imaging modalities



The U-Net architecture is widely applied

Datasets

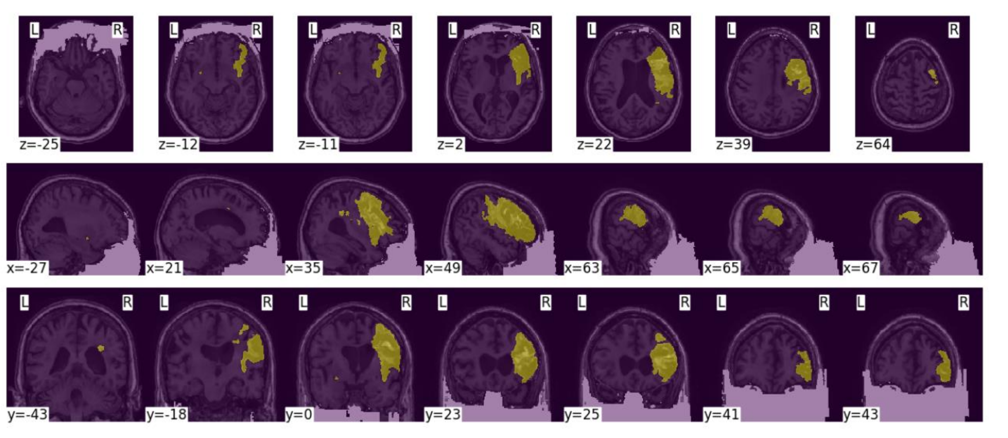
ATLAS v2.0 Dataset



- The ATLAS v2.0 dataset is a key component in the research, featuring:
- 955 MRI images for training and testing.
- Manually segmented masks for accurate lesion identification.
- Global cohort representation for dataset diversity.
- Open-access availability to researchers.
- Use in evaluating the performance of the Residual U-Net model for stroke detection.

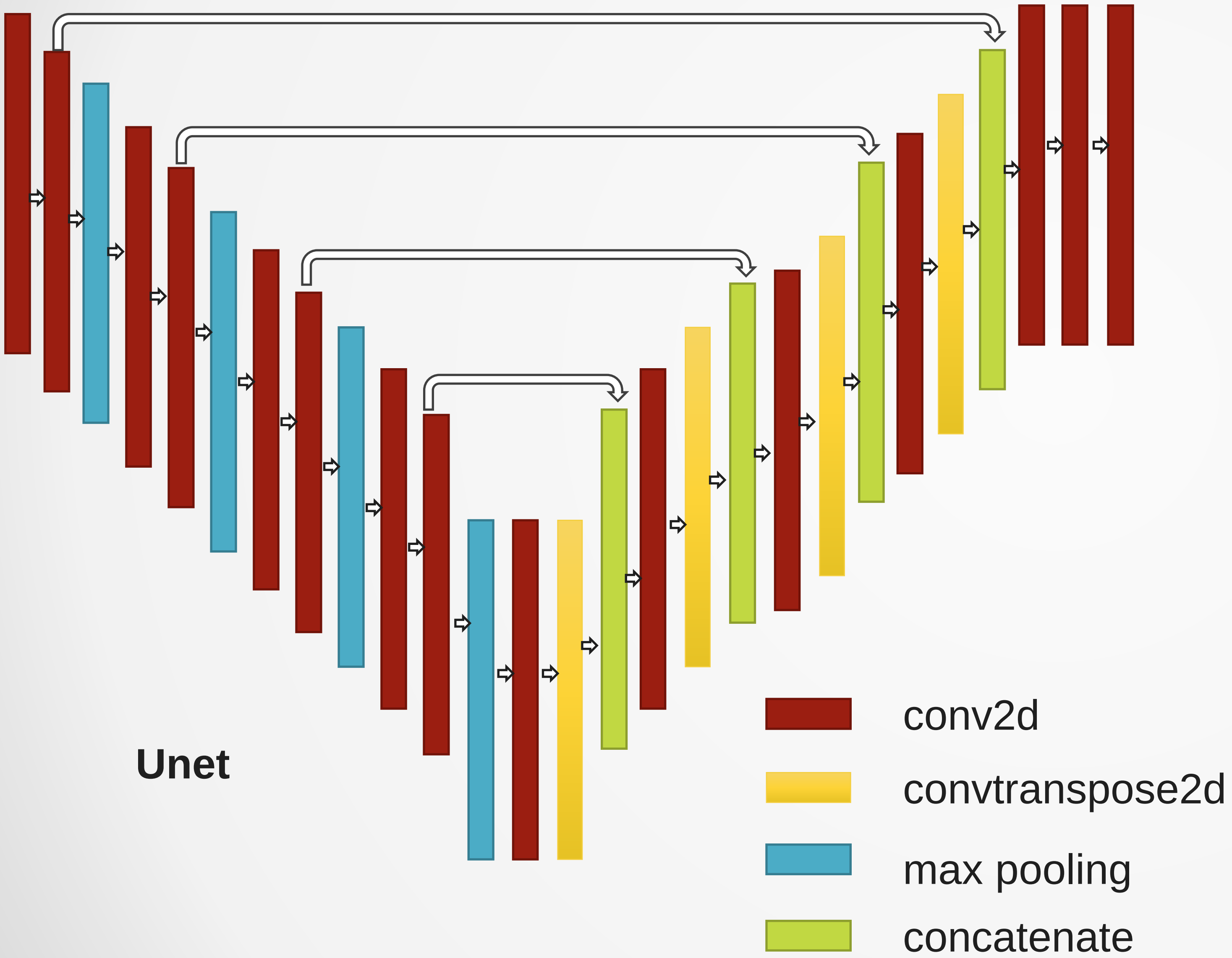
Result

prepare Data



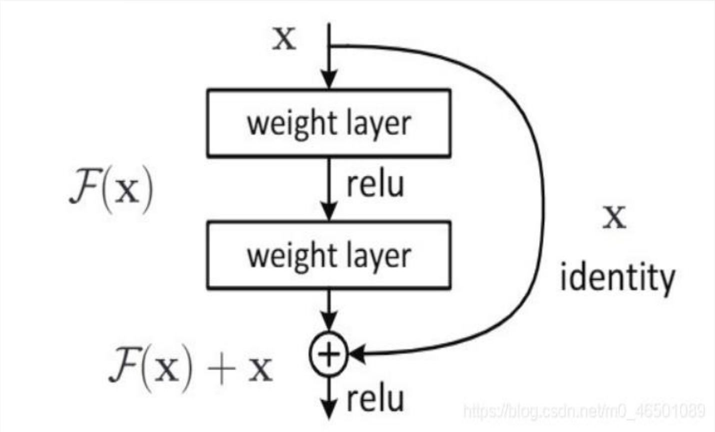
•**Annotated Images:** 655 images with masks for precise segmentation in the ATLAS v2.0 dataset.
•**Test Images:** 300 images for evaluating model performance.
•**Data Split:** Dataset divided into training (60%), validation (20%), and testing (20%) sets.
•**Slicing:** Each 3D sample converted into 100 2D images for processing.
•**Batch Selection:** Batches selected from samples between index 70 and 90.
•**Data Augmentation:** Techniques like normalization, flipping, rotation, and zooming applied to increase dataset size and variability.
•**Augmentation Repetition:** Augmentation process repeated three times to expand training dataset.

Methodology



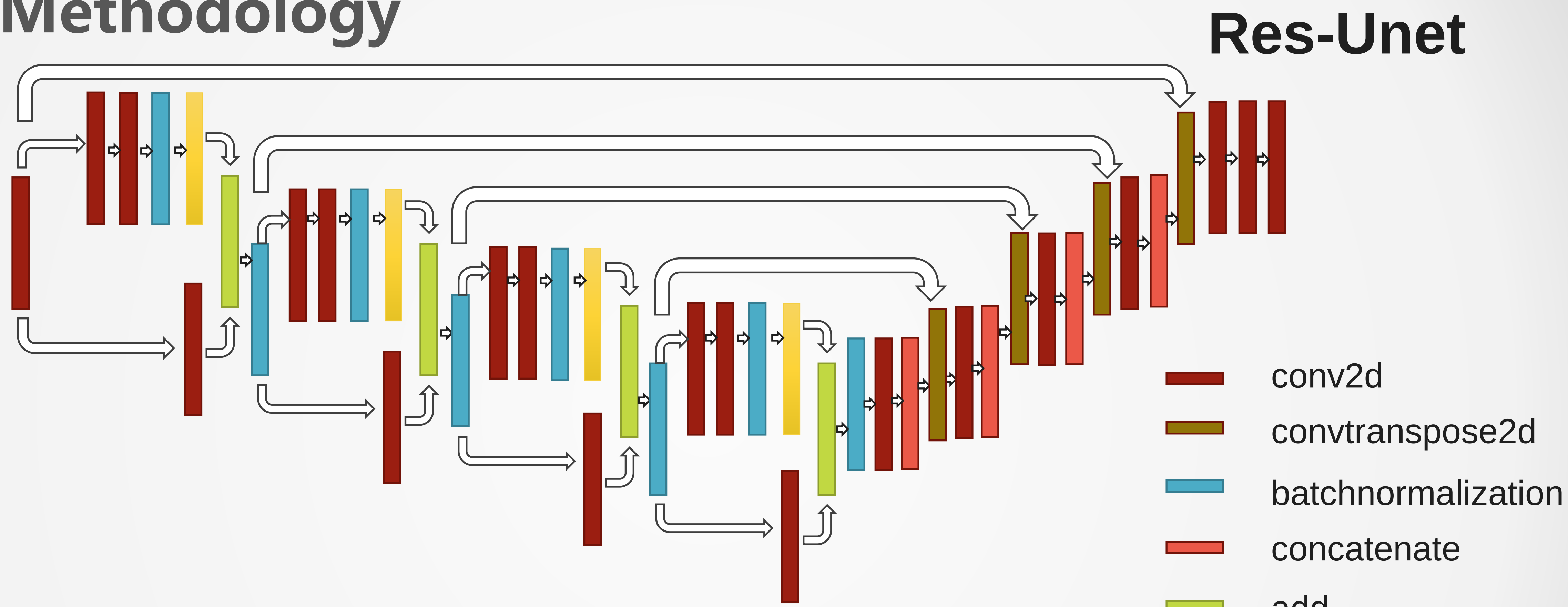
Unet

Res-Block



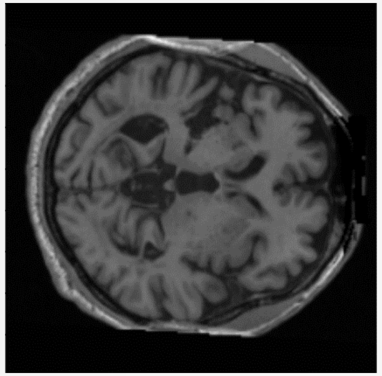
- Mitigates gradient vanishing
- Facilitates training deep networks
- Speeds up training convergence
- Improves gradient flow
- Efficiently captures small changes
- Enhances feature learning
- Addresses degradation in deep networks
- Facilitates feature reuse
- Boosts model performance
- Compatible with various architectures
- Useful across different domains

Methodology



•**Residual Blocks:** Enable deep network training by learning residual connections, addressing vanishing gradients and speeding up convergence.
•**Batch Normalization:** Stabilizes learning and accelerates training by normalizing each layer's input, enhancing the network's feature learning capability.

Result

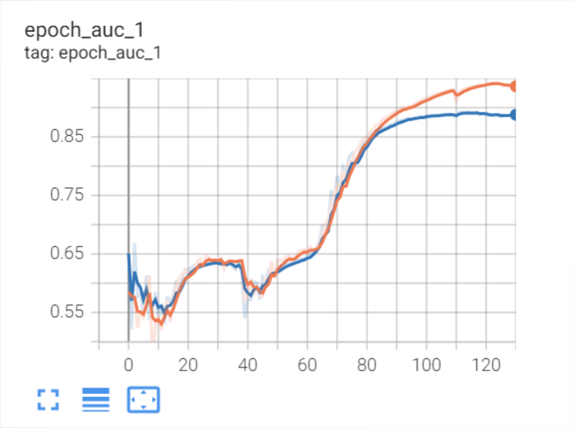


original picture

groundtruth

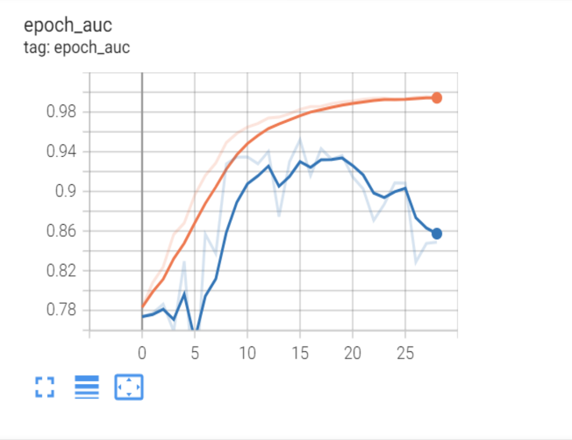
Unet prediction

Res-Unet prediction

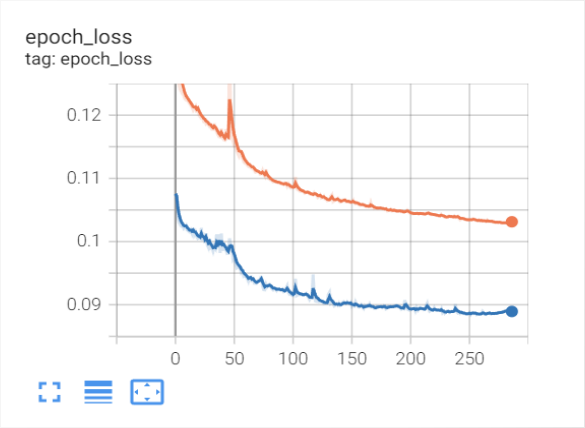


Unet auc

Unet loss



Res-Unet auc



Res-Unet loss

Conclusion

Conclusion

- The Residual U-Net model significantly improves stroke detection accuracy in MRI images.
- The model outperforms traditional U-Net due to its ability to capture deeper features while preserving details.
- The ATLAS v2.0 dataset's diversity and quality facilitate a robust evaluation of the model's performance.
- The method is deemed suitable for clinical applications requiring precise and swift stroke detection.

Conclusion

Improvements

- Increase dataset diversity to encompass a broader range of patients and stroke types.
- Optimize model for real-time processing to meet clinical settings' time-sensitive demands.
- Integrate the model into clinical workflows for seamless adoption.
- Conduct cross-validation for model robustness and to prevent overfitting.
- Explore advanced techniques like attention mechanisms for better pattern recognition.
- Enhance model explainability to improve clinical trust and acceptance.