From Data to River: Bridging Morphology Changes with Machine Learning

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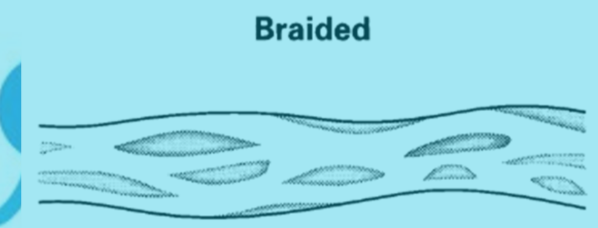
Introduction:

- Predicting river changes is vital for resource management and ecosystem conservation.
- **Braided rivers** challenge traditional models due to their complexity.
- Magherini (2024) used **deep learning** on the **Brahmaputra-Jamuna River**, showing promise but leaving room for improving temporal patterns, testing architectures, and expanding case studies.



Aims:

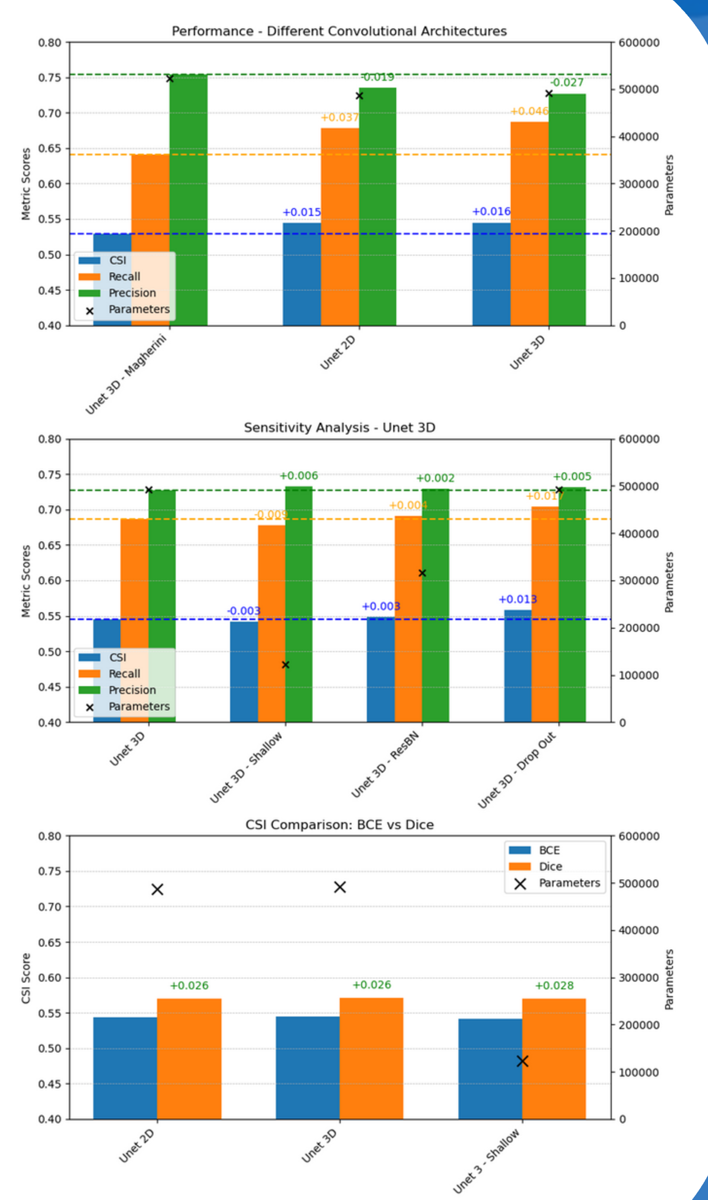
Reproduction & Extension of JamUNet:

- Develop and benchmark new convolutional neural networks against Magherini's model.
- Explore whether different model architectures or loss functions can improve model performance.

Benchmarking with Other Models:

- Implement a model based on feature extraction proposed by Jagers (2003) for comparison.

CNN: UNet



Accuracy:	0.932
Precision:	0.669
Recall:	0.806
F1 score:	0.729
CSI score:	0.574

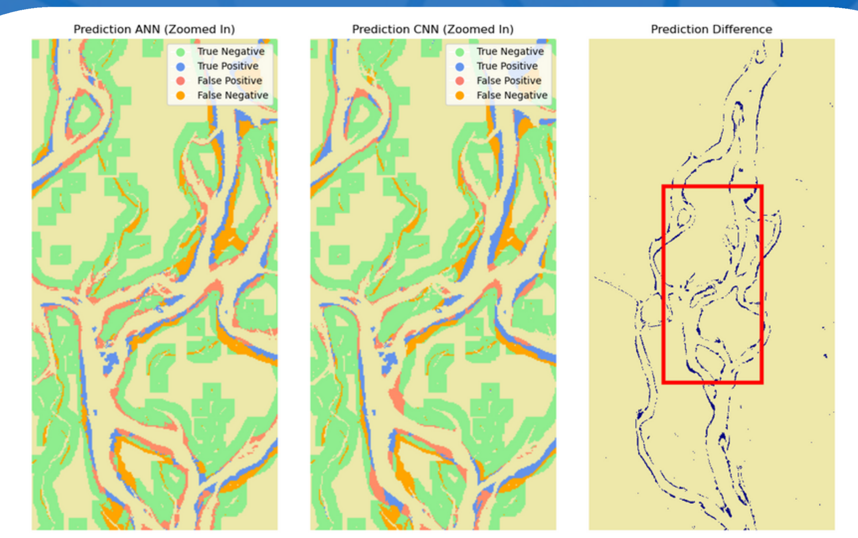
Optimal Model:

- New 3D Architecture
- 8 initial hidden features
- A residual bottleneck
- Dropout rate: 0.1
- Dice Loss
- Trainable parameters: 5.00E+05

Key Take-Aways

- Performance differences are minimal across architectures
- Dice loss drives the most significant gains
- Similar performance achievable with fewer parameters

Jager vs UNet



Conclusion

- Visually similar predictions
- JamUNet achieves higher CSI
- ANN parameters: (~4,000)
- UNet: parameters (~500,000)
- ~ Similar training time

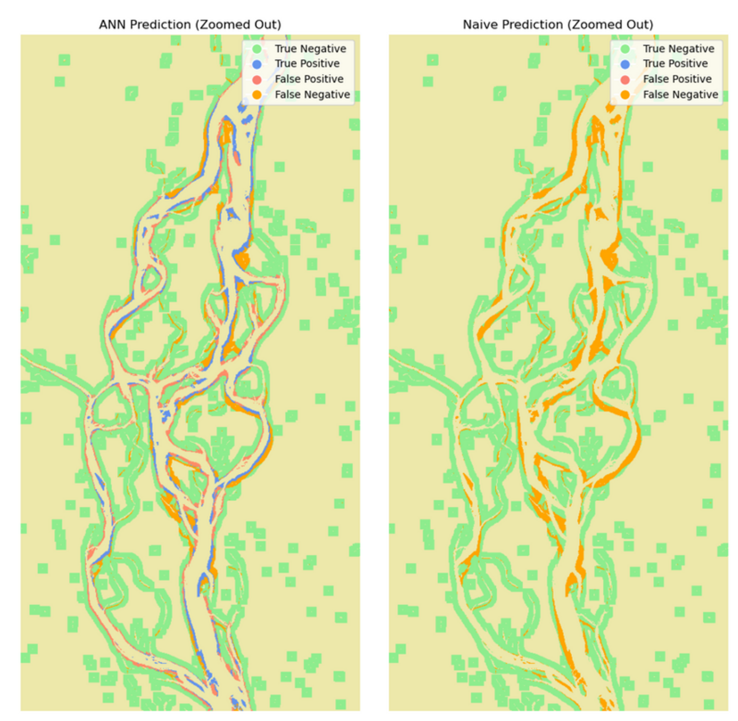
Discussion

- Jager only predicts erosion. UNet also predict deposition.
- Jager only trained on the test area, limiting generalization. Lower performance expected in other river sections.

Recommendations

- Increase temporal density and shorten the prediction window.
- Incorporate full satellite images as an additional input dimension.
- Integrate physiological parameters related to riverbank stability (e.g., slopes, soil moisture, type of material).

ANN: Jager, 2003



Accuracy:	0.916
Precision:	0.585
Recall:	0.805
F1 score:	0.678
CSI score:	0.513

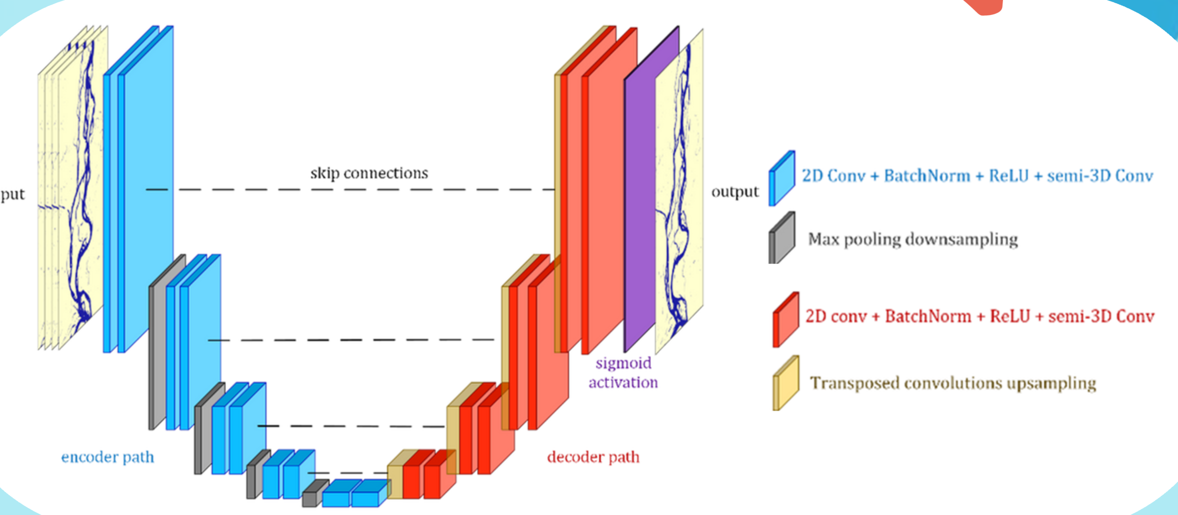
Key Take-Aways

- Increasing depth creates no significant improvement of the predictions.
- Closer to the river banks, the amount of false predictions increase
- Adding Regularization prohibits training of the data.
- Using a Relu activation functions, results in a better model instead of the original Sigmoid activation.
- 3 main rules trained.
  - Points close to channel erode quicker than further away
  - Channels tend to migrate downward
  - Erosion is more likely to occur along wider channels

CNN: JamUNet

- Utilizes CNN for pixel-level classification to distinguish water and non-water areas.
- Based on the JRC Surface Water dataset, using **4 years** of satellite imagery (during low-flow seasons) as input to predict river morphology in the **5th year**.

- **Optimization of convolutional blocks:**
  - Original 3D: 2D -> BN -> ReLU-> 3D
  - Full 2D: 2D-> BN-> ReLU -> 2D-> BN-> ReLU
  - New 3D: 3D-> BN-> ReLU -> 3D-> BN-> ReLU
- **Benchmark metric**: CSI score
- **Different combinations of these blocks were used:**
  - Magherini's CNN: only original 3D blocks.
  - Full 2D: only 2D blocks.
  - Proposed CNN: one new 3D Block, followed by 2 or 3 2D blocks.
  - Optional: Residual bottleneck for gradient issues



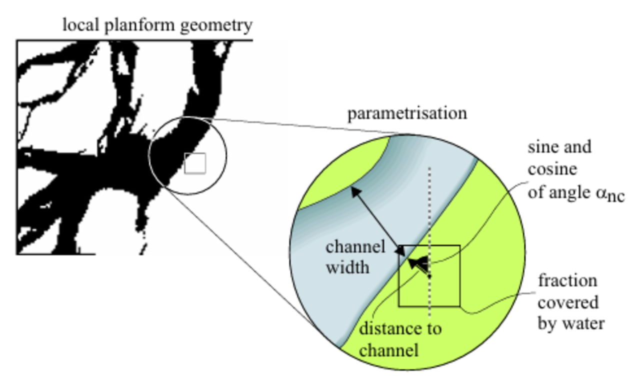
Introduce new loss function: Dice Loss

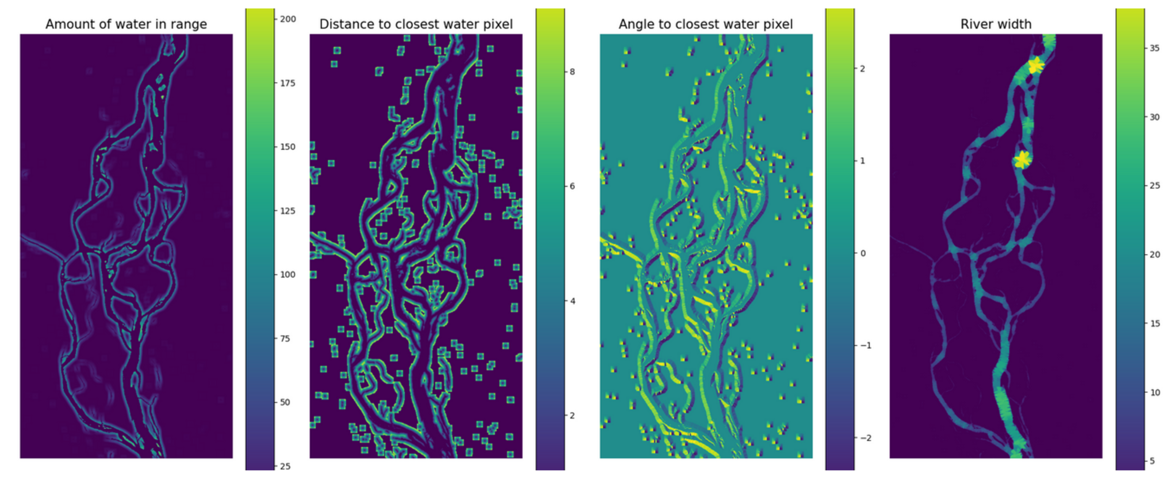
- Dice Loss focuses directly on the overlap, making it less sensitive to class imbalance compared to pixel-wise losses.
- Dice Loss focuses on maximizing the intersection between predicted and ground truth regions.

$$DL = 1 - \frac{2p_1 y_1 + \epsilon}{p_1^2 + y_1^2 + \epsilon}$$

ANN: Jager 2003

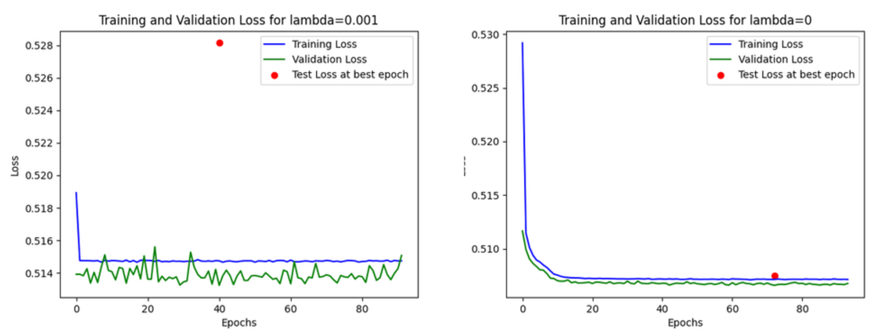
Data Processing:



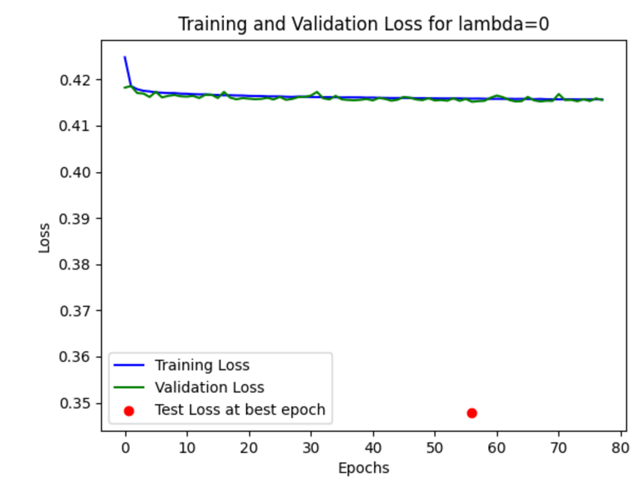


Model Training:

- *4* Hyper Parameters
  - Lambda - Regularization
  - N hidden layers
  - M hidden Nodes
  - Activation Functions
- Final Model (NXM)
  - 10x20, Lambda = 0
  - 3921 parameters



Neural Network Jager 2003
1 hidden layer, 5 hidden nodes



NN (10x20), targets 25% water and 75% land