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# Optimizing U-Net Architecture Using Differential Evolution for Brain Tumor Segmentation

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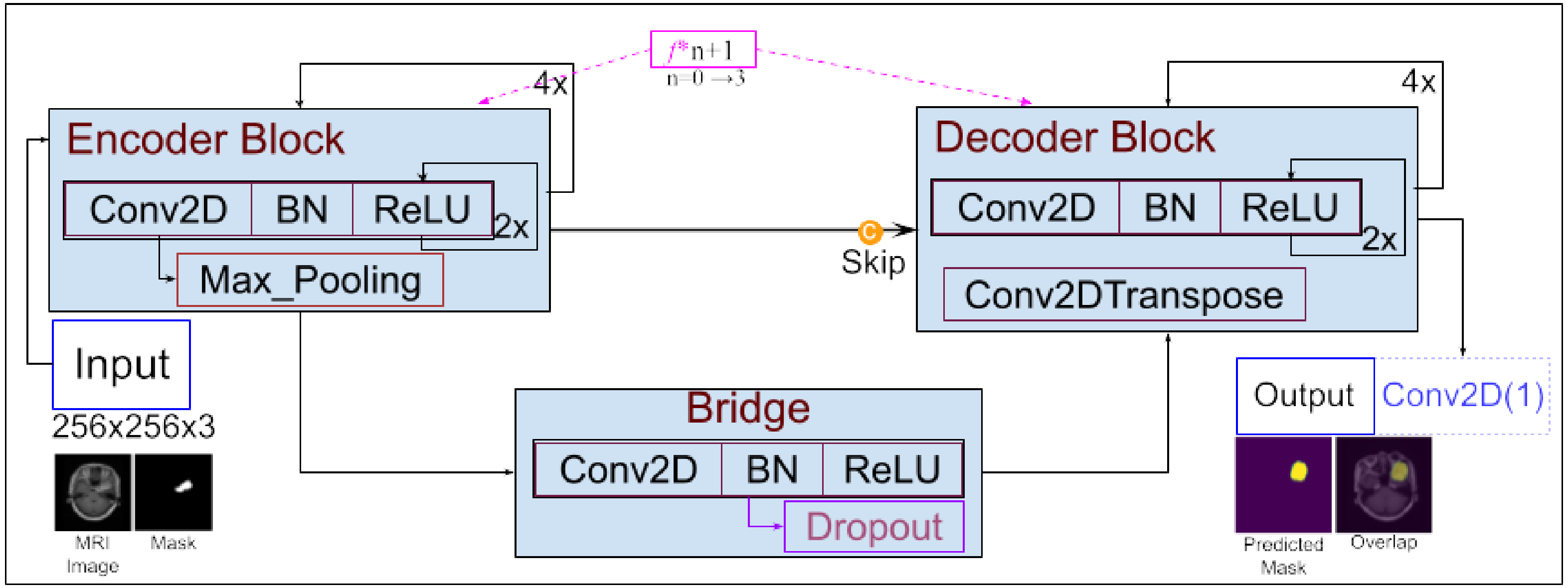
# Why Brain Tumor Segmentation?

- Accurate segmentation critical for diagnosis and treatment
- Manual segmentation is time-consuming and inconsistent
- Need for robust automatic models that generalize across MRI modalities

# Key Contributions

- Proposed DE-UNet: U-Net optimized using Differential Evolution (DE)
- Automatically tunes hyperparameters: learning rate, dropout, batch size, filter size
- Outperforms state-of-the-art models on FBTS and BraTS 2021 datasets

# DE-UNet Framework




- Base model: U-Net with skip connections
- DE tunes 4 key hyperparameters

- Optimization minimizes composite loss: $L_{\text{total}} = 1 - \alpha \cdot \text{DSC} - (1 - \alpha) \cdot \text{JI}$

# Differential Evolution Strategy

- Population-based metaheuristic
- Mutation, crossover, and selection
- 10 generations with population size = 5

**Algorithm 1** DE Algorithm for U-Net hyperparameter optimization.

**Require:** $NP$, $F$, $CR$, $G$
**Ensure:** Optimized hyperparameter configuration $x^*$

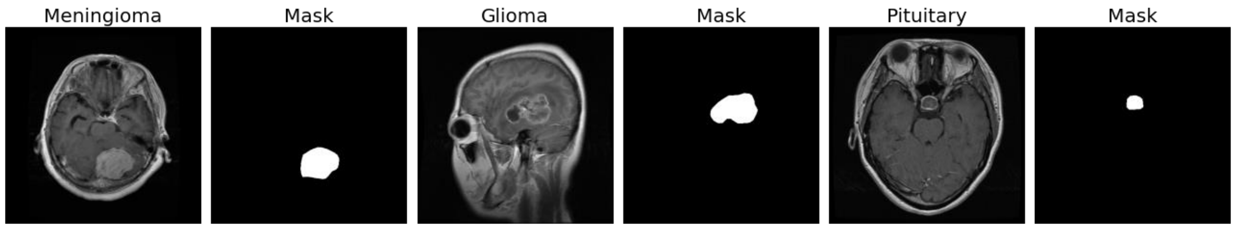
```
Initialize a population of NP candidate solutions within predefined bounds.
for generation g = 1 to G do
    for each candidate solution x_i in the population do
        Mutation: Randomly select 3 distinct solutions (x_a, x_b, x_c) from the population.
        Generate mutant vector: v_i = x_a + F · (x_b − x_c)
        Crossover: Generate trial vector u_i as:
```

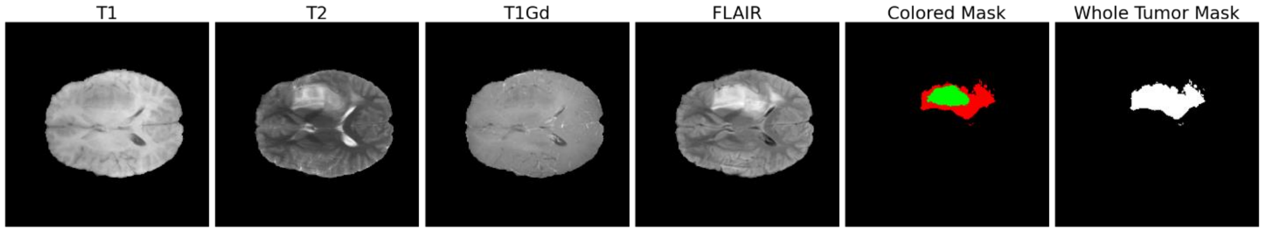
$$u_{ij} = \begin{cases} v_{ij} & \text{if } \mathrm{rand}(0,1) < CR \text{ or } j = j_{\mathrm{rand}} \\ x_{ij} & \text{otherwise} \end{cases}$$

```
        Selection: Replace x_i with u_i if f(u_i) < f(x_i)
    end for
end for
Return the best-performing solution x*
```

# Datasets and Preprocessing

- FBTS: 3064 slices, 3 tumor types (Meningioma, Glioma, Pituitary)
- BraTS 2021: 1251 slices, 4 modalities (T1, T1-CE, T2, FLAIR)
- Resized to 256×256, normalized to [0,1]



# Performance Summary

| Tumor Type | Training | | | | Validation | | | |
|---|---|---|---|---|---|---|---|---|
| | Accuracy | Loss | DSC | JI | Accuracy | Loss | DSC | JI |
| Meningioma | 0.9983 | 0.0042 | 0.9286 | 0.8677 | 0.9984 | 0.0038 | 0.9348 | 0.8784 |
| Glioma | 0.9971 | 0.0070 | 0.9023 | 0.8231 | 0.9968 | 0.0080 | 0.8943 | 0.8103 |
| Pituitary | 0.9991 | 0.0022 | 0.9183 | 0.8509 | 0.9991 | 0.0021 | 0.9200 | 0.8539 |

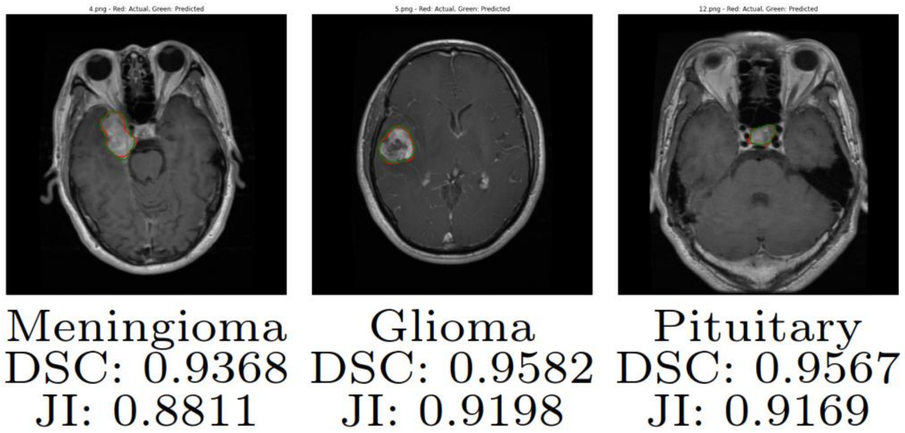
| Modality | Training | | | | Validation | | | |
|---|---|---|---|---|---|---|---|---|
| | Accuracy (pp) | Loss (pp) | DSC (pp) | JI (pp) | Accuracy (pp) | Loss (pp) | DSC (pp) | JI (pp) |
| FLAIR | 0.9956 (+0.18) | 0.0110 (-0.47) | 0.8941 (+4.31) | 0.8103 (+7.21) | 0.9961 (+0.15) | 0.0095 (-0.37) | 0.9068 (+3.31) | 0.8304 (+5.69) |
| T1 | 0.9935 (+0.32) | 0.0157 (-0.79) | 0.8464 (+7.58) | 0.7353 (+12.12) | 0.9930 (+0.39) | 0.0168 (-0.96) | 0.8327 (+9.07) | 0.7154 (+14.3) |
| T1-CE | 0.9950 (+0.34) | 0.0119 (-0.82) | 0.8823 (+8.05) | 0.7900 (+13.86) | 0.9940 (+0.43) | 0.0147 (-1.06) | 0.8576 (+10.37) | 0.7524 (+17.34) |
| T2 | 0.9946 (+0.28) | 0.0135 (-0.72) | 0.8707 (+6.65) | 0.7714 (+11.1) | 0.9942 (+0.34) | 0.0147 (-0.89) | 0.8602 (+7.97) | 0.7550 (+13.23) |

*Note: "+" indicate performance improvement in pp. "-" loss values represent reduction.*

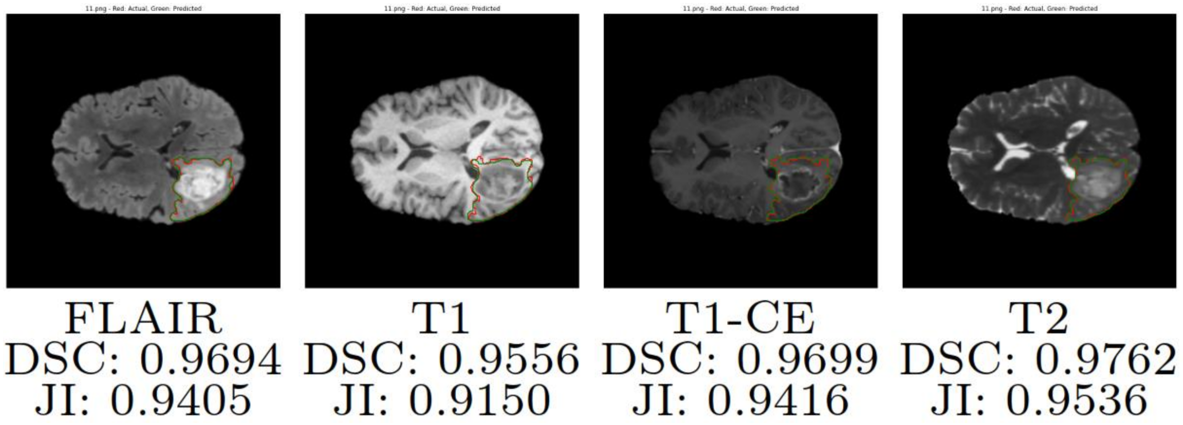
- FBTS: DSC = 0.9160, JI = 0.8472
- BraTS 2021: DSC = 0.9094, JI = 0.8371
- Consistent gains across all tumor types and modalities

# Qualitative Segmentation Examples

## FBTS




## BraTS 2021




- Red = Ground Truth, Green = Prediction
- Strong boundary alignment, especially in T1-CE and FLAIR

# DE-UNet vs. State-of-the-Art

| Method | FBTS Dataset | | Method | BraTS 2021 | |
|---|---|---|---|---|---|
| | DSC | JI | | DSC | JI |
| **Proposed DE-UNet** | **0.9160** | **0.8472** | **Proposed DE-UNet** | **0.9094** | **0.8371** |
| DeepLabV3+Xception | 0.8115 | 0.8018 | UNet | 0.8600 | 0.7807 |
| KFCM-CNN | 0.8884 | 0.8204 | U-Net base | 0.9080 | - |
| U-Net based | 0.8900 | 0.8100 | SPPNet-2 | 0.9040 | - |
| MST-based | 0.8469 | 0.7443 | UNCE-NODE | 0.8949 | - |
| U-Net with ResNet | 0.9011 | - | nnU-Net | 0.8900 | - |

- DE-UNet outperforms models like U-Net, DeepLabV3+, UNCE-NODE
- Higher DSC and JI without manual tuning

# Conclusion & Future Directions

- DE-UNet provides accurate, robust brain tumor segmentation
- Effective hyperparameter tuning across modalities
- Future work: hybrid metaheuristics, more datasets, clinical deployment