# Multi class image semantic segmentation

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## Data Preparation Process

1. **Dataset**: IPProjectDataset24, containing images and corresponding masks.
2. **Preprocessing**:

* Resized images to 256x256.
* Data augmentation (rotation, width/height shift, shear, zoom) for training.
* Normalized pixel values.

## Implemented Models and Modifications

1. **U-Net**: Classic architecture with batch normalization and dropout.
2. **FCN (Fully Convolutional Network)**: Simplified architecture with convolutional and upsampling layers.
3. **SegNet**: Encoder-decoder architecture with batch normalization and dropout.

## Results and Analysis

### U-Net (150 Epochs)

* **Accuracy**: 68.7% (validation)
* **IoU**: 0.24
* **Dice Coefficient**: 0.39
* **Precision**: 0.4355
* **Recall**: 0.4396

### FCN (50 Epochs)

* **Accuracy**: 74.1% (validation)
* **IoU**: 0.20
* **Dice Coefficient**: 0.345
* **Precision**: 0.325
* **Recall**: 0.3687

### SegNet (50 Epochs)

* **Accuracy**: 65.3% (validation)
* **IoU**: 0.15
* **Dice Coefficient**: 0.255
* **Precision**: 0.27
* **Recall**: 0.2792

## Conclusions and Insights

1. U-Net outperformed FCN and SegNet in accuracy and IoU.
2. SegNet showed better performance than FCN.
3. Data augmentation significantly improved model performance.
4. Batch normalization and dropout helped prevent overfitting.

**Code Repository**

[GitHub Repository](https://github.com/Yousef-116/multi-class-image-semantic-segmentation)