**Title : Image segmentation using U-Net and Mask R-CNN architectures .**

**1.Review:**

A convolutional neural network architecture called U-Net was created for the segmentation of biological images. It comprises of a path that contracts to capture context and a path that expands symmetrically to allow for exact localisation. The network uses data augmentation to increase generalizability and is trained end-to-end on tiny datasets. Cell segmentation, retinal blood vessel segmentation, and brain tumour segmentation are just a few of the biomedical segmentation tasks for which U-Net has been successfully used. It has spread widely in the sector and sparked a number of modifications and advancements.

**2.Review:**

The U-Net is a deep learning system for accurate and effective image processing that mixes skip connections with convolutional neural network architecture. It has been utilised in a range of applications, such as skeleton extraction, where it may yield extremely precise and comprehensive skeletization of challenging 3D forms. A very accurate and effective skeletonization model is produced by the U-Net by extracting low-level picture information in the beginning layers and gradually raising the degree of abstraction in the latter layers.

**3.Review:**

In a research comparing U-Net and Mask R-CNN's abilities to segment nuclei in histology pictures, it was discovered that U-Net performed better than Mask R-CNN in terms of precision, recall, and F1 score. Additionally, U-Net processed the photos more quickly. The study comes to the conclusion that U-Net, because of its higher performance and computational economy, is an appropriate candidate for nuclei segmentation in histology pictures.

**4.Review:**

In comparison to existing models, the Squeeze U-Net is a unique image segmentation network that produces competitive results with fewer parameters and processing resources. While being memory and energy-efficient, it employs squeeze-and-excitation blocks and depth-wise separable convolutions to increase segmentation accuracy. The model's potential for cost- and energy-effective picture segmentation has been assessed against benchmark datasets.

**5.Review:**

A machine learning approach called the U-Net Based Discriminator for Generative Adversarial Networks uses the U-Net architecture to distinguish between real and fraudulent pictures in a GAN. Skip connections are incorporated into the U-Net design to enhance the network's ability to discriminate between high-level characteristics. The authors showed that their U-Net-based discriminator outperformed conventional discriminators on a variety of datasets, including MNIST, CIFAR-10, and CelebA, in terms of picture quality and diversity.

**6.Review:**

The study suggests an instance segmentation technique for quick and precise autonomous detection of stacked electrical components based on an enhanced Mask R-CNN algorithm. By making the feature extraction network more efficient, Mask R-CNN performs better. A dataset of 1200 photos of electronic components is created, and tests on the dataset show that the suggested model is faster, lighter, and more accurate than Mask R-CNN. The model has an average accuracy (AP) that is around two points higher than Mask R-CNN while being 0.35 times smaller and moving twice as quickly.

**7.Review:**

We offer a theoretically straightforward, adaptable, and all-encompassing framework for object instance segmentation. With the help of our method, each item in an image is quickly and accurately detected, and its corresponding segmentation mask is produced to a high standard. By adding a branch for object mask prediction in addition to the current branch for bounding box recognition, the technique known as Mask R-CNN expands Faster R-CNN. Faster R-CNN's 5 fps counterpart, Mask R-CNN, is easy to train and incurs minimal overhead. Additionally, Mask R-CNN is simple to generalise to various applications, such as enabling us to estimate human postures inside the same framework.

Instance segmentation, bounding-box object detection, and person keypoint identification are three of the three COCO challenge tracks in which we achieve the best results. Mask is not a trick.

**8.Review:**

An innovative segmentation technique dubbed Feedback U-Net, which makes use of a feedback mechanism from the upper layer to the bottom layer, is suggested in the paper. Based on the features obtained in the first round, the proposed technique employs Convolutional LSTM to extract features in the subsequent round. The second round's input is fed back into the U-Net model's output. The suggested approach is contrasted with the traditional U-Net model, which exclusively employs the feedforward method using datasets of cell images from Drosophila and Mouse. The experimental findings demonstrate that in terms of segmentation accuracy, the suggested Feedback U-Net model performs better than the traditional U-Net model.

**9.Review:**

The technique described in the paper creates picture segmentations using customizable test-time cues, which may be text- or image-based. The model is built on the CLIP backbone and has a transformer-based decoder for dense prediction. It can perform three typical segmentation tasks. The system may produce binary segmentation maps for photos based on free-text prompts or extra images expressing the inquiry after training on an expanded version of the PhraseCut dataset. The system provides for dynamic adaptation to any binary segmentation job and can adapt to generalised questions using affordances or characteristics.

**10.Review:**

Low memory and compute requirements are essential for enabling the deployment of deep neural networks on embedded devices, especially for real-time mobile application. In this study, we propose a SqueezeNet-inspired version of U-Net for image segmentation that reduces model size by 12X to 32MB and MACs by 3.2X to 88 billion ops from 287 billion ops for inference on the CamVid data set while maintaining accuracy. Our suggested Squeeze U-Net is effective in terms of reduced MACs and memory consumption. Squeeze U-Net outperforms U-Net for the same accuracy in our performance tests using Tensorflow 1.14 with Python 3.6, CUDA 10.1.243, and an NVIDIA K40 GPU by 17% for inference and by 52% for training.

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