Introduction (1 minute)

Good morning/afternoon everyone. I am Venkat Naraharisetty from Vishnu Institute of Technology. Today, I'll be presenting our project on "Low-Complexity Convolutional Neural Network for Salt and Pepper Noise Removal in Digital Images."

We'll start with a brief introduction to image denoising and the challenges associated with it. Then, we'll discuss the need for advanced denoising techniques and provide an overview of the Residual Convolutional Neural Network (RCNN) architecture we've proposed. Finally, we'll go through the results and conclusions of our study.

Image Denoising and Challenges (1 minute)

Digital images are often affected by various types of noise, such as salt and pepper noise and Additive White Gaussian Noise (AWGN). These noises can degrade image quality and hinder accurate analysis and interpretation in various applications, including medical imaging, surveillance, photography, and satellite imagery.

Existing denoising methods often struggle to effectively remove noise while preserving important image details, highlighting the need for innovative approaches.

Need for Advanced Denoising Techniques (1 minute)

The demand for high-quality images is increasing across various fields, as noise in images can hinder accurate decision-making. Traditional denoising techniques often blur important details along with noise, while advanced methods require precise noise characterization, limiting their applicability.

Advanced denoising techniques based on deep learning offer promising solutions by learning complex noise patterns and distinguishing noise from actual image features, leading to more accurate denoising.

Introduction to RCNN Architecture (1 minute)

Our proposed approach is the Residual Convolutional Neural Network (RCNN), which utilizes residual learning and skip connections to address challenges in deep network training.

The RCNN architecture consists of three stages: convolutional layers, batch normalization, and transpose convolution layers. It leverages residual learning to mitigate the vanishing gradient problem and skip connections to reuse earlier layer activations, facilitating better gradient flow and training efficiency.

Proposed Method and Implementation (1 minute)

We implemented the RCNN architecture using MATLAB's deep learning toolbox and trained it with a dataset of 12 images for 30 epochs using Adam's optimizer, which is an adaptive learning rate optimization algorithm.

The training process involved applying a noise level of σ = 50 and took approximately 21 hours on a CPU.

Results and Discussion (1 minute)

Our simulation results demonstrate the effectiveness of RCNN in image denoising. We compared the denoising performance with existing methods, such as deconvolution, and observed significant improvements in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values.

We'll present some visual examples to illustrate the clear and visually appealing images obtained after denoising with RCNN compared to the noisy input images.

Conclusion (1 minute)

In conclusion, our proposed RCNN approach demonstrated superior performance in image denoising compared to traditional and deep learning-based methods.

The innovative architecture and training approach of RCNN offer a promising solution for challenging denoising tasks, and we recommend exploring its applications in various domains, such as medical imaging, surveillance, and remote sensing.

We acknowledge the support and guidance from our institute, faculty, and project committee members in successfully completing this project.

That's all from my side. Thank you for your attention, and I'll be happy to address any questions you may have.