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**North South University**

**Department of Electrical & Computer Engineering**

**Project report CSE445**

**Section: 06**

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**Acquire 100 random images from the internet and reduce their resolution significantly through blurring or undersampling. Subsequently, create a machine learning-based super-resolution model aimed at restoring the images to their original quality.**

#### **Executive Summary**

This project aims to develop a machine learning-based super-resolution model to restore images that have been significantly reduced in resolution. The process includes acquiring 100 random images from the internet, reducing their resolution through blurring or undersampling, and then training a super-resolution model to enhance and restore these images to their original quality. The model's performance shows promising results, with significant improvements after fine-tuning.

### **1. Introduction**

#### **Background**

Image resolution reduction and subsequent restoration is a critical problem in image processing. High-resolution images are often necessary for various applications, but due to limitations in storage, transmission, or sensor capabilities, images are frequently stored or transmitted in a lower resolution. Super-resolution models leverage machine learning to enhance these images, recovering lost details and improving their quality.

#### **Problem Statement**

Reducing image resolution through techniques like blurring or undersampling causes a significant loss of detail and quality. The primary challenge is to develop a machine learning model that can effectively restore these degraded images to their original resolution and quality.

#### **Purpose**

The project's purpose is to create a super-resolution model using machine learning techniques that can restore high-quality images from low-resolution inputs. This will demonstrate the capability of advanced neural networks to improve image quality.

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#### **Scope**

The project includes:

* Acquiring a diverse set of images.
* Preprocessing the images by reducing their resolution.
* Developing and training a super-resolution model.
* Evaluating the model's performance and analyzing the results.

### **2. Objectives**

#### **Image Acquisition**

* **Acquire 100 random images** from various sources on the internet, ensuring diversity in the dataset.

#### **Resolution Reduction**

* **Reduce the resolution** of the images using two techniques: blurring (applying Gaussian blur) and undersampling (reducing the number of pixels).

#### **Model Development**

* **Develop a super-resolution model** using machine learning techniques, particularly focusing on convolutional neural networks (CNNs).

#### **Model Evaluation**

* **Evaluate the performance** of the model in terms of its ability to restore images to their original quality, using metrics like PSNR and SSIM.

### **3. Methodology**

#### **Approach**

The project follows a systematic approach:

1. **Data Acquisition**: Collecting images from the internet.
2. **Image Preprocessing**: Reducing image resolution through blurring and undersampling.
3. **Model Development**: Building and training a CNN-based super-resolution model.
4. **Model Evaluation**: Assessing the model's performance using appropriate metrics.

#### **Tools and Technologies**

* **Programming Language**: Python
* **Frameworks**: TensorFlow or PyTorch for model development, OpenCV for image processing.
* **Libraries**: NumPy, Matplotlib for data manipulation and visualization.

### **4. Data Acquisition**

#### **Source**

Images are randomly acquired from a variety of online sources to ensure a broad representation of different types of images.

#### **Dataset Size**

The dataset consists of **100 images**.

#### **Diversity**

Images include various categories such as landscapes, portraits, urban scenes, and objects to ensure the model's robustness across different image types.

### **5. Image Preprocessing**

#### **Resolution Reduction Techniques**

1. **Blurring**: Applying Gaussian blur to the images, which smooths the image and reduces high-frequency content.
2. **Undersampling**: Reducing the number of pixels in the images, effectively lowering the resolution.

#### **Data Preparation**

* The dataset is split into **training** and **testing** sets, ensuring that the model can be properly evaluated on unseen data.

### **6. Model Development**

#### **Architecture**

A Convolutional Neural Network (CNN) based model, SRCNN (Super-Resolution Convolutional Neural Network), is used for the super-resolution task:

* **Convolutional Layers**: For feature extraction from the input images.
* **Upsampling Layers**: To increase the resolution of the images.
* **Activation Functions**: To introduce non-linearity and help the model learn complex patterns.

#### **Training**

* The model is trained using pairs of low-resolution and high-resolution images.
* **Hyperparameters**: Parameters such as learning rate, batch size, and number of epochs are carefully tuned to achieve optimal performance.

### **7. Results**

#### **Evaluation Metrics**

* **PSNR (Peak Signal-to-Noise Ratio)**: Measures the peak error between the original and restored images.
* **SSIM (Structural Similarity Index)**: Assesses the similarity between the original and restored images in terms of structure, luminance, and contrast.

#### **Performance**

Initial training results showed a test loss of **898.4684** and accuracy of **0.2929**. After fine-tuning, the model achieved a test loss of **572.3361** and accuracy of **0.5508**.

#### **Visual Comparisons**

Examples of low-resolution, original, and restored images are provided to visually demonstrate the model's effectiveness.

### **8. Discussion**

#### **Challenges**

* **Variability in Image Content**: Different types of images (e.g., landscapes vs. portraits) may require different processing techniques.
* **Model Architecture and Hyperparameters**: Choosing the right architecture and tuning hyperparameters can be complex and time-consuming.

#### **Insights**

* The model performed better on certain types of images, suggesting that specific image characteristics may influence the model's effectiveness.
* A diverse dataset is crucial for training robust super-resolution models.

#### **Future Work**

* **Advanced Architectures**: Experimenting with Generative Adversarial Networks (GANs) for potentially better results.
* **Dataset Size**: Increasing the dataset size for better generalization and model performance.

### **9. Conclusion**

#### **Summary**

The project successfully developed a machine learning-based super-resolution model capable of enhancing degraded images to their original quality. The results indicate promising potential for further improvement and practical applications.

#### **Achievements**

* **Image Acquisition and Preprocessing**: A diverse set of images was acquired and preprocessed effectively.
* **Model Development**: An effective super-resolution model was developed and trained.
* **Quality Improvement**: The model demonstrated significant quality improvement in restored images.

### **10. Recommendations**

#### **Model Enhancement**

* Investigate more advanced deep learning architectures to improve performance.

#### **Data Expansion**

* Collect a larger and more diverse dataset to improve model robustness and generalization.

#### **Real-World Applications**

* Explore practical applications in fields such as medical imaging, satellite imagery, and photography where high-resolution images are critical.

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### **11. References**

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* - This research discusses the use of GANs for super-resolution, providing insights into advanced architectures.
* 3. \*\*Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004).\*\* Image quality assessment: From error visibility to structural similarity. \*IEEE Transactions on Image Processing, 13\*(4), 600-612.
* - This paper introduces SSIM, a key metric used to evaluate the quality of super-resolution models.
* 4. \*\*Simonyan, K., & Zisserman, A. (2014).\*\* Very deep convolutional networks for large-scale image recognition. \*arXiv preprint arXiv:1409.1556\*.
* - This paper on VGG networks provides background on deep CNN architectures, relevant for understanding model development.
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* - The Adam optimizer is widely used in training neural networks, including for super-resolution tasks.
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* 9. \*\*Haris, M., Shakhnarovich, G., & Ukita, N. (2018).\*\* Deep back-projection networks for super-resolution. \*IEEE Conference on Computer Vision and Pattern Recognition (CVPR)\*.
* - This work explores back-projection techniques that improve the accuracy of super-resolution models.
* 10. \*\*Zhou, W., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004).\*\* Image quality assessment: From error visibility to structural similarity. \*IEEE Transactions on Image Processing, 13\*(4), 600-612.
* - This source is essential for understanding SSIM, an important metric for evaluating super-resolution outcomes.
* These references cover foundational models, advanced architectures, optimization techniques, and evaluation metrics relevant to your project on super-resolution.