IMAGE RESTORATION

A report on
Deep Learning Lab Project
[CSE-3281]

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Abstract*—This comprehensive report delves into state-of-the-art image processing methodologies utilizing deep learning, focusing on key areas such as image denoising, colorization, and super-resolution. It delves into the intricate workings of an autoencoder for denoising, revealing how it extracts and refines essential features to produce clear, noise-free images. Additionally, a detailed exploration of a Generative Adversarial Network (GAN)-based framework for colorization showcases the network's ability to imbue grayscale images with vibrant colors, enriching visual content. Moreover, the report delves into the sophisticated SRGAN architecture, demonstrating its prowess in upscaling low-resolution images to high fidelity, preserving intricate details with remarkable precision. Through these methodologies, the report underscores the transformative impact of deep learning in elevating image quality and delivering adaptable solutions for diverse image processing challenges.

***Keywords*— Deep learning, image processing, image denoising, autoencoder, Generative Adversarial Network (GAN), colorization, super-resolution, SRGAN architecture**

I. INTRODUCTION

In today's digital world, images are a form of identity and essential documentation. People use images for personal and official purposes. This may be to document family lineage, an important event, or a crime scene. Due to the degrading nature of physical images, this documentation is unsure of surviving the test of time. This is slowly changing with the help of newly emerging image restoration technologies focusing on restoring lost information in an image. A rustic method of implementing such a technology is through spatial filtering, where information is regained through convolution [1]. Colour restoration techniques such as 'mean sample matching' or 'linear approximation' have been used to replicate the original appearance of images[2]. In recent years, there has been a shift from using mathematical models for image restoration to using learning-based and data-driven methods. Today, deep learning applications are widely relied on for this purpose. We explore this application further in this paper. We focus on restoring details from physical images using deep learning techniques and neural networks. The project can be broken down into three broad stages: denoising, colourization and image super-resolution. We utilize autoencoders, generative adversarial neural networks (GANs), and Convolutional neural networks to implement our goal results. We also leverage pre-existing work by including transfer learning to improvise and build upon our model.

II. LITERATURE REVIEW

The first stage in our pipeline is denoising the image to remove any irregularities. In [3], the authors suggest a novel method called enhanced deep CNN for processing images with high noise levels. EDCNN consists of 52 weight layers that possess a large receptive field. To combat the gradient vanishing problem, the authors use residual learning strategy and global residual learning to improvise the learning of the network. A remarkable feature of the papers seems to be the network's ability to adapt to increasing depth. They have found that the EDCNN works remarkably well for denoising images. Global residual learning aims to learn how to map from the input image to the residual image, obtain the most useful information from the input image, and discard noise in that process. Local residual learning Involves building short paths between consecutive blocks to alleviate the gradient vanishing problem, enhancing the flow of information in deep neural networks. The outputs of the network are tested using the MSE loss function. A notable part of their paper is using multiple datasets to test their model. Their experimentation technique involves varying the noise levels in different ways for greyscale and colour images. Grayscale images are varied with noise levels, and coloured images are set with Gaussian noise of different standard deviations. Overall denoising performance is calculated using peak signal-to-noise ratio. The model is tested thoroughly with many different datasets and variations within the dataset. Apart from this, the model is further analysed in three aspects: residual excitation, number of parameters, and difference to DnCNN. Upon comparison with their EDCNN, it is found that despite having three times more parameters and layers compared to DnCNN, the superior denoising performance of EDCNN is not solely attributed to its larger network size. A smaller version of EDCNN, with parameters similar to DnCNN, still outperforms DnCNN across all noise levels. This suggests that factors beyond just the number of parameters contribute to the enhanced performance of EDCNN. The residual excitation structure incorporated results in a short path between input and output blocks. This is found to improve denoising images with high noise levels significantly.

A challenge that all scholars and researchers face is choosing the correct parameters and hyperparameters for their model. Methods like grid search and gradient search exist for this purpose, but they are tedious and not very effective for all models. Since our application particularly involves images, it would be convenient to have a method to choose hyperparameters designed to fit image-denoising algorithms. The authors of [4] propose a multiscale method for automatic choice of the denoising parameters developed for a wide class of classical image ridge and edge-preserving denoising algorithms. Two hybrid denoising methods: DRCN+TV and NLRN+TV are used, followed by CNN and TV with automatic parameter choice.

The working of DRCN and be broken down simply as: It first takes the blurry image and breaks it down into smaller pieces, called feature maps, to understand its details better. Then, DRCN uses a set of repeated operations to enhance the image details, making it sharper. These repeated operations help maintain depth in the network without adding too many extra calculations. Finally, the enhanced features are put back together to recreate the high-resolution image, making it look much better than the original blurry version.

The NLRN method works similarly, consisting of 3 sub-networks: embedding, inference, and reconstruction networks, all trained together. NLRN employs a non-local module within its inference network to capture feature correlations, similar to how LSTM networks capture contextual information in text processing. This allows for effective enhancement of image features during the super-resolution process.

The network was evaluated with Additive White Gaussian Noise (AWGN) at various levels. The DRCN network was trained with optimal recursion depths determined empirically for each noise level, while the NLRN's weights were obtained from the original article. Similar to [3], the authors use multiple datasets for training, testing and validation. Adam optimizer was used to improve results. This method effectively determined the optimal TV parameter by analyzing the mutual information curve, selecting the point corresponding to the steepest increase in the derivative of mutual information. The suggested no-reference method for parameter estimation yielded acceptable differences between the estimated parameters and the points of maximal value of the full-reference Structural Similarity Index Measure (SSIM) curve.

In summary, the proposed method effectively combines RNN architectures with total variation denoising, with the TV parameter chosen based on analysis of the mutual information curve.

[5] This paper proposes MIRNet-v2, a multi-scale residual network architecture for various image restoration and enhancement tasks including defocus deblurring, image denoising, super-resolution, and low-light enhancement. The key features of the proposed network are: It maintains high-resolution features throughout the network to preserve spatial details, while utilizing parallel lower resolution streams to provide contextual information. It progressively fuses information from the coarse-to-fine resolution streams, exchanging and aggregating features. It uses selective kernel feature fusion to dynamically combine features from the parallel streams while preserving their distinct characteristics.

It employs residual contextual blocks to extract useful features from within each resolution stream.It uses a progressive training regime where the network is initially trained on small image patches and then gradually on larger patches.The experiments show that the proposed MIRNet-v2 achieves state-of-the-art results on six benchmark datasets for the aforementioned image restoration tasks, demonstrating its effectiveness. The proposed network also generalizes well to datasets with different noise characteristics.

[6] This paper proposes a method to colorize grayscale images using convolutional neural networks. Grayscale images lack color information to properly understand the image. Coloring these images can provide more insights and information. Traditionally, image colorization was done manually but now automated solutions using neural networks have become popular.

The proposed method uses convolutional neural networks with an encoder-decoder architecture. The encoder downsamples the input grayscale image and the decoder upsamples the output to the original image size. An Inception ResNet V2 network is used as a feature extractor to extract features from the image. The features are then combined with the encoder output and passed through the decoder to get the final colored output image.

Different epochs and batch sizes are experimented with to find the optimal parameters. Higher epochs and batch sizes take more time and memory but generally provide better results. The results obtained so far look realistic and the model performs satisfactorily. The accuracy and performance of the model is improved compared to previous methods. The complexity is also reduced. The model efficiently colors the grayscale images with low loss rates.

[9] The paper "Image Super-Resolution Using Deep Convolutional Networks" by Dong et al. (2014) addresses the critical task of enhancing image resolution, particularly focusing on low-resolution images. The authors introduce a novel approach that leverages deep learning techniques, specifically convolutional neural networks (CNNs), to achieve remarkable improvements in image quality and detail.
The significance of super-resolution lies in its ability to enhance the visual perception of images, making them suitable for various applications where high-resolution and detailed images are essential. This includes medical imaging, surveillance systems, satellite imagery, and digital photography.
Dong et al. (2014) highlight the limitations of traditional interpolation-based methods for image super-resolution and propose a data-driven approach using CNNs. The key contribution of their work lies in the training of deep networks to learn the underlying mapping from low-resolution images to their corresponding high-resolution counterparts. This learning process enables the network to capture complex patterns and features, leading to more accurate and visually pleasing results compared to traditional methods.
By utilizing deep convolutional networks, the proposed approach not only enhances image resolution but also preserves important details and textures, resulting in images that are both visually appealing and informative. The success of their method is demonstrated through extensive experiments on benchmark datasets, showcasing significant improvements in image quality metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).
Overall, Dong et al. (2014) contribute significantly to the field of image super-resolution by introducing a data-driven deep learning approach that achieves superior results compared to traditional methods, marking a significant advancement in enhancing image resolution and quality.

[10] The paper "Image Denoising with Deep Convolutional Neural Networks" by Zhang et al. (2017) presents a groundbreaking method for image denoising using deep convolutional neural networks (CNNs). The focus of this work is on removing noise from images while preserving important details and enhancing overall image quality.
Image denoising is a crucial preprocessing step in various image processing tasks, including medical imaging, surveillance, digital photography, and scientific imaging. The presence of noise in images can degrade their quality, making it challenging to extract meaningful information and perform accurate analysis.
Zhang et al. (2017) address the limitations of traditional denoising techniques, which often rely on handcrafted features and simplistic models. Their approach, based on deep learning, involves training CNNs to learn the mapping function from noisy images to clean images. This learning process enables the network to capture intricate patterns and features in the data, leading to more effective noise removal and preservation of image details.
The key innovation of their method lies in the hierarchical representation learned by deep CNNs, allowing for the extraction of both low-level and high-level features essential for denoising. By utilizing large-scale datasets and advanced network architectures, their approach achieves state-of-the-art performance in image denoising tasks.
Extensive experiments and evaluations on benchmark datasets demonstrate the superiority of their deep learning-based denoising method compared to traditional techniques. The results show significant improvements in image quality metrics such as PSNR and SSIM, indicating better noise reduction and preservation of image content.
In conclusion, Zhang et al. (2017) contribute significantly to the field of image denoising by introducing a data-driven approach based on deep CNNs, offering superior performance and advancing the state-of-the-art in image quality enhancement and noise reduction.

III. METHODOLOGY

A. Image Denoising-

An autoencoder is an unsupervised learning technique for neural networks that learns efficient data representations (encoding) by training the network to ignore signal “noise.” Autoencoders can be used for image denoising, image compression, and, in some cases, even generation of image data.

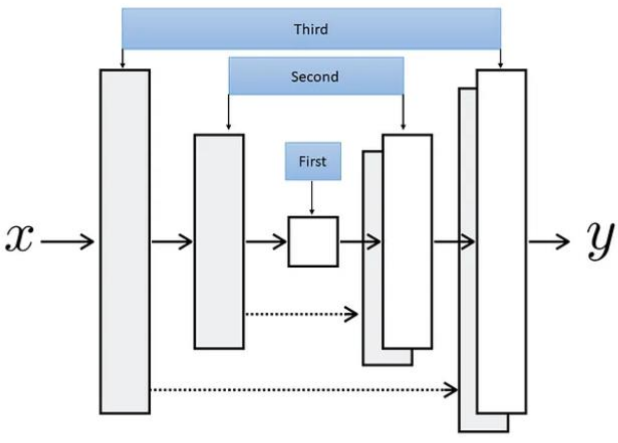
Noisy Image -> Encoder -> Compressed Representation -> Decoder -> Reconstruct Clear Image.

Encoder: The encoder module extracts high-level features from the noisy input images, capturing essential information for denoising. Apply convolution operations to the input image to extract spatial features. Activation function (e.g., ReLU): Introduce non-linearity to the network, allowing it to learn complex mappings. Pooling layers (e.g., MaxPooling): Downsample the feature maps to reduce spatial dimensions while preserving important features.

Compressed RepresentationThis layer represents the bottleneck of the autoencoder, where the extracted features are compressed into a lower-dimensional representation. Flatten layer: Reshape the output of the encoder into a one-dimensional vector. Dense layer: Reduce the dimensionality of the feature vector to obtain the compressed representation.
Decoder: The decoder module reconstructs the clear image from the compressed representation, effectively removing noise. Dense layer: Expand the dimensionality of the compressed representation. Reshape layer: Reshape the output of the dense layer to match the dimensions of the feature maps in the encoder. Convolutional layers: Apply convolutional operations to reconstruct spatial details. Activation function (e.g., ReLU): Introduce non-linearity to the network to refine the reconstruction. Upsampling layers (e.g., UpSampling): Increase the spatial dimensions to match those of the original image.
Noisy Image: This is the input image corrupted by noise. In the case of the BSDS dataset, noise may include various types such as Gaussian noise, salt and pepper noise, or motion blur.
Encoder: The encoder module consists of convolutional layers followed by activation functions such as ReLU. These layers progressively extract spatial features from the noisy input image, capturing patterns relevant for denoising.
Compressed Representation: After passing through the encoder, the extracted features are flattened and compressed into a lower-dimensional representation. This compressed representation captures the essential information necessary for reconstructing the clear image while discarding noise.
Decoder: The decoder module receives the compressed representation and reconstructs the clear image. It consists of convolutional layers with activation functions, which refine the reconstructed image by adding spatial detail. Upsampling layers increase the spatial dimensions to match those of the original image. Reconstructed Clear Image: This is the output of the decoder, which represents the denoised version of the input image. The autoencoder learns to reconstruct the clear image from the compressed representation, effectively removing noise while preserving important features
This architecture leverages the power of autoencoders to denoise images from the Berkeley Segmentation Dataset. By encoding noisy input images into a compressed representation and then reconstructing clear images through the decoder, the model effectively removes noise and enhances image quality. This approach can be further optimized and extended to handle various types of noise and achieve superior denoising performance.

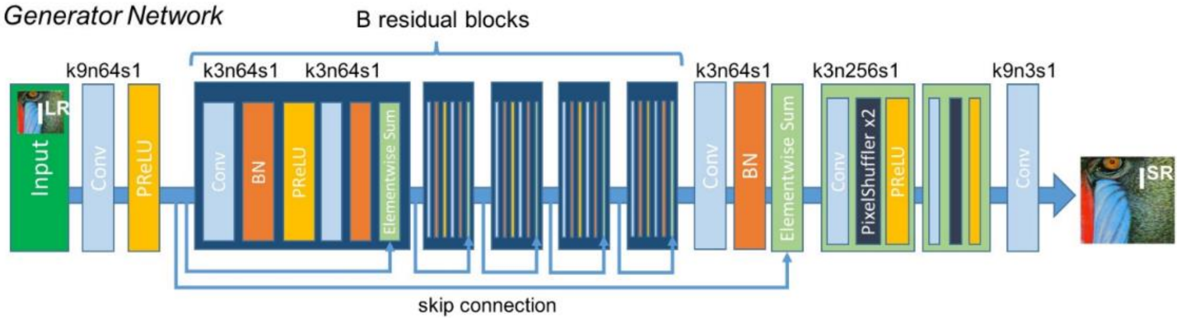
B. **Image Colorization:**

For image colorization, we use a Generator, Discriminator and Loss functions.
Generator:
UnetBlock Class: The UnetBlock class defines the basic building block of the U-Net architecture used as the generator. It encapsulates the operations for a single block of the U-Net, which includes convolution, activation, and normalization layers. The block can be configured to be an innermost block, outermost block, or a regular block with optional dropout.[7]
Unet Class: The Unet class constructs the U-Net generator using multiple instances of UnetBlock. It defines the entire architecture of the U-Net, including the down-sampling and up-sampling paths. The number of down-sampling layers, the number of filters, and other parameters are configurable.
MainModel Class: The MainModel class brings together the generator, discriminator, loss functions, and optimization logic. It initializes the generator and discriminator networks. Defines the loss functions, including the GAN loss and L1 loss. Implements the training procedure for both the generator and discriminator using gradient descent.



Discriminator:
PatchDiscriminator Class: The PatchDiscriminator class defines the discriminator network. It consists of convolutional layers with leaky ReLU activations and batch normalization. The discriminator outputs one value for each patch of the input image to discriminate between real and fake patches.
Loss Functions:
GANLoss Class: The GANLoss class encapsulates the adversarial loss function used in training the GAN. It supports both vanilla GAN and least squares GAN loss functions. Provides methods to generate real and fake labels and compute the loss.
Training Process: Initialization: Initialize the generator, discriminator, loss functions, and optimizers. Optionally, load pre-trained weights for the generator.
Pretraining the Generator: Train the generator separately on the colorization task using L1 loss. Utilize a pre-trained ResNet backbone followed by a U-Net architecture for efficient training. Save the weights of the pre-trained generator for future use.
Main Training Loop: Instantiate the MainModel with the pre-trained generator. Train the combined GAN model using a dataset containing grayscale images and their corresponding colorized versions. Utilize the GAN loss and L1 loss for training the generator. Employ the PatchDiscriminator for adversarial training to distinguish between real and fake colorized images. Alternate between training the generator and discriminator in each iteration, updating their respective parameters.
By employing a U-Net architecture with a pre-trained ResNet backbone and combining adversarial training with L1 loss, the described model aims to improve colorization performance. The pretraining strategy helps the model to learn meaningful features before engaging in adversarial training, potentially leading to better convergence and improved colorization results.

C. **Super Resolution:**
Breaking Down the SRGAN Architecture: In this section, we delve deeper into the architecture of the SRGAN (Super-Resolution Generative Adversarial Network), understanding both the generator and discriminator components separately to grasp their functionality and interaction. The SRGAN is designed to generate high-quality super-resolution images by leveraging a combination of convolutional neural networks (CNNs) and adversarial training.[8]
Generator: The generator architecture of SRGAN, based on the SRRESNET model, transforms low-resolution input images into high-resolution counterparts. Here's a detailed breakdown of its components:
Initial Convolutional Layer: The process begins with an initial convolutional layer featuring 9×9 kernels and 64 feature maps, followed by a Parametric ReLU activation function. Parametric ReLU is chosen as the primary activation function due to its effectiveness in mapping low-resolution to high-resolution images. Unlike ReLU or Leaky ReLU, Parametric ReLU allows the network to autonomously determine the best parameters, enhancing its adaptability.



Residual Blocks: The core of the generator comprises multiple residual blocks, each containing: Convolutional layer with 3×3 kernels and 64 feature maps. Batch normalization layer. Parametric ReLU activation function. Another convolutional layer with batch normalization. Elementwise sum operation to combine the feed-forward output with the skip connection output. These residual blocks facilitate the extraction of high-level features while mitigating the vanishing gradient problem commonly encountered in deep networks.
Padding and Convolution: Notably, each convolutional layer employs similar padding to ensure consistent input and output sizes, preserving spatial information throughout the network. Unlike architectures like U-Net that utilize pooling layers for downsampling, SRGAN maintains image size integrity, crucial for super-resolution tasks.
Pixel Shuffler: After 4x upsampling via convolutional layers, the generator incorporates pixel shufflers to rearrange channel values into height and width dimensions. This operation effectively doubles both height and width while halving the channel dimension, aiding in the production of super-resolution images.

Discriminator: The discriminator, serving as an image classifier, evaluates the authenticity of generated images compared to real ones. Here's a breakdown of its architecture:

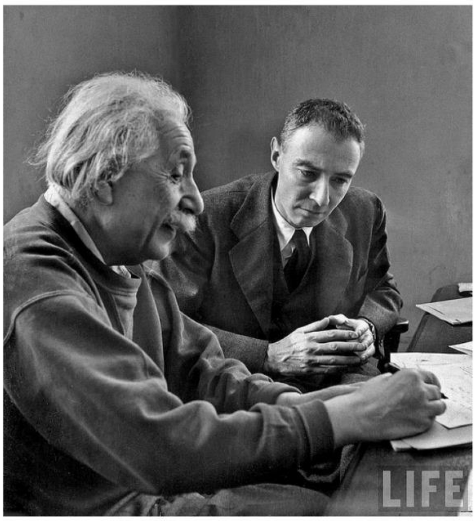
Convolutional Layers: The discriminator begins with an initial convolutional layer, followed by a Leaky ReLU activation function with an alpha value of 0.2. Subsequent layers consist of repeating blocks, each comprising convolutional layers, batch normalization, and Leaky ReLU activation functions. These layers progressively increase the receptive field to capture high-level features while maintaining discriminative power.

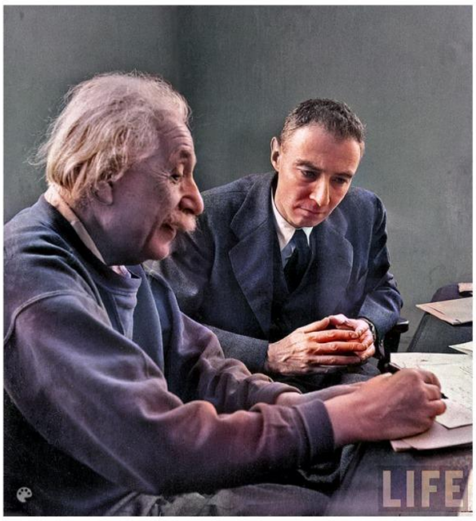
Dense Layers and Classification: Following the convolutional layers, dense layers are employed to further process features extracted from the image. The network concludes with a sigmoid activation function, facilitating binary classification to determine the authenticity of input images.

The generator and discriminator engage in a competitive learning process, characteristic of GANs. While the discriminator aims to differentiate between real and generated images, the generator strives to produce realistic images to deceive the discriminator. This adversarial interplay drives both networks to improve iteratively, resulting in the generation of high-quality super-resolution images. In summary, the SRGAN architecture combines sophisticated generator and discriminator components, each tailored to their respective tasks, to achieve the overarching goal of generating natural-looking super-resolution images with high perceptual quality.

IV. RESULTS AND DISCUSSION

Below are the given input and respective output images after applying the aforementioned pipeline.Execution time is around 1 minute for each image. A video colorization can be implemented by taking each frame and colorizing it which would be a future prospect.





V. CONCLUSIONS

The methodologies explored in this report represent a significant leap forward in the field of image processing powered by deep learning. The autoencoder's ability to decipher and reconstruct clear images from noisy inputs showcases its robustness in extracting essential features and eliminating distortions. Likewise, the Generative Adversarial Network (GAN) framework's prowess in infusing grayscale images with lifelike colors reveals a nuanced understanding of image aesthetics and content enrichment.

The adoption of state-of-the-art architectures like the [11]RTSRGAN for real-time super-resolution (Hu et al., 2019) and the innovative [12] Ensemble of Deep Convolutional Neural Networks for automatic image colorization (Oza et al., 2022) marks a milestone in image enhancement, offering real-time solutions and accurate colorization with multi-level features.

These methodologies collectively highlight deep learning's transformative impact on image quality and its adaptability across a spectrum of image processing challenges.
As technology continues to evolve, these methodologies serve as a testament to the innovative strides made in computer vision and image analysis. They open doors to new possibilities and pave the way for future advancements in enhancing visual content with unparalleled precision and realism.

VI. FUTURE WORK

The methods implemented in the paper can be upgraded to become a complete application for users to restore their personal images. We look forward to equipping our solution with an interactive and easy-to-use UI combined with various other features where users can select the degree of processing their image will go through and choose to omit a stage (ex., Super-resolution) according to their requirement. We can integrate batch processing into the network to allow users to restore multiple images at once. The application is quite versatile and can be used to remove undesired damages to newer pictures as well, such as scratches, stains and discoloration. This would allow the project to be expanded into image enhancing and not be limited to just old image restoration.We also look forward to experimenting with other DL techniques that could improve model performance.

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AMAN DAS:
I have worked on the super-resolution part of the model. I have also contributed to data preparation and cleansing and tuning the model. In the report, I made the abstract, conclusions and part of literature review.

KARTHIK REDDY:
I have worked on the image colorization part of the model and contributed to hypertuning, data augmentation and a minor part in data analysis. In the report I worked on methodology, literature review and results.

HARIKA BOPPANA:
I have worked on building the denoising part of the project and major part of data analysis. In the report I worked on the introduction, acknowledgement, future work and part of literature review.