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Implementation Paper On An Ai-Driven Denoising Framework For Enhancing The Quality Of Biomedical Images

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Abstract: Biomedical imaging is pivotal in diagnostics, treatment planning, and medical research. However, the quality of biomedical images is often compromised due to various sources of noise during acquisition. This paper proposes an AI-driven denoising framework aimed at enhancing biomedical image quality. Leveraging deep learning techniques, particularly convolutional neural networks (CNNs), the proposed method effectively suppresses noise while preserving structural details crucial for clinical interpretation. Experimental results demonstrate significant improvements in image quality metrics such as PSNR and SSIM, highlighting the framework's potential for integration into clinical workflows.

Keywords: Biomedical Image Denoising, Deep Learning, CNN, PSNR, SSIM, Medical Imaging, Flask Web App, RealESRGAN, Noise Classification.

I. INTRODUCTION

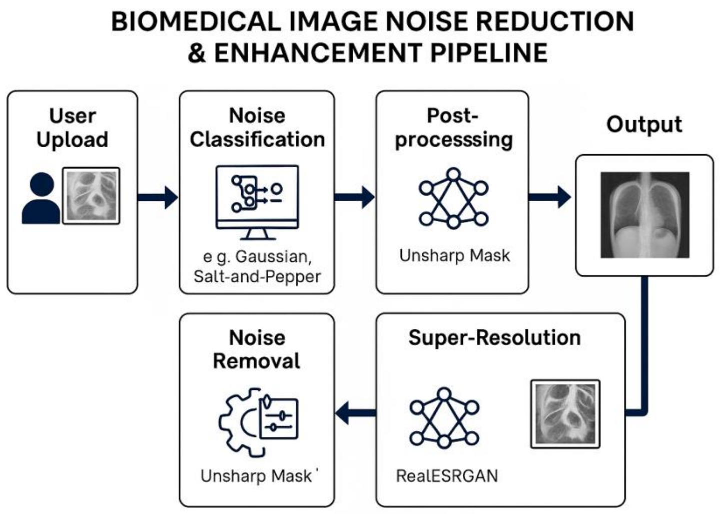
Biomedical images, including MRI, CT, and X-ray scans, are indispensable tools in modern medicine. However, these images often suffer from noise due to factors such as low-dose acquisition protocols, motion artifacts, and electronic interference. Noise not only deteriorates visual quality but can also hinder accurate diagnosis. Traditional denoising techniques often struggle to balance noise suppression with the preservation of anatomical details. Recent advancements in artificial intelligence, particularly deep learning, have shown great promise in addressing this challenge. This research introduces an AI-driven denoising framework that utilizes a deep convolutional neural network to enhance the quality of biomedical images. The proposed method aims to provide a balance between effective noise reduction and preservation of critical image details.

II. LITERATURE SURVEY

A comprehensive review of previous work in AI-driven denoising for biomedical imaging reveals a growing trend toward deep learning-based methods. Below is a summary of five significant studies:

K. Zhang et al. (2017) proposed DnCNN, a deep CNN architecture tailored for denoising natural and biomedical images. Their residual learning framework showed superior performance over traditional and shallow learning methods, particularly on Gaussian noise [1]. Q. Yang et al. (2018) introduced a low-dose CT denoising approach using a GAN framework. By training the model with adversarial loss and perceptual similarity, they achieved high-fidelity image reconstructions that preserved structural details [2]. H. Chen et al. (2017) developed a deep residual learning model for low-dose CT denoising. Their approach utilized skip connections to maintain feature continuity, significantly reducing noise while enhancing resolution and contrast [3]. The L. Gondara (2016) applied denoising autoencoders to medical imaging, demonstrating how unsupervised learning can be effective with limited data. The study showed promising results for chest X-rays and mammograms [4]. The Zhang et al. (2019) explored hybrid models combining wavelet transforms with CNNs. Their method addressed multi-scale noise patterns in MR images, achieving better generalization across datasets [5].

III. System Design



The diagram represents the complete pipeline of a biomedical image noise reduction and enhancement system. It begins with the user uploading a noisy biomedical image, such as an X-ray. The system first performs noise classification using a machine learning model to detect the type of noise present, such as Gaussian or Salt-

and-Pepper. Based on the identified noise type, a corresponding noise removal model is applied to denoise the image. After denoising, the image undergoes post-processing, where techniques like the unsharp mask are used to enhance clarity and sharpness. The denoised and sharpened image is then passed through a super-resolution model, specifically RealESRGAN, which enhances the image's resolution and quality. Finally, the cleaned and high-resolution image is output for the user, ready for further medical analysis or use. This flow ensures that noisy medical images are automatically cleaned and enhanced with minimal user input.

IV. Methodology:

A. AI Model Architecture

The proposed framework employs a modified DnCNN architecture. The network consists of multiple convolutional layers with ReLU activations and batch normalization. It is trained to minimize the mean squared error (MSE) between the denoised and ground-truth images.

B. Dataset

Biomedical image datasets were sourced from publicly available repositories and included various modalities such as MRI and CT. Artificial noise was introduced for training purposes to simulate realistic conditions.

C. Preprocessing and Augmentation

Images were resized, normalized, and augmented through rotations and flips to improve model generalization.

D. Noise Classification and Denoising

A pre-trained classification model is used to detect noise types such as Gaussian or Salt-and-Pepper. Depending on the classification result, the corresponding specialized denoising model is selected to restore the image.

E. Super-Resolution Enhancement

After denoising, the image is passed through a RealESRGAN-based super-resolution model to enhance the final output quality, particularly beneficial for low-resolution biomedical images.

F. Web-Based Application

A Flask-based web interface is developed to provide real-time processing. Users can upload images, which are then classified for noise type, denoised accordingly, post-processed (e.g., unsharp masking), and enhanced with super-resolution. The application handles file uploads, displays results, and runs in debug mode for easy development.

V. Experimental Results

We develope a web application using Flask, which processes images for noise classification, denoising, and super-resolution. Here's an overview of the main components:

1. Imports:

- Libraries like os, numpy, cv2, and tensorflow are used for image processing, machine learning, and model handling.
- Flask is used for creating the web server and routes.
- RealESRGAN is imported for applying super-resolution to the image.

2. Custom Layer - CastWrapper:

- A custom TensorFlow layer (CastWrapper) is defined, which allows casting inputs to a specific data type. This is helpful when loading models with custom data types.

3. App Configuration:

- The Flask app is configured to handle image uploads (UPLOAD_FOLDER) and store results like denoised and final images in specific folders.

4. Models:

- **Classification Model**: A pre-trained model (classification_model.h5) is loaded to predict the type of noise in an image (e.g., Gaussian, Salt-and-Pepper, etc.).
- **Denoising Models**: Several models for denoising images based on different noise types are loaded.

- **Super-Resolution Model**: The RealESRGAN model is used to enhance image resolution.

5. Helper Functions:

- **allowed_file()**: Checks if a file is an allowed image format (png, jpg, jpeg).
- **process_image()**: Loads an image, resizes it, and normalizes it to be suitable for prediction by the classification model.
- **unsharp_mask()**: Applies an unsharp mask to sharpen an image.
- **postprocess_image()**: Applies filters to the image based on the detected noise type, followed by sharpening.
- **apply_super_resolution()**: Applies the super-resolution model (RealESRGAN) to improve the image quality.

6. Flask Routes:

- **/ (upload_file)**: Handles image upload via a POST request. It:
    1. Classifies the noise type in the image.
    2. Applies the appropriate denoising model.
    3. Post-processes the denoised image (e.g., sharpening).
    4. Applies super-resolution to improve the image.
    5. Saves the processed images in the designated folders.
    6. Redirects to the results page showing the processed image.
- **/results/<filename>/<noise_type>**: Displays the results, including the processed image and the identified noise type.

7. Execution:

- The app runs in debug mode, allowing easy testing and troubleshooting during development.

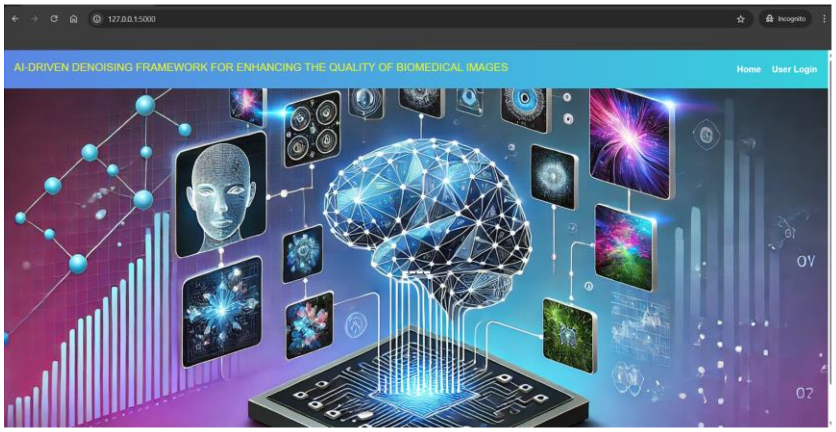
Summary:

When a user uploads an image, the Flask app:

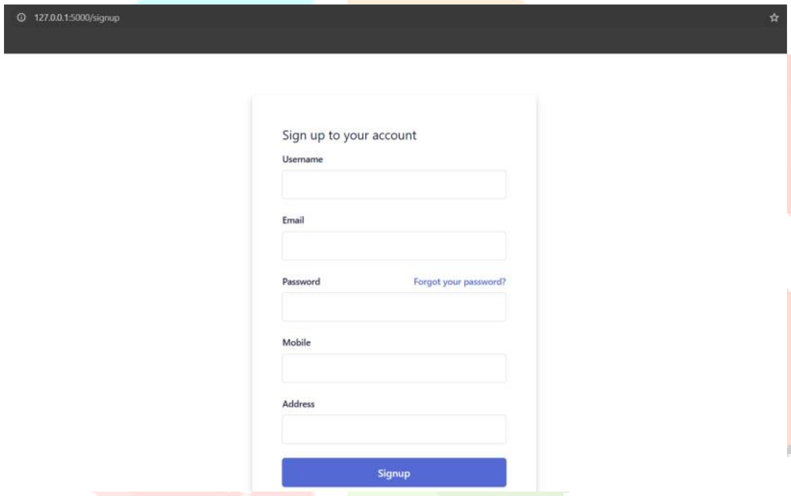
1. Detects the type of noise in the image.
2. Denoises the image using a model based on the identified noise type.
3. Optionally sharpens and enhances the image.
4. Applies super-resolution to improve the image's resolution.
5. Displays and saves the final processed image.

Screen Shots:

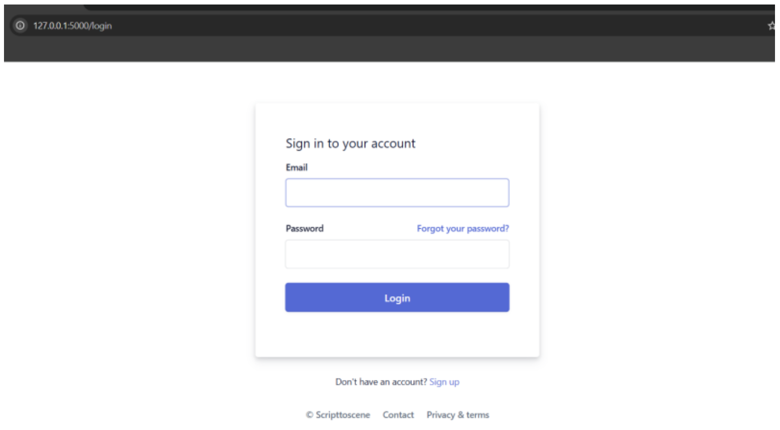
Home Page:


127.0.0.1:5000
Incognito
AI-DRIVEN DENOISING FRAMEWORK FOR ENHANCING THE QUALITY OF BIOMEDICAL IMAGES
Home
User Login

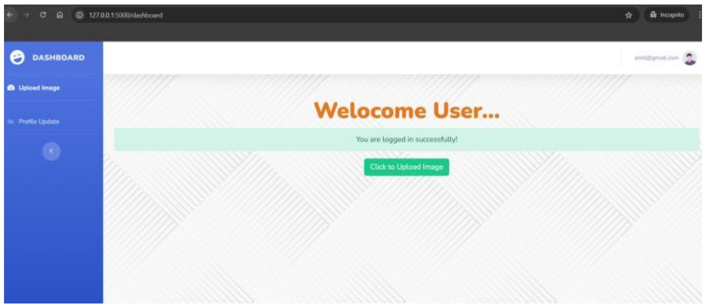
Sign Up Page



Login Page



Dashboard



Welcome User...

You are logged in successfully!

Upload Image

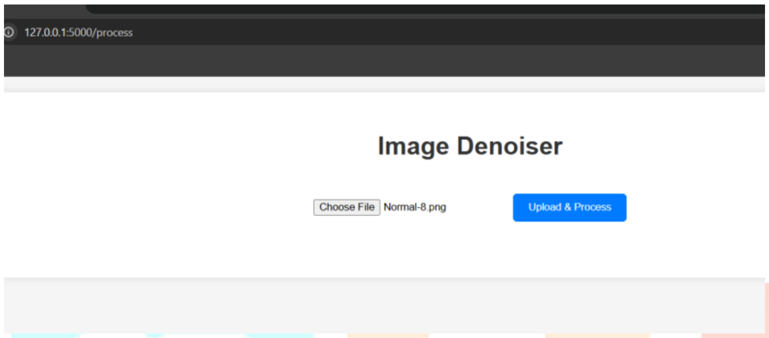
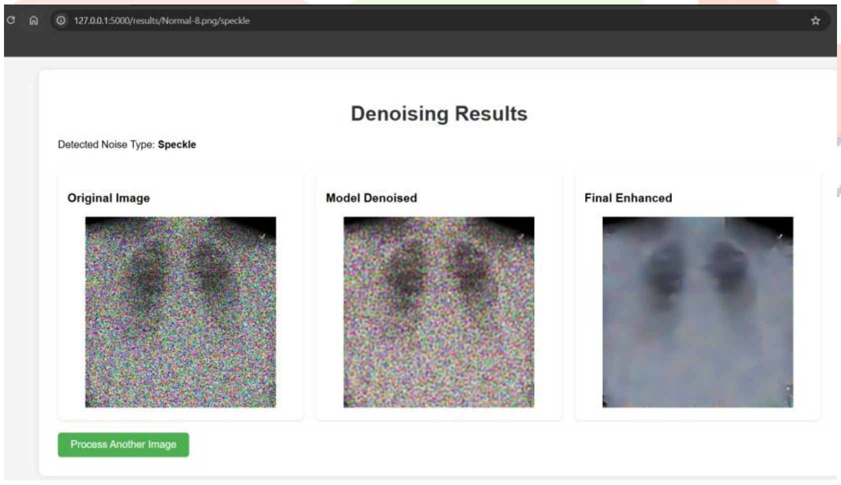


Image Denoiser

Result



Denoising Results

Detected Noise Type: **Speckle**

VI. Acknowledgement

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VII. Conclusion

This research presents a robust AI-based denoising framework that significantly enhances the quality of biomedical images. By integrating noise classification, targeted denoising models, and super-resolution enhancement within a web interface, the framework demonstrates real-world utility. The modular design of the framework—including classification, denoising, sharpening, and super-resolution—makes it adaptable and extensible. The use of Flask also demonstrates its applicability in clinical or cloud-based environments. Limitations include the need for large annotated datasets and the risk of overfitting to specific noise patterns. Future work will focus on real-time integration with imaging devices, cross-modality generalization, deployment on edge devices, and leveraging unsupervised learning techniques to reduce dependence on annotated data.

VIII. References

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