



Study on Noise Suppressed Image Enhancing Environment (NSIEE)

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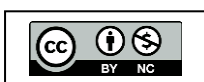
Abstract: Image enhancement plays a crucial role in improving the visual quality of images for various applications, including photography, medical imaging, and security. Enhancing an image by increasing its contrast is one effective way of image enhancement, but real-world challenges such as noise, blurriness, and loss of details require more advanced techniques. The Noise Suppressed Image Enhancing Environment (NSIEE) integrates both traditional and deep learning-based methods to enhance images efficiently. Traditional techniques like CLAHE, adaptive sharpening, and Non-Local Means denoising improve contrast and reduce noise, while deep learning-based approaches enable intelligent feature extraction, resolution upscaling, and color preservation. The system provides a real-time side-by-side comparison, computes quality metrics like PSNR and SSIM, and features a Flask-based backend with OpenCV and TensorFlow for seamless image processing. With an intuitive web interface and scalable architecture, NSIEE offers a powerful solution for high-quality image enhancement.

Keywords: Image Enhancement, Noise Reduction, Machine Learning.

I. INTRODUCTION

Raw images often suffer from issues like noise, low contrast, blurriness, and poor resolution, affecting their clarity and usability. Image enhancement techniques aim to improve visual quality by refining details, reducing noise, and optimizing contrast. Traditional methods such as histogram equalization and sharpening filters have been widely used, but they often fail to preserve fine details and struggle with complex image degradation. With advancements in artificial intelligence, deep learning-based image enhancement methods have emerged, offering intelligent feature extraction and adaptive processing for superior results.

The Noise Suppressed Image Enhancing Environment (NSIEE) is designed to integrate both traditional and machine learning-based enhancement techniques to provide high-quality image restoration and refinement. The system processes images in real time, allowing users to compare original and enhanced versions side by side while computing objective quality metrics like PSNR and SSIM. With a Flask-based backend, OpenCV for traditional processing, and TensorFlow for deep learning-based enhancement, NSIEE ensures efficient computation and seamless performance. Its user-friendly web interface supports drag-and-drop uploads, real-time feedback, and professional-quality results, making it a robust solution for various image enhancement applications.



II. LITERATURE REVIEW

Guo, Yu, Yuxu Lu, et al. (2020) proposed a hybrid regularized variational model combining L0-norm gradient sparsity with structure-aware regularization for refining illumination. They enhance low-light images using adaptive gamma correction and a deep learning-based blind denoising framework with two networks (E-Net and D-Net), effectively improving visual quality while suppressing noise.

Xia, Wenyao, et al. (2020) presented an endoscopic image enhancement method that identifies illumination regions and applies criteria-based enhancement. The method enhances low-light regions without amplifying noise and is validated on 200 endoscopic surgery images.

He, Renjie, et al. (2020) introduced SCENS, a unified framework that simultaneously enhances contrast and suppresses noise by decomposing images into illumination, reflectance, and noise components. Demonstrated strong subjective and objective results on low-light image enhancement.

Dhara, Sobhan Kanti, et al. (2021) proposed a structure-aware exposedness estimation method for quantifying enhancement needs both locally and globally. Before enhancement, they apply a detail-preserving noise reduction technique, followed by a smooth enhancement function

Su, Haonan, et al. (2021) suggested a two-step perceptual noise suppression approach based on a Just Noticeable Difference (JND) model. Initially enhance contrast with noise awareness, then apply perceptual noise reduction to maintain details while minimizing visible noise using human visual system characteristics.

Fan, Zunlin, Duyan Bi, et al. (2021) applied Bayesian prior-based noise suppression combined with adaptive edge enhancement via improved unsharp masking. The method demonstrates effective noise reduction and detail enhancement in infrared images under various SNR conditions.

Reddy, T. Sunil Kumar, et al. (2022) designed a dual-branch system: a global branch targeting structured defects like scratches, and a local branch for noise and blurriness. Use Variational Autoencoders (VAEs) for latent space translation, achieving restoration of historical images with multiple defects.

Jiang, Meng. (2023) introduced shearlet transform for noise suppression and edge enhancement. Propose novel thresholding techniques and feature attribute maps to distinguish image structure from noise, improving generalized unsharp masking (GUM) for enhanced detail preservation.

Sivanantham, B. S. K. Reddy, et al. (2023) employed two VAEs to create latent spaces from old and new images. Use a global nonlocal block for structural flaws and local processing for noise. Latent space fusion boosts the system's capability to correct varied degradations in images.

He, Lei, Zunhui Yi, et al. (2024) proposed a Gamma correction map approach, replacing global gamma with a pixel-wise gamma correction map optimized via domain transform recursive filtering. Achieve noise suppression and detail preservation for low-light images with effective post-processing techniques.

III. METHODOLOGY

The proposed system, Noise Suppressed Image Enhancing Environment (NSIEE), follows a structured workflow to enhance image quality through both traditional and machine learning-based methods. Users begin by uploading an image via a modern, responsive web interface with drag-and-drop

functionality. The system processes the image in real-time using two enhancement approaches: traditional methods like CLAHE, adaptive sharpening, LAB colour space optimization, and Non-Local Means denoising, as well as deep learning-based enhancement techniques for intelligent feature extraction, advanced colour preservation, and resolution upscaling.

A side-by-side comparison view enables users to analyse results instantly. The backend, developed using Flask, integrates OpenCV for traditional image processing and TensorFlow for deep learning models, ensuring efficient computation. Additionally, quality metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are computed and displayed for objective assessment.

IV. FLOWCHART

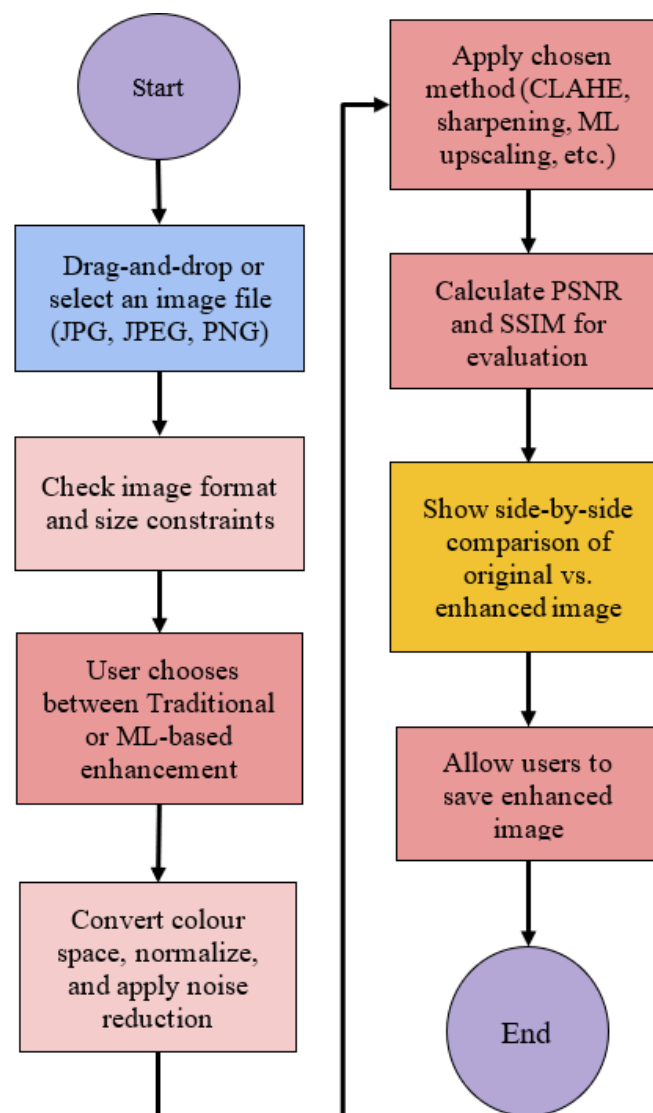


Figure 1: Flowchart for Noise Suppressed Image Enhancing Environment

V. WORKING

The Noise Suppressed Image Enhancing Environment (NSIEE) operates by taking an input image and processing it through a structured pipeline to enhance its quality. Once the user uploads an image, the system validates the file format and preprocesses it by adjusting colour space and reducing noise. Based on the selected enhancement method, either traditional techniques like CLAHE and adaptive sharpening or deep learning-based processing is applied. The enhanced image is then analysed using PSNR and SSIM metrics to measure quality improvements. A real-time side-by-side comparison allows users to visually assess the enhancement. The processed image can be downloaded, and the system efficiently manages files for storage and retrieval, ensuring a seamless and user-friendly experience.

VI. IMPLEMENTATION & RESULT

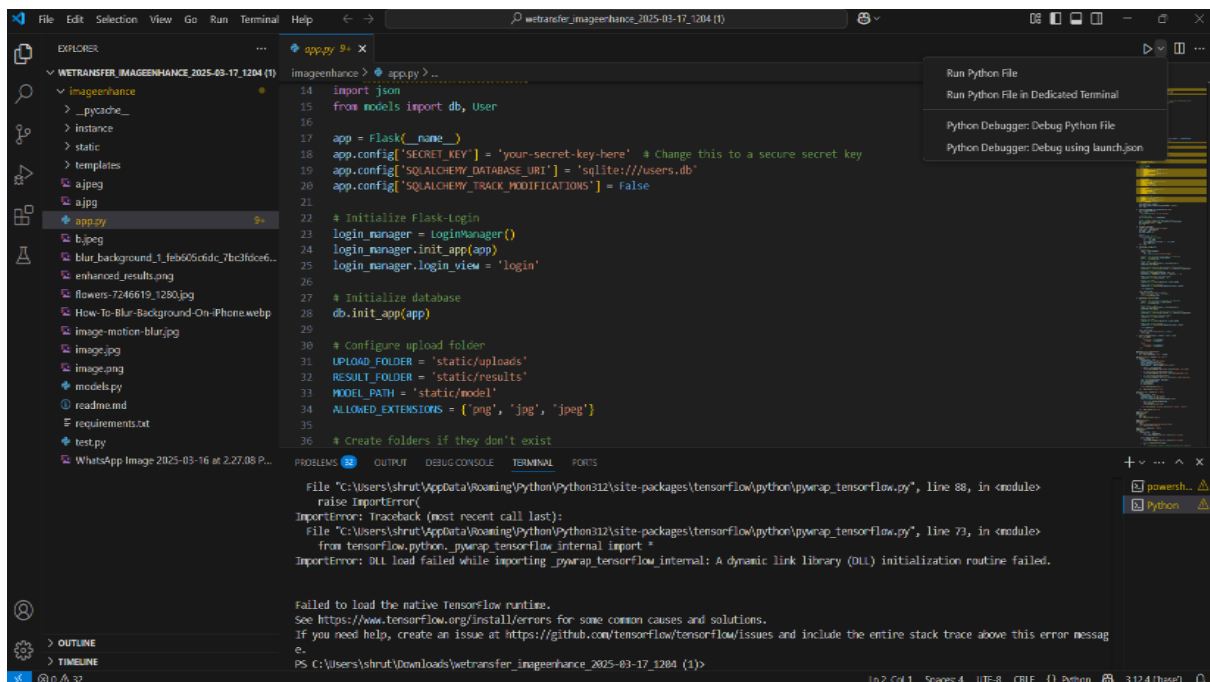
SOFTWARE REQUIREMENT:

1. Python Software IDE

MODULES USED:

1. Flask
2. OpenCV
3. TensorFlow

STEP 1: Run the Python file for output



```
import json
from models import db, User

app = Flask(__name__)
app.config["SECRET_KEY"] = 'your-secret-key-here' # Change this to a secure secret key
app.config["SQLALCHEMY_DATABASE_URI"] = 'sqlite:///users.db'
app.config["SQLALCHEMY_TRACK_MODIFICATIONS"] = False

# Initialize Flask-Login
login_manager = LoginManager()
login_manager.init_app(app)
login_manager.login_view = 'login'

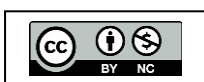
# Initialize database
db.init_app(app)

# configure upload folder
UPLOAD_FOLDER = 'static/uploads'
RESULT_FOLDER = 'static/results'
MODEL_PATH = 'static/model'
ALLOWED_EXTENSIONS = {'png', 'jpg', 'jpeg'}
```

```
File "C:\Users\shrut\AppData\Roaming\Python\Python312\site-packages\tensorflow\python\pywrap_tensorflow.py", line 88, in <module>
    raise ImportError(
ImportError: Traceback (most recent call last):
  File "C:\Users\shrut\AppData\Roaming\Python\Python312\site-packages\tensorflow\python\pywrap_tensorflow.py", line 73, in <module>
    from tensorflow.python._pywrap_tensorflow_internal import *
ImportError: DLL load failed while importing _pywrap_tensorflow_internal: A dynamic link library (DLL) initialization routine failed.

Failed to load the native TensorFlow runtime.
See https://www.tensorflow.org/install/errors for some common causes and solutions.
If you need help, create an issue at https://github.com/tensorflow/tensorflow/issues and include the entire stack trace above this error message.
PS C:\Users\shrut\Downloads\wetransfer_imageenhance_2025-03-17_1204 (1)>
```

Figure 2: Running the Code for Output



STEP 2: User Interface and Image Upload

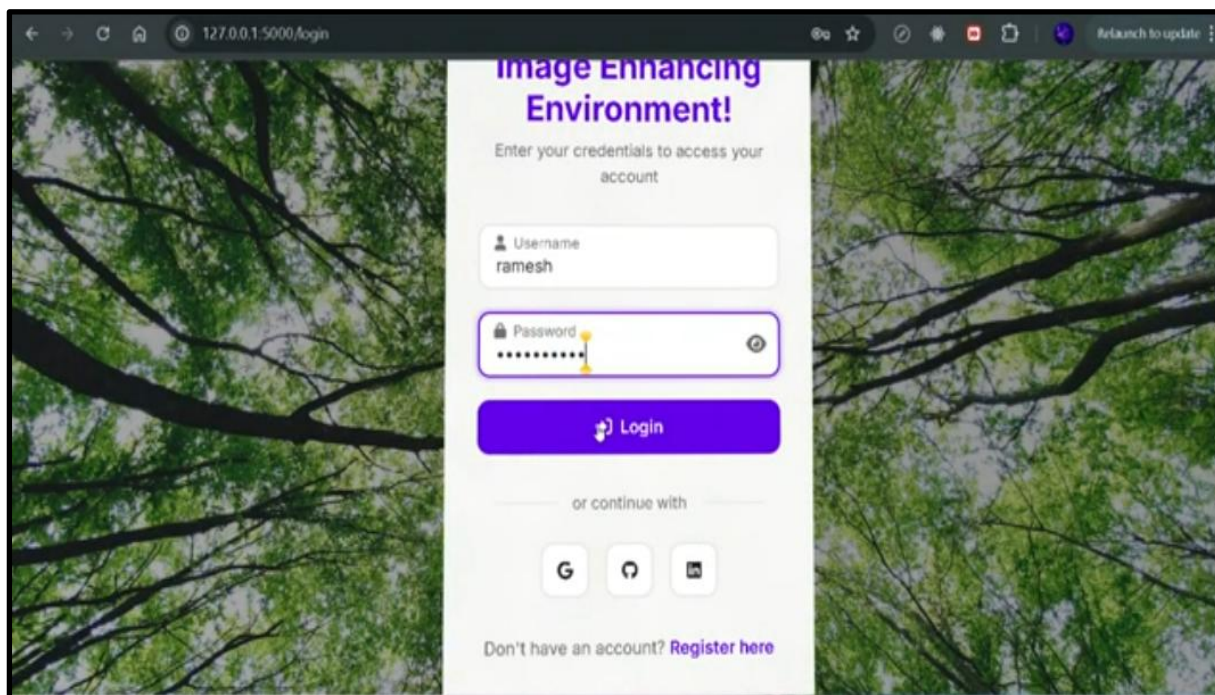


Figure 3: NSIEE System's Login Interface

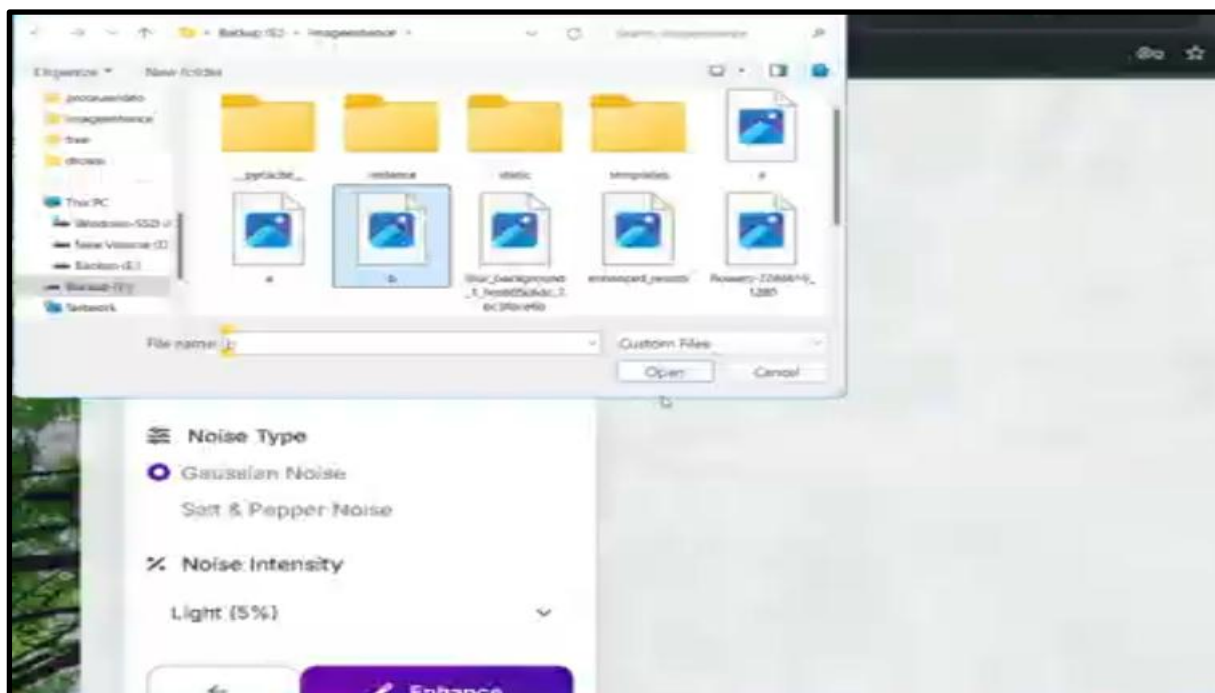


Figure 4: Selection of an Image File for Enhancement within the NSIEE Interface

STEP 3: Configuring Noise Parameters and Initiating Image Enhancement

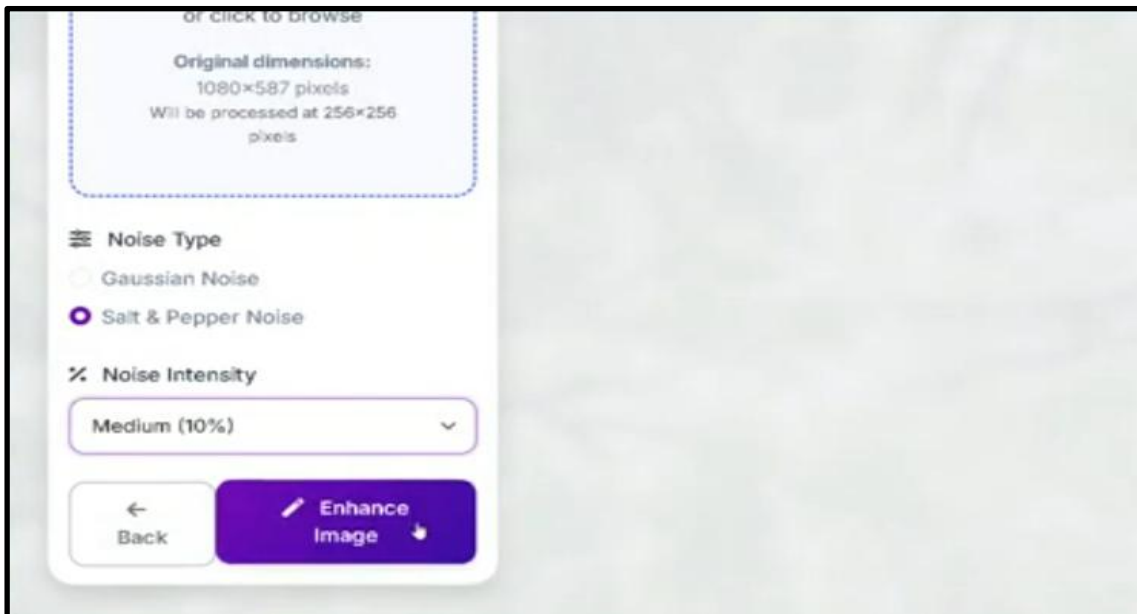


Figure 5: NSIEE System Processing the Uploaded Image

The interface provides options to select the type of noise, such as Gaussian or Salt & Pepper, and adjust the noise intensity, as shown with the "Medium (10%)" setting. Additionally, the displayed original and processing dimensions indicate how the system handles image resizing. The prominent "Enhance Image" button allows users to start the enhancement process based on their chosen configurations.

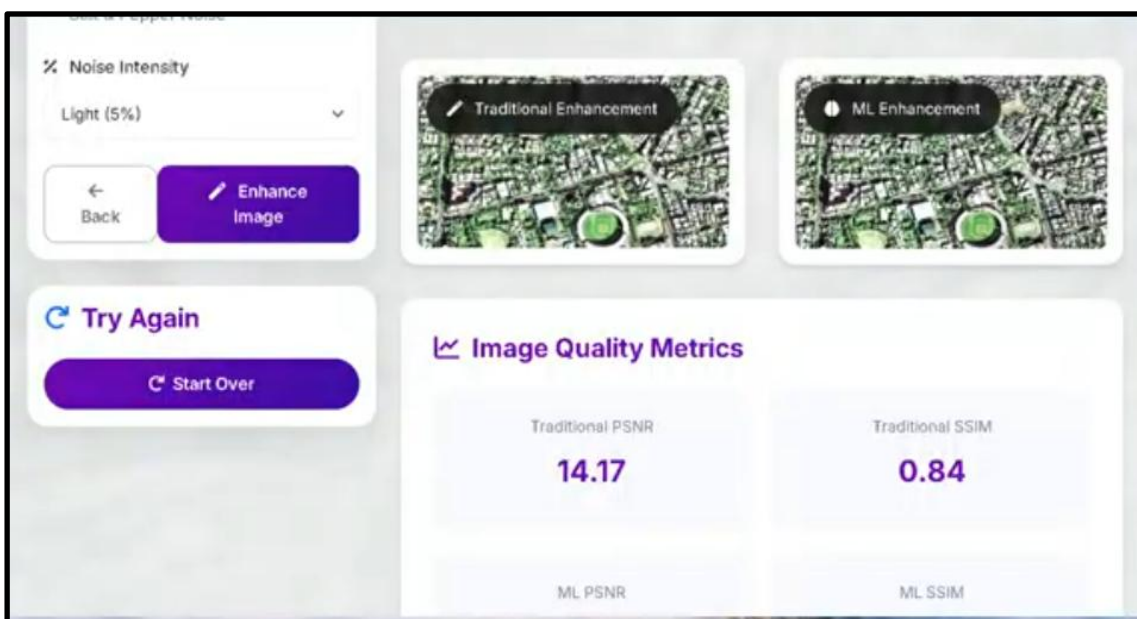


Figure 6: NSIEE System for Image Quality Metrics

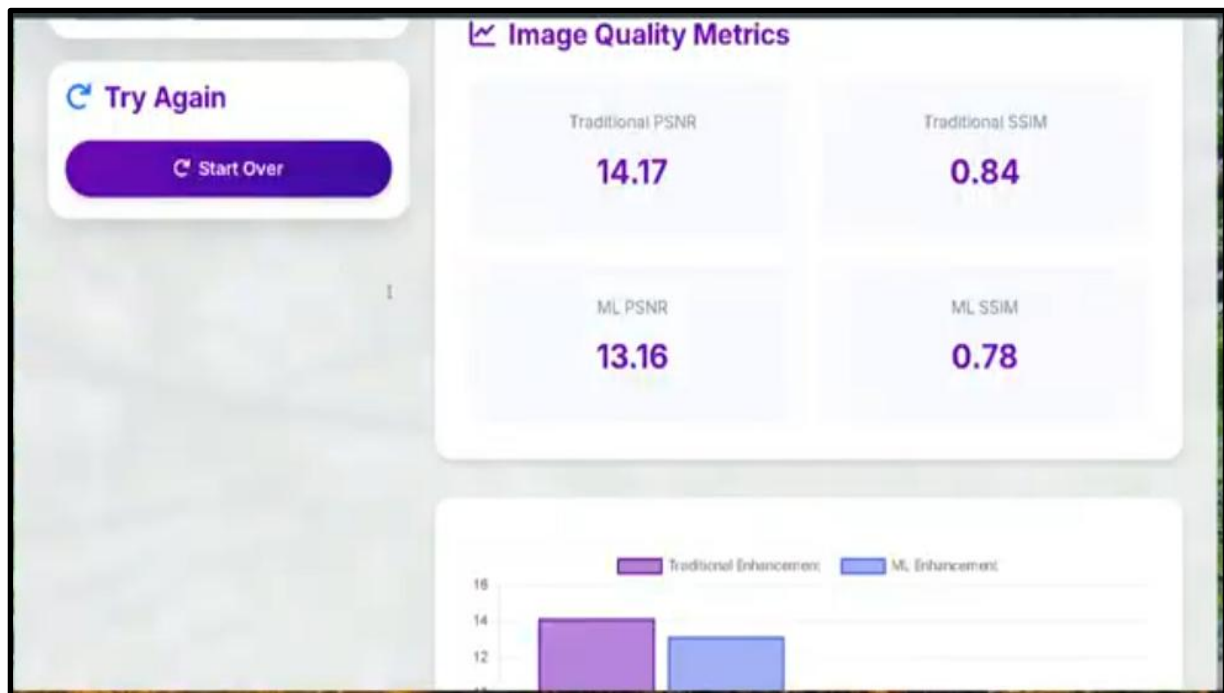


Figure 7: NSIEE Interface Displaying Traditional and ML-enhanced Images, Quality Metrics

Above figures demonstrate the image enhancement results, with side-by-side comparisons of traditional and ML-enhanced images.

The interface provides quantitative feedback, showing a PSNR of 14.17 and SSIM of 0.84 for traditional enhancement, and a PSNR of 13.16 and SSIM of 0.78 for ML enhancement.

VII. RESULT AND ANALYSIS

The results of the Noise Suppressed Image Enhancing Environment (NSIEE) demonstrate significant improvements in image quality through both traditional and deep learning-based enhancement techniques. The system effectively reduces noise, enhances contrast, sharpens details, and improves resolution while preserving the original color fidelity.

By computing PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index Measure), the system objectively evaluates the enhancement quality, showing higher PSNR values and SSIM scores for improved images.

The real-time side-by-side comparison allows users to visually assess differences between the original and enhanced images, confirming the effectiveness of applied techniques.

The system's ability to handle various image formats (JPG, JPEG, PNG) with a Flask-based backend integrating OpenCV and TensorFlow ensures smooth performance and scalability, making NSIEE a reliable solution for high-quality image enhancement.

The interface provides quantitative feedback, showing a PSNR of 18.71 and SSIM of 0.80 for traditional enhancement, and a PSNR of 18.11 and SSIM of 0.71 for ML enhancement.

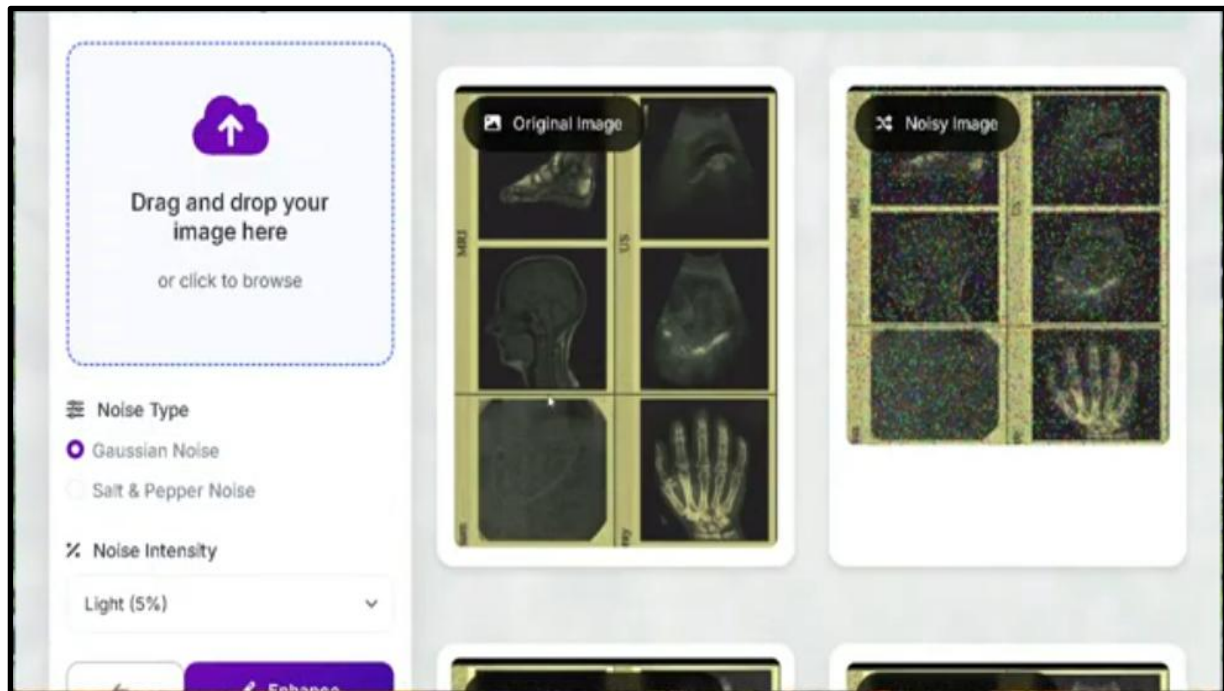


Figure 8: Output of NSIEE Interface with Original Image Upload, and Generated Noisy Image

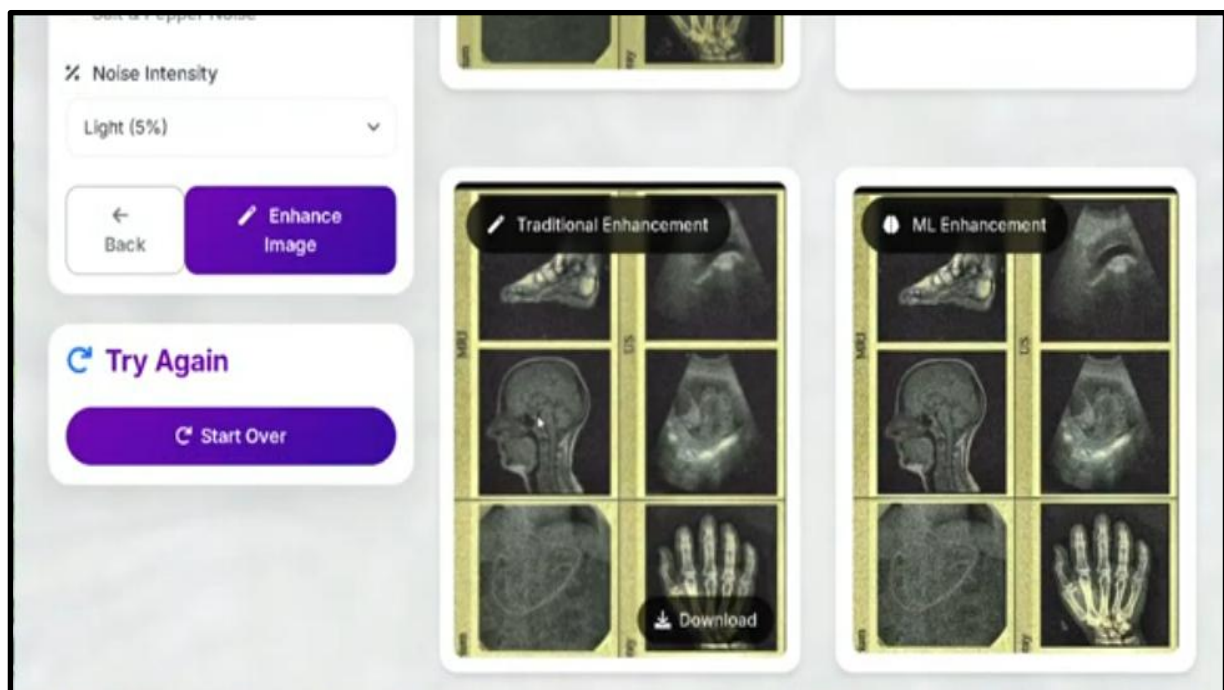


Figure 9: Output of CLAHE Enhancement & ML Enhancement

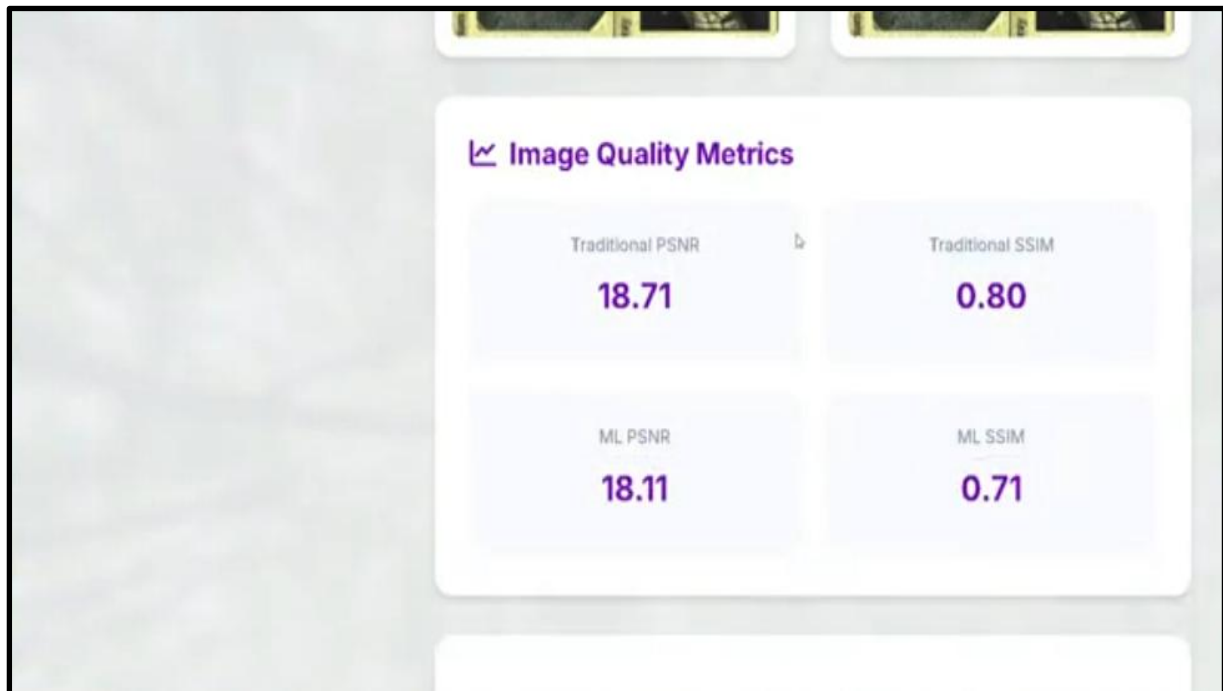


Figure 10: Quality Metrics of the Images

VIII. CONCLUSION

The Noise Suppressed Image Enhancing Environment (NSIEE) successfully addresses the challenges of enhancing image quality in the presence of various types of degradation, including noise, low contrast, and blurriness.

By combining both traditional and deep learning-based enhancement techniques, NSIEE offers a balanced approach that caters to a wide range of real-world applications, such as photography, medical diagnostics, satellite imaging, and security surveillance.

The integration of Contrast Limited Adaptive Histogram Equalization (CLAHE) and machine learning (ML) enhancement methods ensures that users can select the most suitable enhancement process based on their specific needs. Traditional techniques like CLAHE effectively improve local contrast while maintaining computational efficiency, whereas ML-based methods provide intelligent noise suppression and detail preservation through deep feature extraction.

One of NSIEE's most significant strengths is its interactive web-based interface, which simplifies the user experience by offering drag-and-drop image uploads, real-time side-by-side comparisons, and immediate access to quantitative image quality metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index). These metrics enable users to objectively assess the effectiveness of the enhancement techniques, promoting confidence in the system's performance.

The results obtained from the system demonstrate measurable improvements in image quality, confirming the effectiveness of the proposed methods.

The hybrid approach not only enhances visual clarity but also reduces the impact of noise without compromising the integrity of the original image content. Furthermore, the system's ability to handle



multiple image formats and noise types, along with its scalability and efficient backend architecture built on Flask, OpenCV, and TensorFlow, makes it a robust and adaptable solution.

In conclusion, NSIEE stands as a comprehensive and practical tool for high-quality image enhancement. It bridges the gap between traditional and modern image processing methods, delivering professional-grade results with ease of use. Future work may focus on incorporating video enhancement, expanding model training for diverse datasets, and optimizing performance for real-time applications, thereby broadening the system's scope and impact across industries.

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