20PCSE59J

Image Processing Techniques

Mini Project

Inference Report

Task 1:

Problem Definition:

Choose your desired color image, convert it to a black-and-white (BW) image, and apply any four image enhancement techniques. Also, write your inference.

Methodology (Techniques, Models, Tools Used):

Tools Used:

- Python
- OpenCV
- NumPy
- Matplotlib
- scikit-image
- scikit-learn

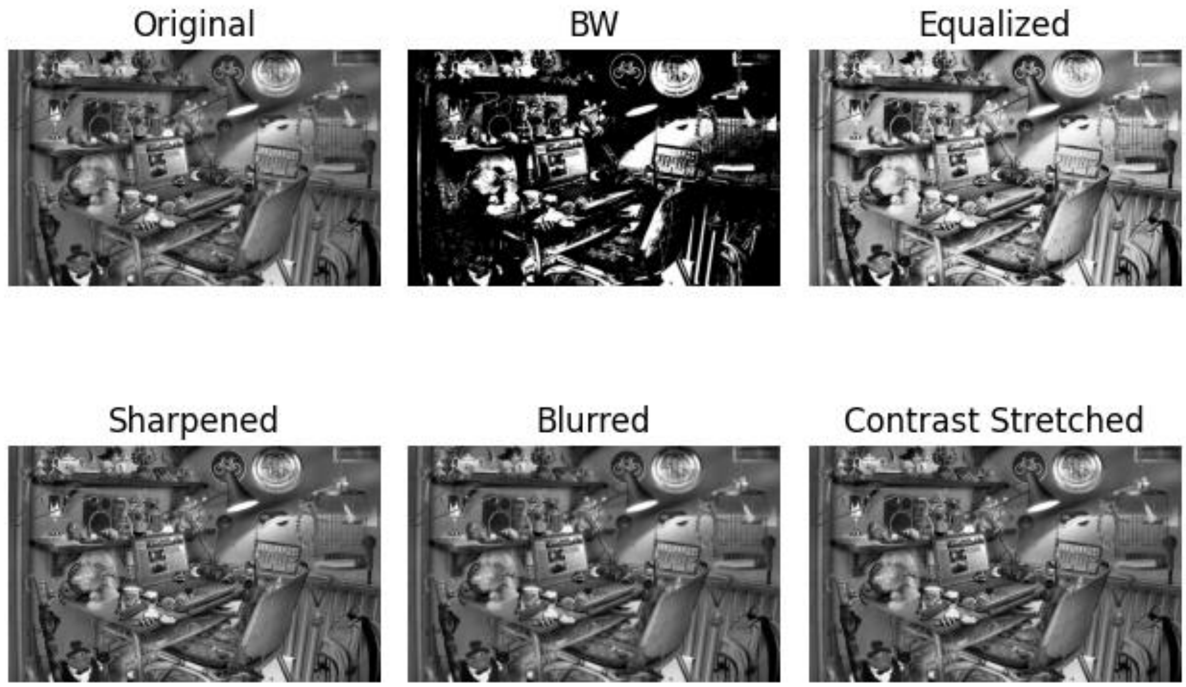
Used OpenCV for:

- Grayscale conversion
- Binary thresholding
- Histogram equalization
- Sharpening filter
- Gaussian blurring
- Contrast stretching

Data Description and Preprocessing Steps:

A color image was chosen and transformed into grayscale. Noisy areas and lighting variations were treated using various enhancement operations to ready the image for segmentation or analysis.

Results:



Inference:

- **Histogram Equalization:** Improved overall contrast
- **Sharpening:** Highlighted edges and fine structures
- **Gaussian Blur:** Reduced noise but slightly blurred details
- **Contrast Stretching:** Boosted intensity range and highlighted low-contrast regions

Task 2:

Problem Definition:

Select any noisy image, apply filters to remove the noise. Using the same image, apply a Fourier transform and implement Ideal High Pass (IHP), Ideal Low Pass (ILP), and Butterworth Pass (BP) filters.

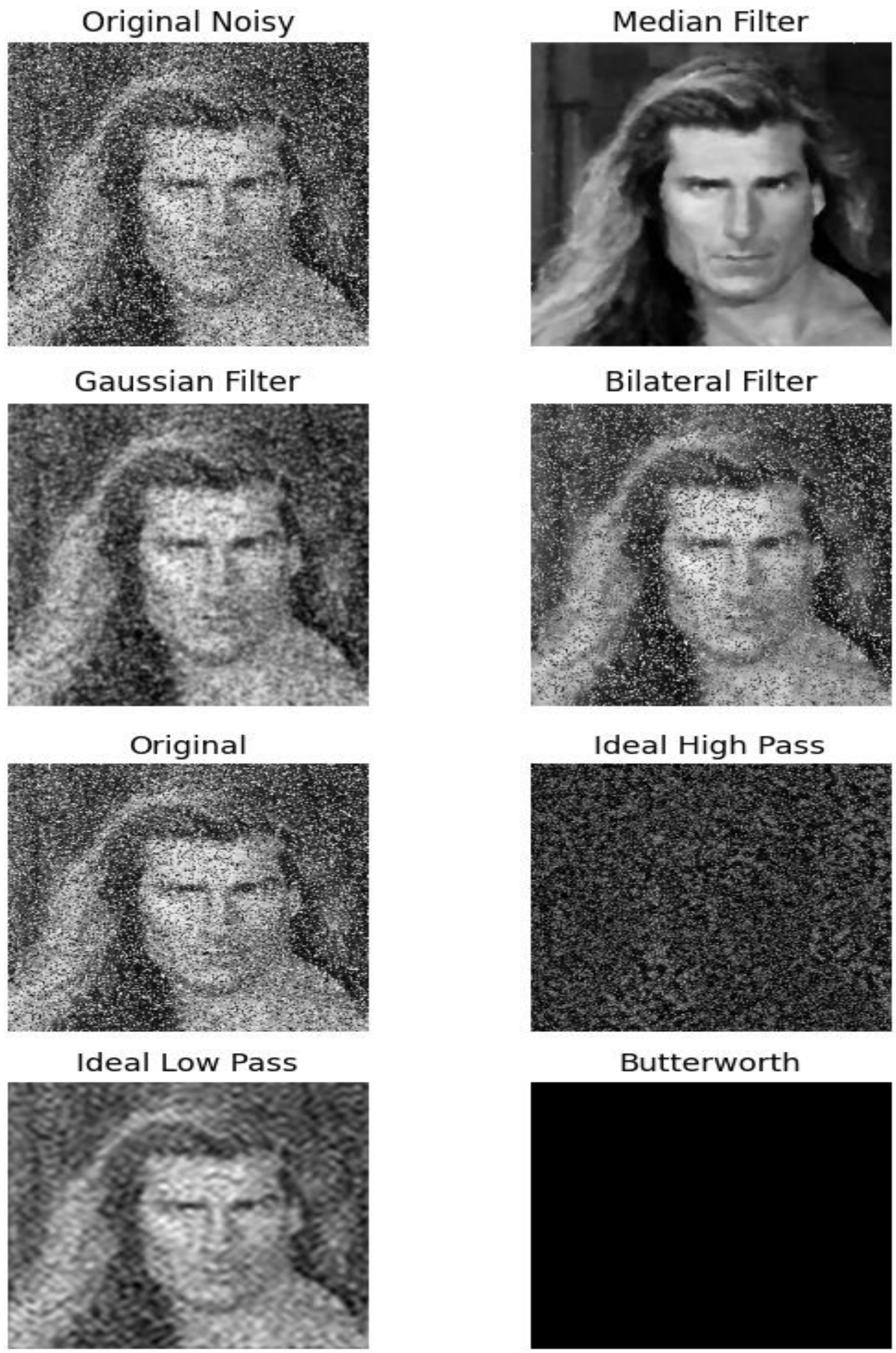
Methodology (Techniques, Models, Tools Used):

- **Spatial Filtering:** Median, Gaussian, Bilateral
- **Frequency Domain:** FFT with Ideal High Pass (IHP), Ideal Low Pass (ILP), Butterworth filters

Data Description and Preprocessing Steps:

A noisy grayscale image was selected. Spatial filters were applied to denoise, followed by FFT and masking to apply frequency domain filtering.

Results:



Inference:

- **Median Filter:** Best at removing salt-and-pepper noise
- **Gaussian:** Smoothed noise but blurred edges
- **Bilateral:** Preserved edges while reducing noise
- **IHP:** Enhanced edges but retained high-frequency noise
- **ILP:** Smoothed image but removed detail
- **Butterworth:** Initial output was blank due to mask errors; fixed by tuning cutoff and normalization

Task 3:

Problem Definition:

Choose any image and apply image segmentation techniques such as Thresholding and Clustering. Additionally, perform Morphological Operations over it.

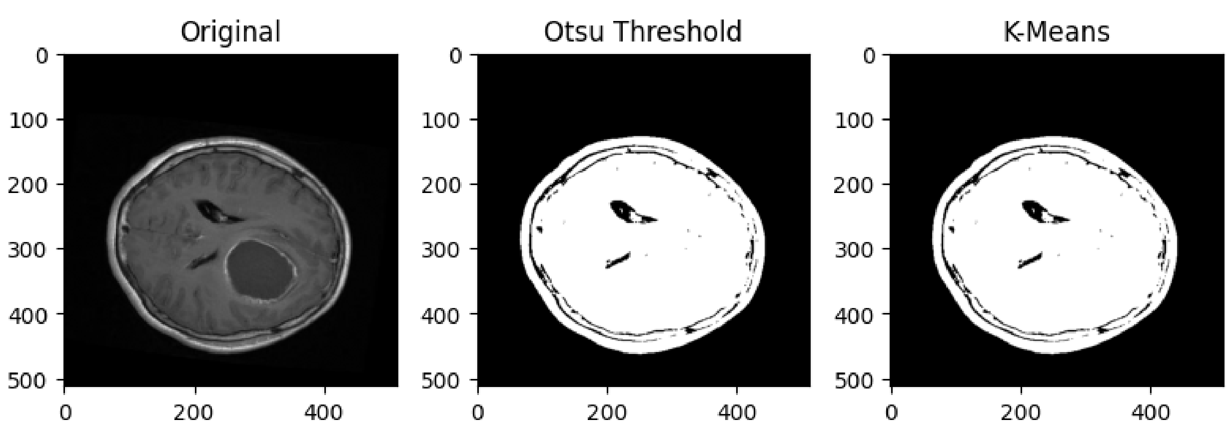
Methodology (Techniques, Models, Tools Used):

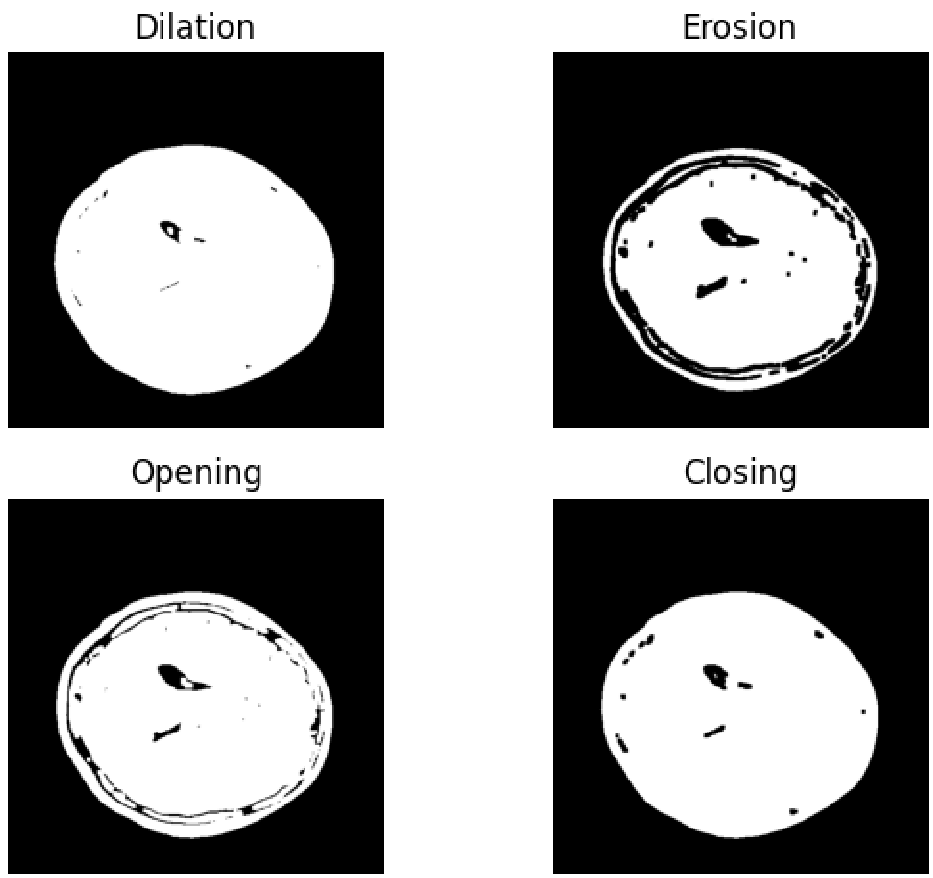
- Otsu Thresholding
- K-Means Clustering
- Morphological Operations: Dilation, Erosion, Opening, Closing (OpenCV)

Data Description and Preprocessing Steps:

A grayscale brain MRI image was used. Segmentation was done using Otsu and K-Means. Morphological operations refined the binary masks by removing noise and closing gaps.

Results:





Inference:

- K-Means provided clearer clusters than Otsu
- Dilation provided Expanded region boundaries
- Erosion removed small noise
- Opening smoothed object edges
- Closing filled internal holes

Task 4:

Problem Definition:

Classify MRI images of brain tumors into three categories using extracted structural and textural features.

Methodology (Techniques, Models, Tools Used):

- **Feature Extraction:** Connected components (structural), GLCM (textural)
- **Model:** Random Forest Classifier (scikit-learn)
- **Tools:** OpenCV, scikit-image, Pandas, NumPy, TQDM

Data Description and Preprocessing Steps:

Dataset: Bangladesh Brain Cancer MRI Dataset

6056 images across 3 classes:

- Brain_Glioma (2004)
- Brain_Menin (2004)
- Brain_Tumor (2048)

Preprocessing:

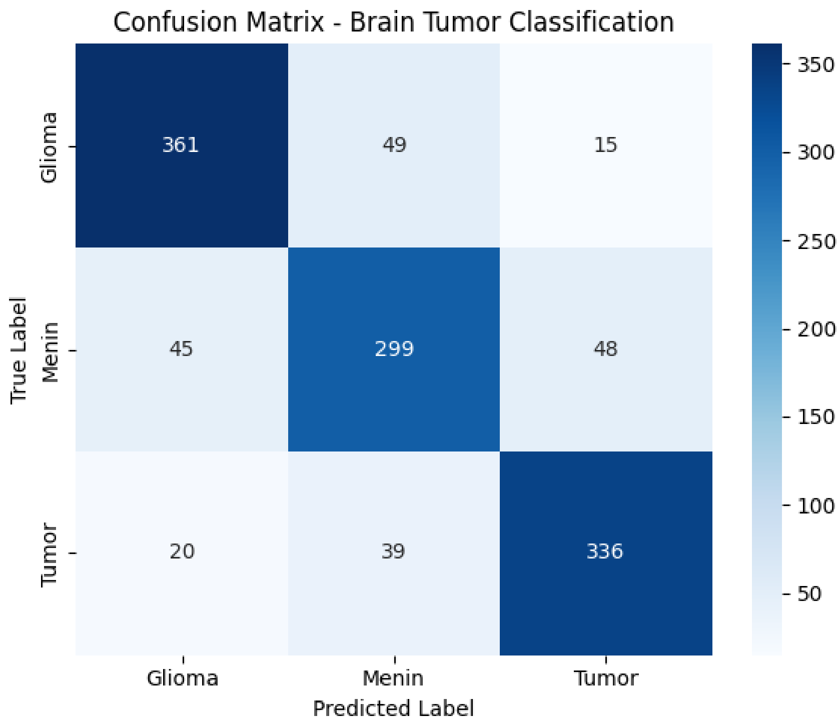
- Resize to 256×256
- Convert to grayscale
- Extract 10+ features per image
- Label and compile into a DataFrame

Results:

```
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.85      0.85       425
           1       0.77      0.76      0.77       392
           2       0.84      0.85      0.85       395

    accuracy                           0.82      1212
   macro avg       0.82      0.82      0.82      1212
weighted avg       0.82      0.82      0.82      1212
```



Inference and Evaluation Metrics:

Accuracy: 82%

Classification Report Highlights:

- **Glioma:** Precision 0.85, Recall 0.85
- **Menin:** Precision 0.77, Recall 0.76
- **Tumor:** Precision 0.84, Recall 0.85

Confusion Matrix:

- Menin class showed overlap with Tumor
- Glioma and Tumor were well classified

Challenges Faced and How They Were Addressed:

- Faced Memory errors on Google Colab. Resolved with image resizing
- GLCM feature extraction was slow. It was resolved using batch processing

Conclusion:

Random Forests yielded solid performance from extracted features.

Future Improvements:

- Switch to CNNs for better feature learning
- Use transfer learning (e.g., ResNet, VGG)
- Add explainability (Grad-CAM)
- Deploy as a diagnostic support tool