Frequency-Domain Feature Extraction Using FFT for X-ray Image Classification

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Introduction

- **Importance:** Accurate X-ray classification is critical for timely medical diagnosis (e.g., pneumonia, fractures).
- **Challenges:** Presence of noise, low contrast, and subtle anatomical variations.
- **Proposed Approach:** Use FFT-based frequency-domain feature extraction coupled with machine learning classifiers.

Objective

- To extract discriminative features from X-ray images using **FFT**.
- Enhance image contrast using **histogram equalization**.
- Derive **statistical descriptors** (energy, entropy, frequency coefficients) from frequency domain.
- Classify images with **SVM**, **Random Forest**, and **Gradient Boosting** algorithms.

Histogram Equalization Transformation:

- Redistributes pixel intensities to enhance image contrast:

$$s = (L-1) \times \sum_{k=0}^{r} p_r(r_k)$$

Preprocessing - Histogram Equalization

- **Purpose:** Improve visibility of structures by enhancing contrast.
- **Effect:** Facilitates better pattern detection in spatial and frequency domains.
- **Mathematical Definition:** Cumulative distribution function (CDF) transformation:

$$s = T(r) = \int_0^r p_r(w)\, dw$$

Frequency-Domain Conversion with FFT

- **Fast Fourier Transform (FFT):** Converts image from spatial domain to frequency domain.
- **Output:** Complex coefficients representing amplitude and phase of frequency components.

2D FFT Formula:

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)}$$

Magnitude Spectrum & Feature Extraction

- **Magnitude Spectrum:** Measures strength of each frequency component:

$$|F(u,v)| = \sqrt{\mathrm{Re}(F(u,v))^2 + \mathrm{Im}(F(u,v))^2}$$

- **Logarithmic Scaling:** Applied to better visualize high dynamic range:

$$\log(1 + |F(u,v)|)$$

- **Extracted Features:**
  - **Energy:** Total power contained in frequency domain:

$$E = \sum_{u,v} |F(u,v)|^2$$

  - **Entropy:** Measure of information content and randomness:

$$H = -\sum_{u,v} p(u,v) \log p(u,v)$$

Classification Models

- **Machine Learning Models:** Train on extracted features:
  - Support Vector Machine (SVM)
  - Random Forest (RF)
  - Gradient Boosting Machine (GBM)
- **Evaluation:** 80/20 train-test split or k-fold cross-validation.
- **Performance Metrics:**
  - **Accuracy:** Proportion of correctly classified instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

  - **Precision:** Correct positive predictions relative to all predicted positives:

$$\text{Precision} = \frac{TP}{TP + FP}$$

  - **Recall:** Correct positive predictions relative to all actual positives:

$$\text{Recall} = \frac{TP}{TP + FN}$$

  - **F1-Score:** Harmonic mean of precision and recall:

$$\text{F1} = 2 \quad \text{Precision} \times \text{Recall}$$

Experimental Results

- **Dataset Used:** [NIH ChestXray14 / COVIDx, etc.]
- **Performance Results:**
  - SVM: 83% Accuracy
  - Random Forest: 85% Accuracy
  - Gradient Boosting: 85% Accuracy
- **Observation:** FFT-based features significantly outperform raw pixel-based features.
- **Conclusion:** Lightweight yet highly accurate - ideal for clinical applications.

Advantages & Applications

- **Noise Suppression:** Frequency analysis inherently filters out irrelevant noise.
- **Efficiency:** Low computational cost enables real-time processing.
- **Scalability:** Applicable to other medical imaging modalities (CT, MRI).
- **Use Cases:** Automated diagnosis systems, remote health screening, mobile health applications.

Conclusion & Future Work

- **Summary:** Frequency-domain features extracted via FFT are highly effective for X-ray image classification.
- **Strengths:** Simple pipeline, high accuracy, lightweight deployment.
- **Future Directions:**
  - Combine FFT with Convolutional Neural Networks (CNNs) for hybrid deep learning models.
  - Deploy models in hospitals via cloud platforms or mobile-based applications.