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**SCHOOL OF COMPUTING**  
**DEPARTMENT OF COMPUTING TECHNOLOGIES**  
**18CSE357T - BIOMETRICS- MINI PROJECT**

# Face Image Quality Assessment

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## Abstract and Objectives

This study introduces an unsupervised approach to assess face image quality for improved face recognition. It leverages a face recognition model to estimate image quality based on embedding variations. Experimental evaluations demonstrate its superiority over existing methods, offering a stable and easily integratable solution for practical applications.

The objective is to Develop a robust unsupervised method for face image quality assessment, improving face recognition, and eliminating reliance on error-prone labels.

## Introduction

Face Image Quality Assessment (FIQA) involves evaluating the quality of a face image, and FIQA algorithms (FIQAA) automate this process. While FIQA shares similarities with general Image Quality Assessment (IQA), it primarily focuses on single face images in the visible spectrum. FIQA aims to provide a Quality Score (QS), which can be a scalar or a vector, measuring various quality-related aspects. The concept of "quality" is subjective and can encompass character, fidelity, and utility. Character relates to inherent attributes of the biometric characteristic, fidelity measures similarity to the original, and utility gauges an image's suitability for a specific biometric function, like face recognition. This survey explores these aspects in the context of facial biometrics and FIQA.



## Existing System

- **BRISQUE** (Blind/Referenceless Image Spatial Quality Evaluator):  
Description: BRISQUE is a no-reference image quality assessment algorithm that works by analyzing spatial domain natural scene statistics. It doesn't require a reference image for comparison.  
Application to Faces: It can be adapted for face images to assess their quality without relying on reference images.
- **PSNR** (Peak Signal-to-Noise Ratio) and **SSIM** (Structural Similarity Index):  
Description: These are traditional image quality assessment metrics commonly used for various types of images.  
Application to Faces: They can be applied to face images, although they may not always align perfectly with human perception of face quality.
- **FACE-QA** (Face Quality Assessment):  
Description: FACE-QA is a system designed explicitly for assessing the quality of face images. It may use a combination of traditional and deep learning-based approaches.  
Application to Faces: FACE-QA focuses specifically on the challenges and characteristics unique to face images.



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# Face Image Quality Assessment

## Proposed System

### **Deep Learning Architecture:**

Utilize advanced CNNs for automatic feature extraction from face images.

### **Feature Extraction:**

Extract relevant facial landmarks and texture patterns for discriminative feature representation.

### **Quality Metrics Integration:**

Combine traditional metrics (PSNR, SSIM) with domain-specific metrics tailored for face images.

### **Reference-Free Approaches:**

Develop algorithms for assessing face image quality without relying on a reference image.

### **Adversarial Learning:**

Explore adversarial techniques to enhance face image quality through network-based improvements.

### **Real-Time Assessment:**

Design the system for real-time face image quality assessment for practical applications.

# Literature Review

<b>Title</b>	"Structural Similarity Index" by Wang, Zhou, Simoncelli
<b>Problem</b>	Inadequacy of traditional image quality metrics in capturing structural similarity, leading to perceptual mismatches.
<b>Proposed Technique</b>	Introduction of the Structural Similarity Index (SSI) as a metric, focusing on luminance, contrast, and structural information for a more accurate assessment of image similarity.
<b>Research Gap</b>	Existing metrics fall short in considering structural aspects, prompting the need for SSI to bridge the gap and offer a more perceptually meaningful image quality assessment.

# Literature Review

<b>Title</b>	"Perceptual Image Quality Assessment Using Deep Learning" by Zhang, Zhang, Zheng, and others
<b>Problem</b>	Limitations of traditional image quality assessment methods in reflecting human perception, especially in the era of complex visual content and diverse preferences.
<b>Proposed Technique</b>	Utilization of Deep Learning for Perceptual Image Quality Assessment, leveraging neural networks to automatically learn and mimic human visual perception patterns.
<b>Research Gap</b>	Existing methods may struggle to adapt to the intricacies of diverse image content and subjective human preferences, prompting the exploration of deep learning techniques to enhance perceptual image quality assessment.

# Literature Review

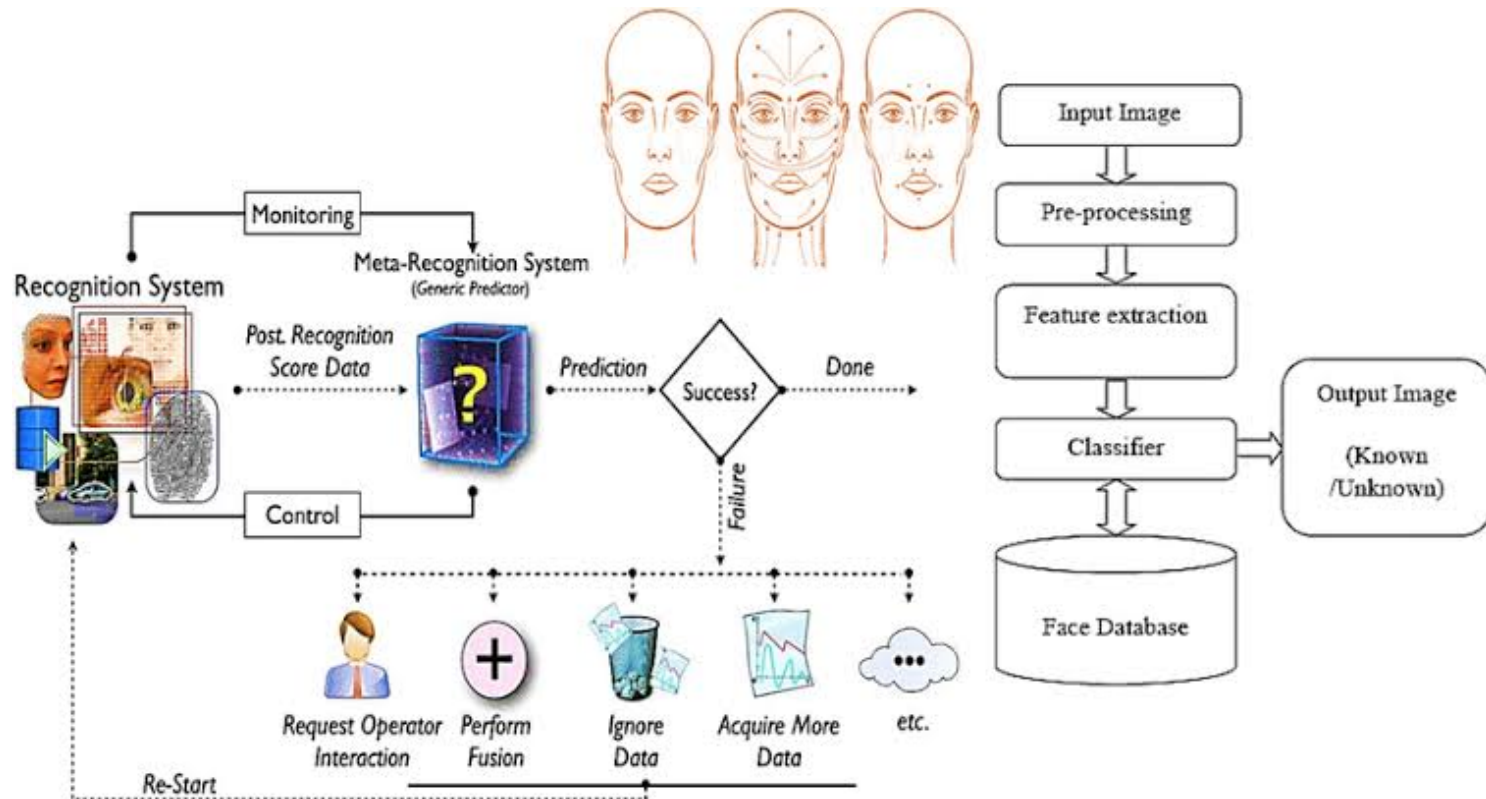
<b>Title</b>	"No-Reference Image Quality Assessment in the Spatial Domain" By Ma, Liu, Wu, Ngan
<b>Problem</b>	Absence of reference information poses a challenge in accurately assessing image quality, particularly in scenarios where a reference image is not available.
<b>Proposed Technique</b>	Development of a No-Reference Image Quality Assessment method in the spatial domain, focusing on spatial features and patterns to evaluate image quality without relying on a reference image.
<b>Research Gap</b>	Existing image quality assessment methods often depend on reference images, limiting their applicability in real-world scenarios where such references are unavailable. The proposed spatial domain approach aims to address this gap by providing a reference-free assessment method.



# Literature Review

<b>Title</b>	"Subjective and Objective Quality Assessment of Images: A Survey" by Sheikh, Bovik, de Veciana
<b>Problem</b>	Divergence between subjective human perception and objective metrics in evaluating image quality, necessitating a comprehensive understanding of both perspectives.
<b>Proposed Technique</b>	Survey-based analysis integrating both subjective and objective measures for image quality assessment, aiming to bridge the gap between human perception and computational metrics.
<b>Research Gap</b>	Limited integration of subjective and objective assessment methods in current literature, highlighting the need for a holistic survey to comprehend and reconcile the differences between human judgment and computational metrics in image quality assessment.

# Architecture Diagram



# Modules

## 1. Image Input Module:

- Accepts input images to be assessed for quality.

## 2. Preprocessing Module:

- Enhances and standardises images, including operations like resizing, normalization, and noise reduction.

## 3. Feature Extraction Module:

- Extracts relevant features from the input images. This can involve low-level features (e.g., color histograms, texture descriptors) and high-level features (e.g., edge information, saliency maps).

## 4. Quality Metric Module:

- Applies one or more quality assessment algorithms or metrics to quantify the image quality. This can include traditional metrics (e.g., SSIM, PSNR) and machine learning-based models.

## 5. Reference Image Database:

- If applicable, a database of reference images for comparison in full-reference quality assessment.

6. Machine Learning Module:

- Utilizes machine learning techniques to predict image quality scores or classifications based on feature vectors.

7. Database and Storage Module:

- Stores image quality scores and metadata for future analysis and reference.

8. Visualization and Reporting Module:

- Generates visual representations and reports to help users interpret the quality assessment results.

9. Integration and Deployment Module:

- Ensures that the system can be integrated into various applications, including image processing pipelines, quality control systems, or multimedia applications.

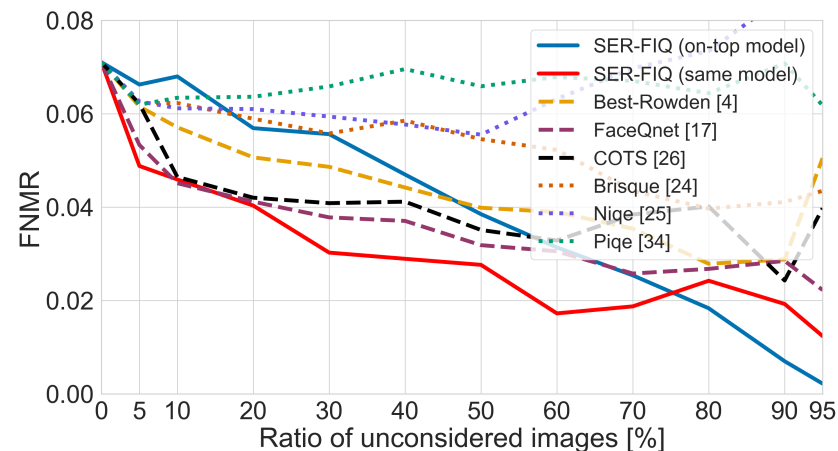
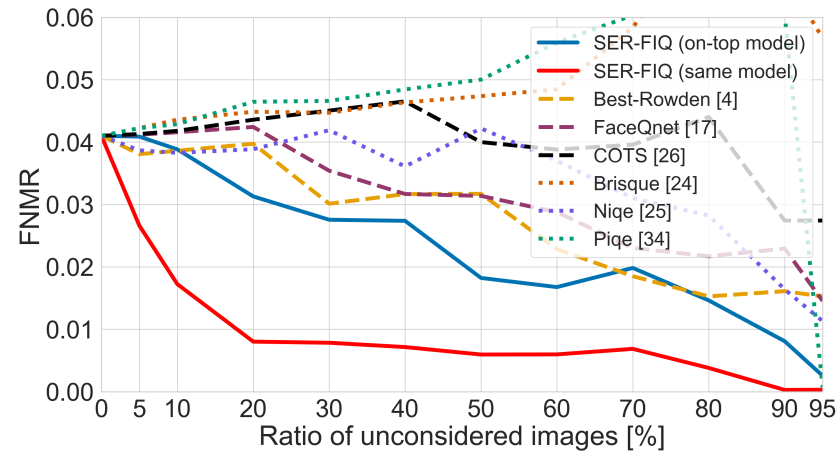
10. Quality Prediction Module:

- Predicts potential issues in images and suggests corrective actions to enhance quality, useful for applications like automated image editing.

11. Feedback and Learning Module:

- Allows the system to learn and improve over time, incorporating user feedback and adapting to changing image quality requirements.

# Sample Snapshot



# Conclusion

Over two decades of research have resulted in successful techniques for recognizing the 2D facial images. In this 285 article, the face recognition method by combining the two popular appearance based techniques such as MPCA and LPP is presented. It also includes the comparison of face recognition approaches MPCA plus LDA and MPCA plus LPP. The combined appearance based technique such as MPCA and LPP yield to produce a high face recognition rate compared to the existing MPCA and LDA technique. Experimental results on FERET and AT&T database demonstrated the effectiveness of the proposed approach with improved recognition accuracy in comparison with the existing approach. In future, combination of various face recognition approaches could be experimented to identify the efficient approach in face recognition.

# References

- <https://github.com/pterhoer/FaceImageQuality>
- <https://ieeexplore.ieee.org/abstract/document/5752512>
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