KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY (KIIT)

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TOPIC: Hybrid Quantum-CNN for Image Enhancement

Summary:

Objective: Enhance low-light images using a hybrid **CNN + Quantum Neural Network (QNN)**.

Dataset: LoL dataset with low-light & high-light image pairs.

Model:

- **CNN Encoder:** Extracts features.
- **QNN Layer:** Processes features with quantum computation.
- **CNN Decoder:** Reconstructs enhanced images.

Training: MSE Loss, Adam Optimizer, 50 epochs.

Evaluation: Measures test loss (MSE) for performance.

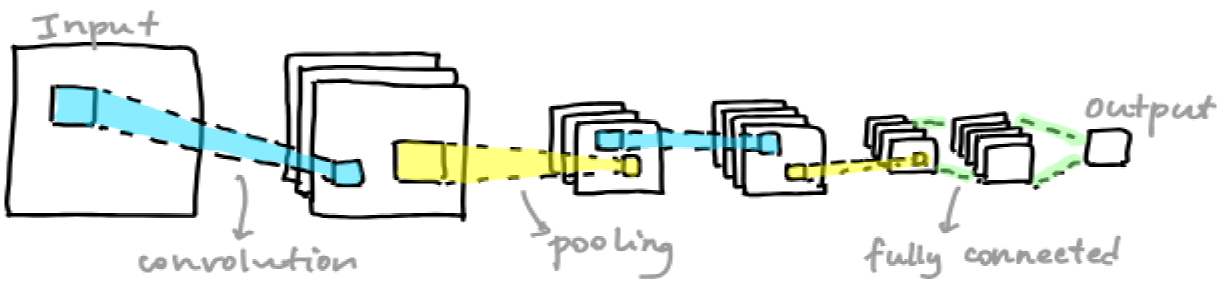
Impact: Combines deep learning & quantum computing for real-world **image enhancement applications**.

Introduction:

Image enhancement in low-light conditions is a crucial challenge in computer vision, affecting areas like photography, surveillance, and medical imaging. This project leverages a Hybrid Quantum-CNN Model, combining Convolutional Neural Networks (CNNs) and Quantum Neural Networks (QNNs) to improve image clarity. CNNs extract meaningful features, while QNNs enhance processing efficiency using quantum computing principles. The model is trained on the LoL dataset, learning to transform low-light images into well-lit, high-quality outputs. By integrating quantum computing with deep learning, this approach aims to push the boundaries of image restoration technology.

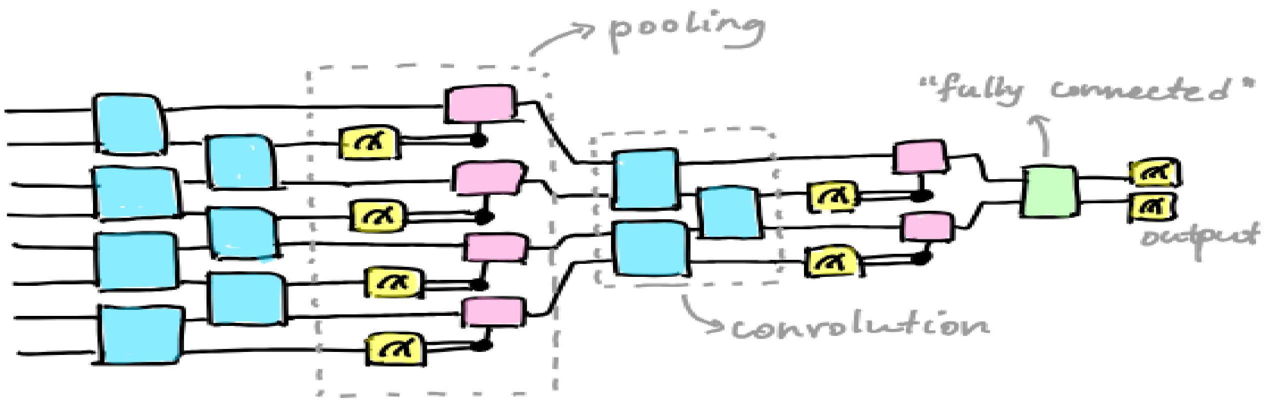
Model:

Convolutional neural networks (CNNs) are a type of classical machine learning model often used in computer vision and image processing applications. The structure of CNNs consists of applying alternating *convolutional layers* (plus an activation function) and *pooling layers* to an input array, typically followed by some fully connected layers before the output.

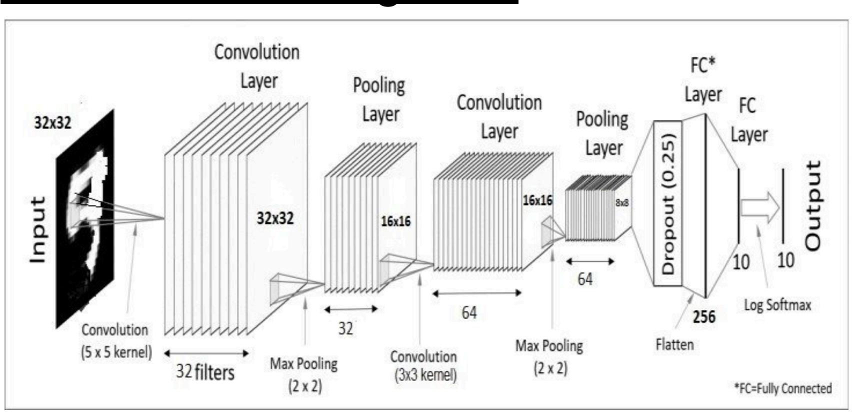


These are used to detect specific features of the image wherever they might appear. Pooling layers are then used to downsample the results of these convolutions to extract the most relevant features and reduce the size of the data, making it easier to process in subsequent layers.

The structure of QCNNs is motivated by that of CNNs:



Actual model diagram :



ARCHITECTURE

- **CNN + Quantum Neural Network (QNN) Hybrid Architecture** for **image enhancement** consists of the following components:
- 📌 **Architecture Breakdown**
- **Convolutional Layers (Feature Extraction)**
    - Conv2D(3 → 32, kernel_size=3, padding=1) → Extracts low-level features.
    - ReLU Activation
    - MaxPool2D(kernel_size=2, stride=2) → Reduces spatial dimensions by half.
    - Conv2D(32 → 64, kernel_size=3, padding=1) → Extracts deeper features.
    - ReLU Activation
    - MaxPool2D(kernel_size=2, stride=2) → Further reduces dimensions.
- **Fully Connected (FC) Layer & Quantum Layer (Hybrid Component)**
    - The CNN feature map is **flattened** into a 1D vector.
    - FC(Flattened → num_qubits) → Maps CNN output to quantum inputs.
    - Quantum Layer (QNN) → Processes information using a **Quantum Circuit**.
    - FC(num_qubits → 256) → Converts quantum output back to classical representation.
- **Deconvolutional Layers (Reconstruction)**
    - ConvTranspose2D(256 → 64, kernel_size=3, padding=1)
    - ReLU Activation
    - ConvTranspose2D(64 → 32, kernel_size=3, padding=1)
    - ReLU Activation
    - ConvTranspose2D(32 → 3, kernel_size=3, padding=1)
    - Sigmoid Activation (outputs enhanced images with pixel values between 0-1).
    - 🔹 **Overall Flow of the Network**
-
- Input: **Low-light Image** (3 × 256 × 256)
- Feature Extraction: **CNN Layers** (convolution + pooling)
- Hybrid Processing: **FC → QNN → FC**
- Reconstruction: **Transpose Convolutions** (upsampling)
- Output: **Enhanced Image** (3 × 256 × 256)

🛠️ Architecture Summary (Layer-wise)

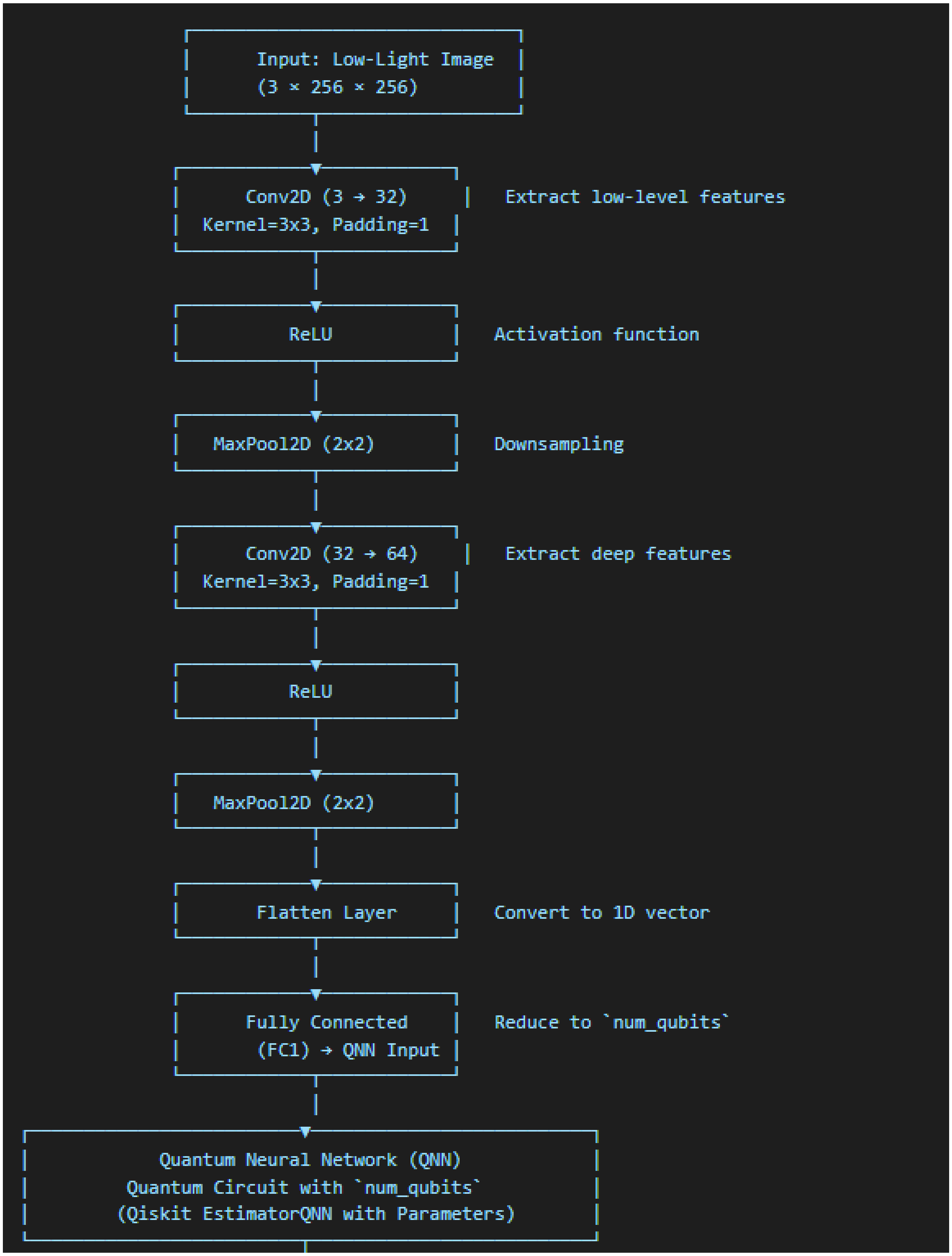
Layer	Type	Input Shape	Output Shape
Input	RGB Image	`(3, 256, 256)`	`(3, 256, 256)`
Conv1	`Conv2D(3 → 32)`	`(3, 256, 256)`	`(32, 256, 256)`
ReLU	Activation	`(32, 256, 256)`	`(32, 256, 256)`
Pool1	`MaxPool2D(2x2)`	`(32, 256, 256)`	`(32, 128, 128)`
Conv2	`Conv2D(32 → 64)`	`(32, 128, 128)`	`(64, 128, 128)`
ReLU	Activation	`(64, 128, 128)`	`(64, 128, 128)`
Pool2	`MaxPool2D(2x2)`	`(64, 128, 128)`	`(64, 64, 64)`
Flatten	Reshape	`(64, 64, 64)`	`(N, 64 × 64 × 64)`
FC1	Fully Connected	`(N, 64 × 64 × 64)`	`(N, num_qubits)`
Quantum Layer (QNN)	Quantum Processing	`(N, num_qubits)`	`(N, num_qubits)`
FC2	Fully Connected	`(N, num_qubits)`	`(N, 256)`
Reshape	Convert to Image Space	`(N, 256)`	`(256, 1, 1)`
ConvTrans1	`ConvTranspose2D(256 → 64)`	`(256, 1, 1)`	`(64, 2, 2)`
ReLU	Activation	`(64, 2, 2)`	`(64, 2, 2)`
ConvTrans2	`ConvTranspose2D(64 → 32)`	`(64, 2, 2)`	`(32, 4, 4)`
ReLU	Activation	`(32, 4, 4)`	`(32, 4, 4)`
ConvTrans3	`ConvTranspose2D(32 → 3)`	`(32, 4, 4)`	`(3, 256, 256)`
Sigmoid	Normalize Output	`(3, 256, 256)`	`(3, 256, 256)`

📌 Key Takeaways

✅ **CNN extracts meaningful image features.**
✅ **Quantum Neural Network (QNN) applies quantum transformations.**
✅ **Deconvolutional layers reconstruct an enhanced image.**
✅ **Hybrid approach leverages classical + quantum advantages.**

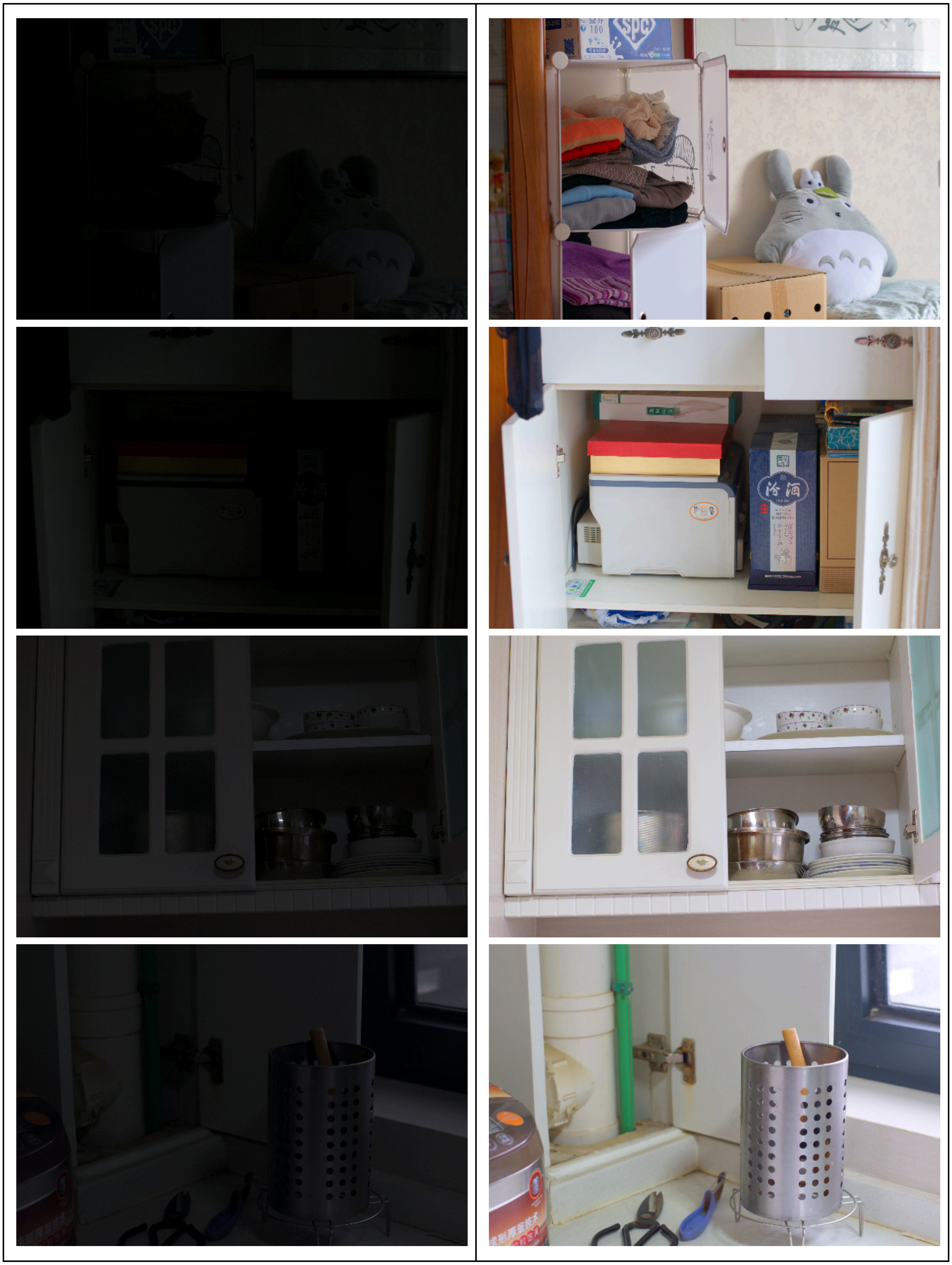
Here's a detailed block diagram for your Hybrid Quantum-CNN Image Enhancement Model:

FLOWCHART


Input: Low-Light Image
(3 × 256 × 256)
Conv2D (3 → 32)
Kernel=3x3, Padding=1
Extract low-level features
ReLU
Activation function
MaxPool2D (2x2)
Downsampling
Conv2D (32 → 64)
Kernel=3x3, Padding=1
Extract deep features
ReLU
MaxPool2D (2x2)
Flatten Layer
Convert to 1D vector
Fully Connected
(FC1) → QNN Input
Reduce to `num_qubits`
Quantum Neural Network (QNN)
Quantum Circuit with `num_qubits`
(Qiskit EstimatorQNN with Parameters)

```
                              │
┌─────────────────────────────▼─────────────────────────────┐
│              Quantum Neural Network (QNN)                 │
│           Quantum Circuit with `num_qubits`               │
│          (Qiskit EstimatorQNN with Parameters)            │
└─────────────────────────────┬─────────────────────────────┘
                              │
               ┌──────────────▼──────────────┐
               │       Fully Connected       │   Convert back to CNN format
               │       (FC2) → 256 Units     │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │  Reshape → (256,1,1)        │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │ ConvTranspose2D (256→64)    │   Upsample
               │  Kernel=3x3, Padding=1      │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │            ReLU             │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │ ConvTranspose2D (64→32)     │   Upsample
               │  Kernel=3x3, Padding=1      │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │            ReLU             │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │ ConvTranspose2D (32→3)      │   Restore RGB channels
               │  Kernel=3x3, Padding=1      │
               └──────────────┬──────────────┘
                              │
               ┌──────────────▼──────────────┐
               │          Sigmoid            │   Normalize pixel values
               └──────────────┬──────────────┘
                              │
                ┌─────────────▼─────────────┐
                │  Output: Enhanced RGB     │
                │    (3 × 256 × 256)        │
                └───────────────────────────┘
```

DATASET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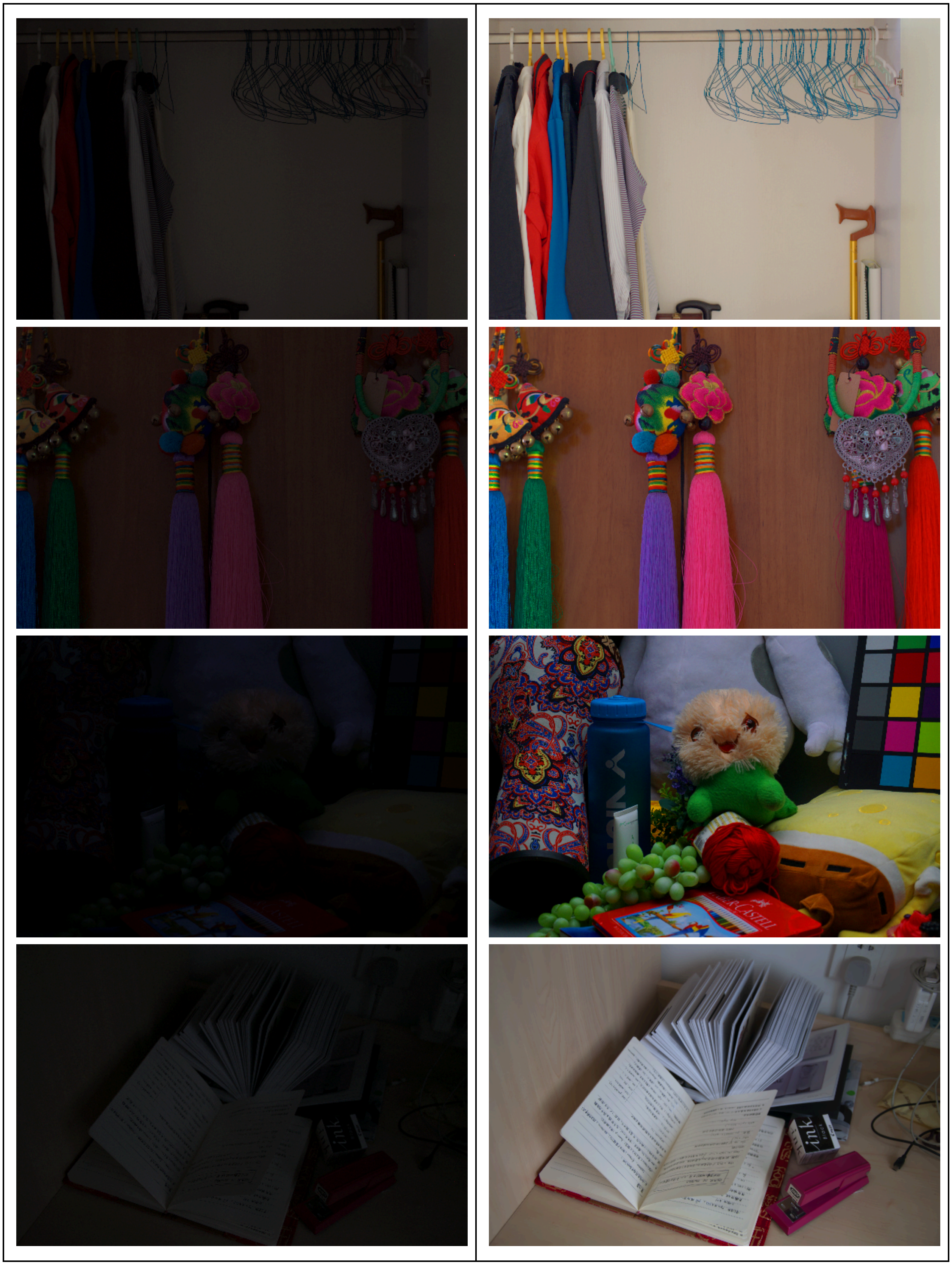
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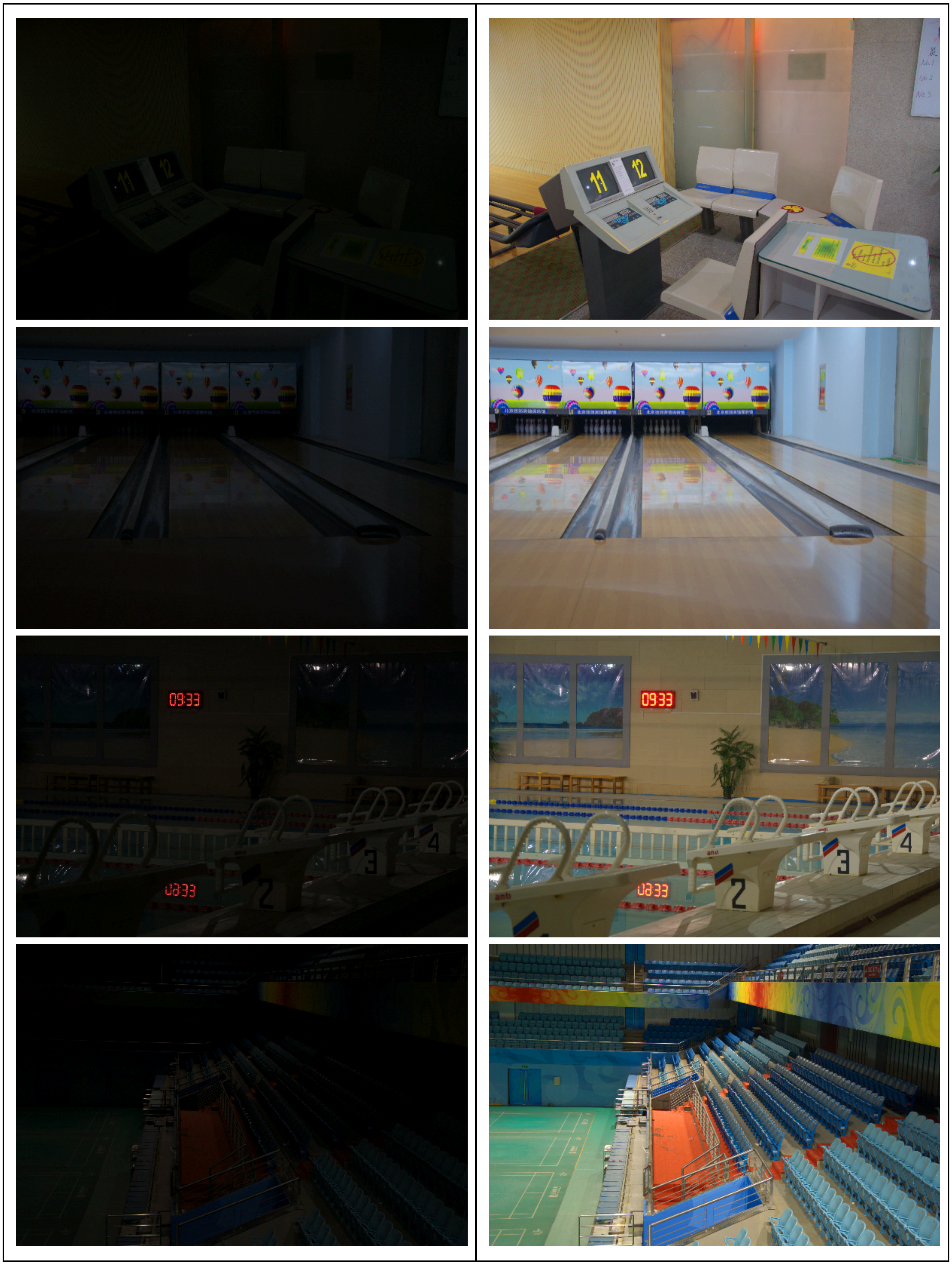
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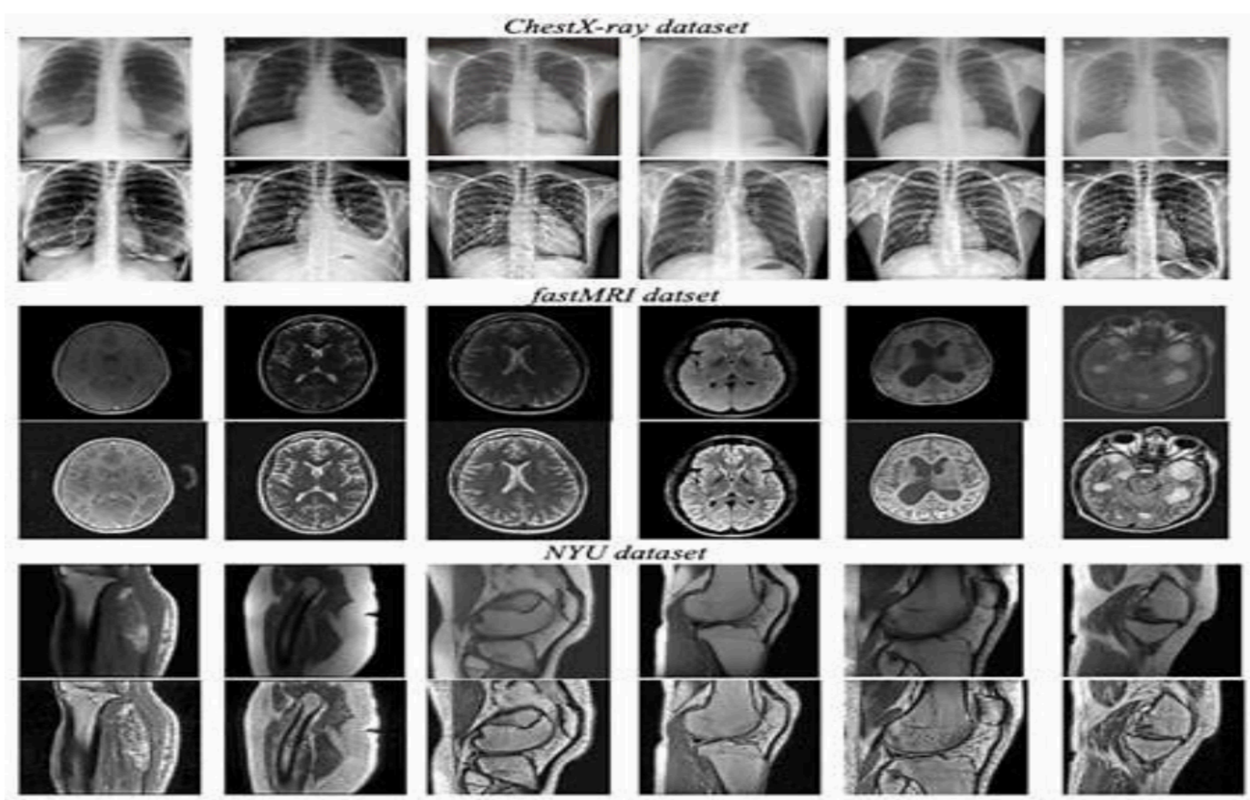
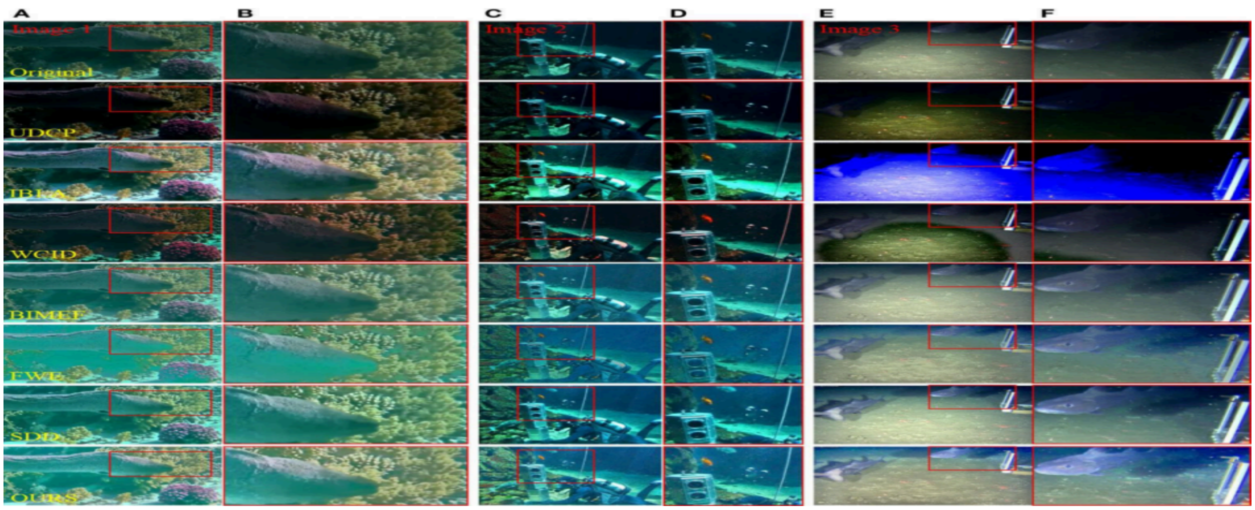
IN MEDICAL PICTURE -

Low-light image enhancement techniques are crucial in medical imaging to improve the visibility of details in underexposed images. For instance, in X-ray and MRI scans, enhancing low-light images can aid medical professionals in accurately analyzing and diagnosing conditions. The following example illustrates the application of image enhancement in medical imaging



IN UNDERWATER PICTURE -

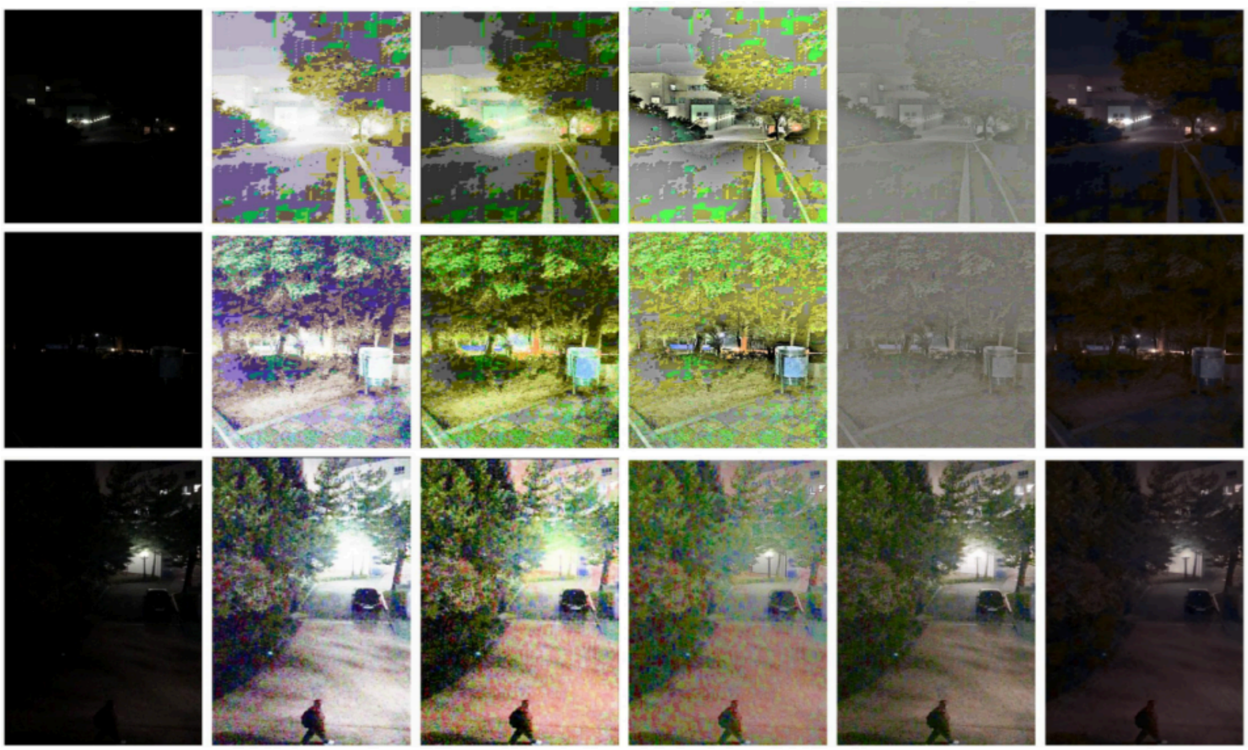
Low-light image enhancement techniques are crucial in underwater photography and videography to improve visibility and reveal obscured details. In underwater environments, images often suffer from poor lighting, low contrast, and color distortion due to light absorption and scattering. Enhancement methods address these issues, resulting in clearer and more informative visuals.



A Input B U and L C L and U D Ours

SURVILLENCE PHOTO -

Low-light image enhancement techniques are crucial in surveillance to improve the visibility of scenes captured under poor lighting conditions. These methods enhance image brightness and clarity, aiding in the accurate identification of individuals and objects.



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Performance Metrics Calculation

This evaluation step quantifies the enhancement quality:

• **Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between maximum possible power of the signal and corrupting noise,

with higher values indicating better quality (typically 30-50dB is considered good).

• **Structural Similarity Index (SSIM):** Evaluates perceived quality based on structural information preservation rather than

absolute errors, with values closer to 1 indicating better structural similarity.

• **Mean Squared Error (MSE):** Measures average squared difference between original and enhanced pixels, with lower values

indicating less distortion.

• **Visual Information Fidelity (VIF):** Assesses information fidelity based on natural scene statistics models, potentially capturing

aspects of human visual perception.

• **Processing Time:** Measures computational efficiency, particularly important for comparing classical-only versus quantum enhanced approaches.

Theoretical Advantages of This Hybrid Approach

The theoretical quantum advantage in this system comes from several unique properties:

• **Quantum Parallelism:** The superposition states process multiple feature combinations simultaneously, potentially offering computational speedup.

• **Entanglement-Based Correlations:** Quantum entanglement creates non-local correlations between image features that classical

systems cannot efficiently model.

• **Interference Effects:** Quantum interference between amplitude paths could enhance important features while suppressing noise

patterns.

• **Probabilistic Processing:** The statistical nature of quantum measurement provides a form of natural regularization that might

reduce overfitting to noise patterns.

• **Exponential State Space:** 8 qubits can represent 256 amplitude values simultaneously, offering a form of compressed information processing.