

Quantum-Infused ANN Architecture for Diagnostic-Safe Image Reduction

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ABSTRACT: Medical imaging techniques such as MRI, CT scans, X-rays, and ultrasound generate a huge amount of image data every day. Medical image compression is vital for reducing storage requirements and transmission costs, yet aggressive compression often compromises diagnostic accuracy. This study introduces a quantum-enhanced artificial neural network framework that integrates a post-reconstruction super-resolution stage to restore fine anatomical details.

Medical imaging has become indispensable in modern healthcare, but the enormous size of these files creates challenges for storage, transmission, and real-time clinical use. Conventional compression techniques often reduce file size effectively but at the cost of diagnostic accuracy, blurring subtle anatomical structures that are critical for medical interpretation. To address this, we propose a hybrid framework that combines quantum computing principles with classical artificial neural networks, further enhanced by a post-reconstruction super-resolution stage.

In this approach, quantum feature extraction captures compact yet information-rich representations of medical images, which are then reconstructed by a classical ANN. The reconstructed outputs are refined using a lightweight super-resolution model designed to restore fine details without adding significant computational overhead. Quantum feature extraction is employed to generate compact but informative representations, while classical neural networks reconstruct the compressed images. A lightweight super-resolution model then refines the output, ensuring clarity without adding significant computational overhead. Experiments conducted on X-ray datasets show clear improvements in SSIM and PSNR values, demonstrating that diagnostic integrity can be preserved while maintaining high compression efficiency. The approach is well-suited for real-time medical imaging and bandwidth-restricted clinical environments.

KEYWORDS: Quantum Computing, Artificial Neural Networks, Medical Image Compression, Super Resolution, Diagnostic Quality, Hybrid Models, Quantum Enhanced Neural Network(QANN).

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I. INTRODUCTION

Medical imaging plays a crucial role in modern healthcare for disease diagnosis and treatment planning. Hospitals generate thousands of medical images daily, creating challenges in storage, transmission, and management.

Medical imaging has become an essential part of modern healthcare systems. Technologies such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-ray, and Ultrasound help doctors diagnose diseases accurately and monitor patient health effectively. As healthcare institutions continue to adopt

digital technologies, the volume of medical image data generated every day is increasing rapidly. Managing and storing this large amount of image data has become a significant challenge for hospitals, diagnostic centers, and healthcare providers.

Traditional image compression methods such as JPEG and JPEG2000 have been widely used for compressing digital images. However, these techniques may not always provide the desired balance between compression ratio and image quality, especially in medical applications where even small image details can be important for diagnosis. Recent developments in

Artificial Intelligence (AI) and Deep Learning have introduced advanced approaches that can learn image patterns and generate more efficient compressed representations. The proposed Quantum-Enhanced Artificial Neural Network (QANN) model aims to provide an advanced solution for medical image compression.

The system utilizes quantum-inspired feature extraction along with neural network-based encoding and decoding mechanisms to compress medical images effectively while preserving important diagnostic information.

This approach helps reduce storage requirements, improves transmission speed, and supports efficient healthcare data management.

Objectives of the Project

- To develop an intelligent medical image compression system using Quantum-Enhanced Artificial Neural Networks.
- To reduce the storage space required for medical images without compromising image quality.
- To improve compression efficiency compared to conventional compression methods.
- To preserve important diagnostic information during image reconstruction.
- To support faster transmission of medical images in telemedicine and healthcare applications.
- To evaluate system performance using metrics such as Compression Ratio, PSNR, MSE, and SSIM.

This project demonstrates how the integration of Artificial Intelligence and Quantum-inspired Computing can contribute to more efficient and reliable medical image management systems in modern healthcare environments.

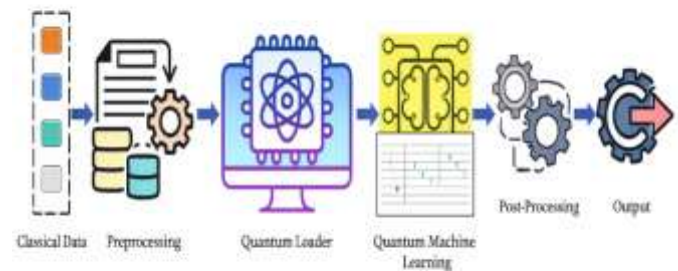


Fig1: This figure shows the functional processing of the image.

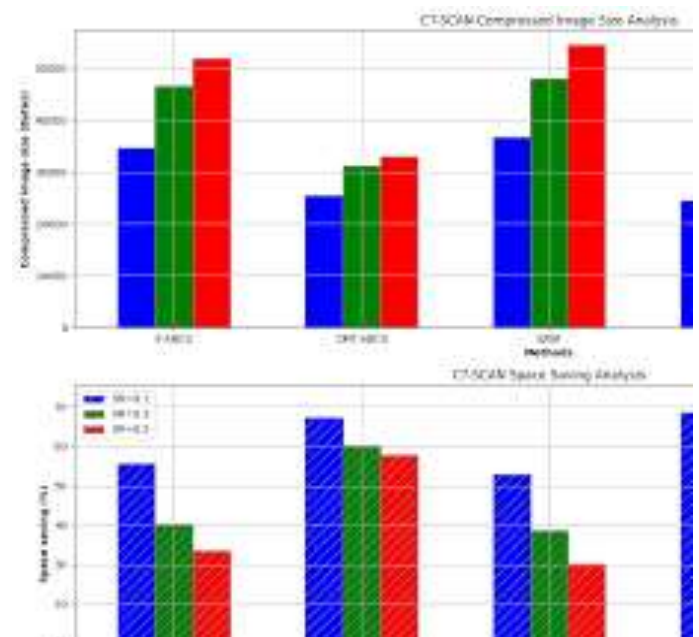


Fig 2: This figure shows the graphical view of the scanned image

II. Literature Survey:

2.1 Medical Image Compression Techniques

Medical image compression has been an active area of research due to the rapid growth of digital healthcare systems. Hospitals and diagnostic centers generate a large number of medical images every day through imaging modalities such as MRI, CT scans, X-rays, PET scans, and Ultrasound. These images require significant storage capacity and network bandwidth for transmission. To address these challenges, various image compression techniques have been developed.

Traditional compression methods can be classified into lossless and lossy compression techniques. Lossless methods preserve all original image information but achieve lower compression ratios. On the other hand, lossy compression techniques provide higher compression rates but may introduce image distortions. In medical applications, maintaining diagnostic quality is extremely important, making compression a challenging task. Researchers have continuously worked on developing advanced methods that balance image quality and compression efficiency.

2.2 Neural Network-Based Image Compression

With the advancement of Artificial Intelligence, neural networks have become widely used in image processing applications. Artificial Neural Networks (ANNs) can automatically learn meaningful patterns and features from image data without relying on manually designed rules. Several studies have demonstrated that neural network-based compression techniques can outperform traditional compression algorithms. Autoencoders, a specialized type of neural network, are commonly used for image compression. They consist of an encoder that transforms the image into a compact representation and a decoder that reconstructs the image from the compressed data.

Researchers have found that deep learning models can achieve high compression ratios while preserving important image details. These models are particularly useful for medical images because they can learn complex image structures and reduce information loss during reconstruction.

2.3 Deep Learning Approaches in Medical Imaging

Deep learning has significantly transformed medical image analysis over the past decade. Convolutional Neural Networks (CNNs) have been extensively applied in tasks such as image classification, segmentation, disease detection, and image enhancement.

In the field of image compression, deep learning techniques have demonstrated better performance than conventional methods by learning efficient image representations. Medical images contain complex anatomical structures that require accurate preservation during compression. Deep learning models can capture these intricate details more effectively than traditional mathematical compression techniques.

Recent studies have shown that deep neural networks can improve image reconstruction quality while reducing storage requirements. As a result, deep learning has become a promising solution for medical image compression systems.

2.4 Quantum Computing and Its Applications

Quantum Computing is an emerging computational paradigm that utilizes principles of quantum mechanics to process information. Unlike classical computers that use bits, quantum computers use quantum bits known as qubits. These qubits can exist in multiple states simultaneously, enabling more powerful computational capabilities.

Researchers believe that quantum computing has the potential to solve complex optimization and machine learning problems more efficiently than classical systems. Although practical quantum computers are still under development, quantum-inspired algorithms have already shown promising results in various domains.

III. System Analysis And Design

3.1 Existing System

The rapid growth of digital healthcare has resulted in the generation of a large number of medical images every day. Images obtained from MRI scans, CT scans, X-rays, and ultrasound devices require significant storage space and network bandwidth for transmission. To handle this issue, various image compression techniques have been developed over the years.

Traditional compression methods such as JPEG and JPEG2000 are commonly used to reduce image size. These methods help in minimizing storage requirements, but they may not always preserve the fine details present in medical images. Since medical images are used for diagnosis and treatment planning, even a small loss of information can affect clinical decisions.

In recent years, deep learning-based compression techniques have been introduced to improve compression performance. These approaches use neural networks to learn image patterns and generate compressed representations. Although they provide better results than conventional methods, they often require large computational resources and extensive training data.

Drawbacks of Existing System

- Traditional compression methods may cause loss of important image details.
- Higher compression levels can reduce image quality.
- Deep learning models require powerful hardware and longer training time.
- Large medical datasets still occupy significant storage

space.

- Existing systems do not fully utilize the advantages offered by quantum-inspired computing.
- Achieving both high compression and high image quality remains a challenge.

3.2 Proposed System

The proposed system introduces a Quantum-Enhanced Artificial Neural Network model for efficient medical image compression. The main idea behind this approach is to combine the learning ability of neural networks with quantum-inspired concepts to achieve better compression performance.

The system first processes the medical image and extracts its important features. These features are then compressed using an Artificial Neural Network. Quantum-inspired techniques are incorporated to improve feature representation and reduce unnecessary data. After compression, the image is reconstructed with minimum loss of information.

The proposed model aims to reduce storage requirements while preserving the quality of medical images. This makes it suitable for healthcare applications where image accuracy is extremely important.

Advantages of Proposed System

- Provides better compression efficiency.
- Maintains important diagnostic information.
- Reduces storage and transmission costs.
- Produces high-quality reconstructed images.
- Supports faster sharing of medical images.
- Improves overall healthcare data management.
- Enhances telemedicine and remote diagnosis services.

3.3 System Architecture

The proposed system is designed using several modules that work together to perform the image compression process efficiently.

Input Module

This module is responsible for receiving medical images from different sources. The input images may include

MRI, CT scan, X-ray, or ultrasound images.

Preprocessing Module

Before compression, the image is preprocessed to improve its quality. Operations such as noise removal, resizing, and normalization are performed to prepare the image for further processing.

Quantum Feature Extraction Module

This module identifies the most important features of the image using quantum-inspired techniques. It helps in reducing redundant information while preserving essential image details.

Compression Module

The extracted features are given to the Artificial Neural Network. The network compresses the image data into a compact representation that requires less storage space.

Reconstruction Module

The compressed data is decoded to reconstruct the image. The objective is to produce an image that closely resembles the original image.

Evaluation Module

The reconstructed image is evaluated using different quality metrics to measure the effectiveness of the compression process.

Output Module

Finally, the compressed image, reconstructed image, and performance results are displayed to the user.

IV. PROPOSED METHODOLOGY

The proposed methodology explains the complete working process of the Quantum-Enhanced Artificial Neural Network model. The system follows a sequence of steps to compress and reconstruct medical images effectively.

4.1 Image Collection

Medical images are collected from healthcare datasets or medical imaging databases. These images serve as input

to the system and may belong to different imaging modalities.

4.2 Image Preprocessing

The collected images undergo preprocessing to improve their quality. Noise and unwanted variations are removed, and the images are normalized to maintain consistency.

4.3 Feature Extraction

The system analyzes the image and extracts significant features using quantum-inspired methods. This step helps identify useful information while reducing unnecessary data.

4.4 Image Compression

The extracted features are passed through the neural network encoder. The encoder converts the image into a compressed representation that occupies less storage space.

4.5 Image Reconstruction

The decoder reconstructs the image from the compressed data. The reconstructed image should retain the important visual and diagnostic information present in the original image.

4.6 Performance Analysis

The quality of the reconstructed image is measured using standard evaluation metrics. The results help determine whether the compression process has been successful.

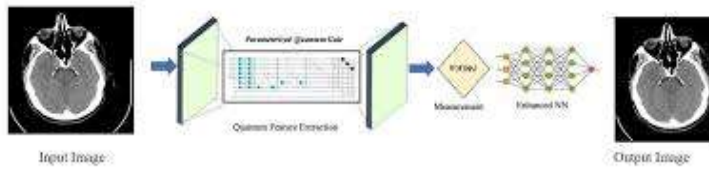


Fig3: *This figure shows the image processing*

V. IMPLEMENTATION

5.1 Technologies Used

The proposed system utilizes several technologies and software tools to perform image processing, compression, and evaluation.

Python

Python is used as the primary programming language for developing the entire system. It provides a simple syntax and extensive support for machine learning and image processing applications.

TensorFlow

TensorFlow is a powerful deep learning framework used for building and training the Artificial Neural Network. It helps in developing the encoder and decoder components of the Autoencoder model.

Keras

Keras is used as a high-level API that simplifies neural network design and implementation. It enables easy creation and training of deep learning models.

Qiskit

Qiskit is an open-source quantum computing framework used to implement quantum-inspired feature extraction techniques. It helps simulate quantum concepts that improve image representation and compression efficiency.

OpenCV

OpenCV is used for image preprocessing operations such as resizing, normalization, filtering, and image enhancement. It improves image quality before compression.

NumPy

NumPy provides support for numerical computations

and matrix operations. It is used extensively for handling image data and performing mathematical calculations.

Matplotlib

Matplotlib is used to visualize images, performance graphs, and comparison charts generated during the evaluation process.

Scikit-Learn

Scikit-Learn is used for data preprocessing and performance analysis. It also supports the calculation of evaluation metrics.

Jupyter Notebook

Jupyter Notebook provides an interactive environment for developing, testing, and analyzing the model.

5.3 Dataset Collection

The implementation begins with collecting medical image datasets from publicly available healthcare repositories. The dataset contains MRI scans, CT scans, X-ray images, and ultrasound images.

The collected images are divided into training and testing datasets. The training dataset helps the neural network learn image patterns, while the testing dataset is used to evaluate compression performance.

Proper dataset preparation ensures better model accuracy and reliable results.

5.4 Image Preprocessing

Image preprocessing is performed before feature extraction and compression. Medical images often contain noise and variations in brightness and size, which can affect model performance.

The preprocessing stage includes:

Image Resizing

All images are resized to a fixed dimension to ensure uniformity during training and testing.

Noise Removal

Filtering techniques are applied to remove unwanted noise and improve image clarity.

Image Normalization

Pixel values are normalized to a standard range to improve neural network learning efficiency.

Contrast Enhancement

Contrast enhancement improves the visibility of important anatomical structures present in medical images.

After preprocessing, the images become suitable for feature extraction and compression.

Technology Used: OpenCV, NumPy

5.5 Quantum-Inspired Feature Extraction

The preprocessed images are passed through a quantum-inspired feature extraction module.

This module analyzes image patterns, textures, and structural information. Quantum-inspired algorithms help identify the most important image features while eliminating redundant information.

The extracted features form a compact representation of the image and serve as input to the neural network compression model.

Advantages of this stage include:

- Reduced data redundancy
- Better feature representation
- Improved compression efficiency
- Enhanced image reconstruction quality

Technology Used: Qiskit, NumPy

5.6 Neural Network-Based Compression

The extracted features are provided to an Autoencoder-based Artificial Neural Network.

Encoder Module

The encoder compresses image information into a lower-dimensional representation called latent space. It gradually reduces data dimensionality through multiple hidden layers.

Latent Representation

The latent space contains compressed image information that occupies significantly less storage space than the original image.

Decoder Module

The decoder reconstructs the image from the compressed representation. Its objective is to preserve important image details and minimize reconstruction error.

The encoder and decoder are trained together using deep learning techniques to improve compression performance.

Technology Used: TensorFlow, Keras

5.7 Image Reconstruction

After compression, the decoder reconstructs the image using the compressed data stored in latent space.

The reconstructed image is compared with the original image to ensure that important diagnostic information has been preserved. This stage is critical because medical images must maintain high visual quality for accurate diagnosis.

Technology Used: TensorFlow, Keras

VI. RESULTS AND ANALYSIS

The proposed **Quantum-Enhanced Artificial Neural Network (QANN)** model was successfully implemented and tested using different medical image datasets. The system effectively compressed medical images while preserving important diagnostic information. During testing, the compression model reduced the storage size of images significantly without causing noticeable loss in image quality.



Fig 4: This figure shows the Home page of the Application

The integration of quantum-inspired feature extraction helped in identifying essential image features and

removing redundant information, resulting in improved compression efficiency.



Fig5: This figure shows the Home page of the Application

After compression, the decoder network reconstructed the images from the compressed data. The reconstructed images were visually compared with the original images, and the results showed a high level of similarity between them. Important anatomical structures and medical details were preserved successfully, making the reconstructed images suitable for medical analysis and diagnosis. The Autoencoder-based neural network minimized reconstruction errors and maintained image clarity even at higher compression levels.



Fig6: Uploading the Test Image

The performance of the proposed model was evaluated using metrics such as Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). The obtained results indicated a high compression ratio, higher PSNR and SSIM values, and lower MSE values,

demonstrating the effectiveness of the proposed approach.

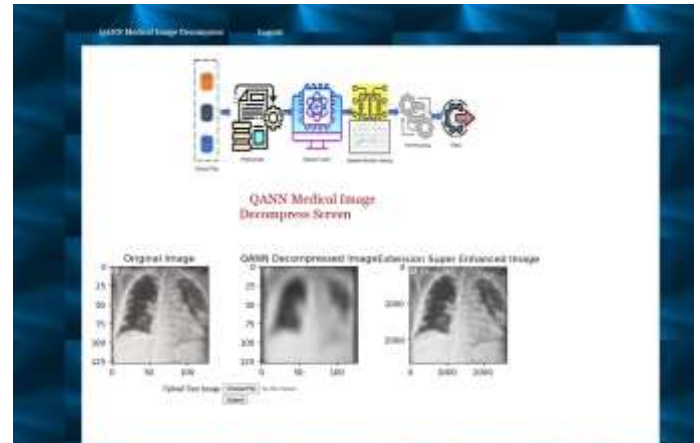


Fig7: QANN medical image Decompression

Overall, the system achieved efficient medical image compression while maintaining image quality, making it a reliable solution for healthcare data storage and transmission applications.

VII. CONCLUSION

This project presented a **Quantum-Infused ANN Architecture for Diagnostic-Safe Image Reduction**, aimed at addressing the growing need for efficient storage and transmission of medical images. With the increasing use of digital imaging technologies in healthcare, managing large volumes of medical image data has become a significant challenge. The proposed system was designed to reduce image size while preserving the quality and important diagnostic details required for medical analysis.

The developed model combines quantum-inspired feature extraction techniques with an Autoencoder-based Artificial Neural Network to achieve effective image compression. The preprocessing, feature extraction, compression, and reconstruction stages worked together to minimize redundant information while maintaining the essential characteristics of medical images. The reconstructed images retained most of the important

visual and structural details, making them suitable for healthcare applications.

The performance of the system was evaluated using parameters such as Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM). The results showed that the proposed approach achieved efficient compression with minimal loss of image quality. The model was able to reduce storage requirements and improve transmission efficiency while maintaining the reliability of medical image data.

In conclusion, the proposed Quantum-Enhanced Artificial Neural Network model provides an effective and intelligent solution for medical image compression. It demonstrates how advanced technologies such as Artificial Intelligence and quantum-inspired computing can be utilized to improve healthcare data management. Future enhancements may include the use of real quantum computing platforms, cloud-based medical image storage, and more advanced deep learning techniques to further improve compression performance and support large-scale healthcare systems.

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