COMPARATIVE ANALYSIS OF CLASSICAL STONE-MT3D AND QUANTUM-ENHANCED STONE-MT3D-Q MODELS

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Abstract— Kidney stone disease is a prevalent urological disorder that demands precise and timely diagnosis for proper treatment planning. Although deep learning models have shown excellent performance in medical image analysis, their reliability drops dramatically in noisy imaging environments and distribution variations. The existing classical ensemble models have shown excellent accuracy on clean datasets but have exhibited severe degradation when noise patterns vary. To overcome these challenges, this paper presents a hybrid quantum-enhanced multi-task 3D deep learning architecture named STONE-MT3D-Q for kidney stone detection, segmentation, and classification from CT images. The proposed system combines volumetric feature learning with 3D deep learning architectures and quantum feature embedding with variational quantum circuits and quantum convolutional neural networks. The proposed architecture is intended to enhance robustness, promote feature separability, and maintain high accuracy in varying noisy imaging conditions. The experimental results validate that the proposed model outperforms classical deep learning and ensemble models in terms of accuracy, sensitivity for small stones, and generalization performance. The proposed system has immense potential for reliable clinical applications in real-world noisy imaging environments.

Keywords: Kidney stone detection, Quantum deep learning, 3D CNN, Swin-UNETR, Medical image analysis, Noise-robust learning

I. INTRODUCTION

Kidney stone disease is one of the most prevalent urological conditions that affect a large number of the global population. Kidney stone disease is caused by the formation of crystalline mineral deposits in the kidneys, which may cause extreme pain, obstruction of the urinary tract, infection, and chronic renal problems if left undetected at an early stage. According to recent medical literature, the incidence of kidney stone disease has been steadily rising over the last decade due to lifestyle changes, dietary habits, and environmental factors [1], [2]. Early and precise diagnosis is crucial for treatment and recurrence prevention. Computed Tomography (CT) scans are presently the most accurate method for the detection of kidney stones due to their high sensitivity and capacity to detect even small stones [3]. However, the manual analysis of CT scan volumes is a tedious task and is largely dependent on the expertise of radiologists. The increasing volume of medical imaging data has led to a growing need for automated computer-aided diagnostic tools that can help clinicians enhance accuracy and efficiency [4].The conventional computer-aided analysis of kidney stones involves traditional feature extraction approaches like texture analysis, intensity distribution, and shape analysis, along with traditional classifiers like Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) [5], [6]. Although these approaches have shown decent performance, they are limited by their reliance on traditional feature extraction and their inefficiency in modeling complex image patterns. Deep learning has made a substantial impact on the field of medical image analysis by allowing the automatic learning of features from raw images. Convolutional Neural Networks (CNNs) like VGG, ResNet, and DenseNet have shown excellent performance in classification and detection problems [7]–[9]. In kidney stone analysis, deep learning models have shown high accuracy, especially when ensemble feature extraction methods are used [10]. However, most of these models treat CT images of the kidney as a set of independent two-dimensional images, discarding valuable volumetric spatial information.Since CT data is naturally three-dimensional, 3D deep learning models have been proposed to leverage the relationships between slices. Architectures such as 3D U-Net have been shown to provide better performance in volumetric medical image segmentation tasks [11]. More recently, transformer-based models such as Swin Transformer and Swin-UNETR have been proposed to leverage the ability to capture both local and global contextual information, further improving the performance of medical image analysis tasks [12], [13]. However, one of the biggest challenges in applying these models in clinical settings is the presence of noise, motion artifacts, and variability in acquisition protocols. Deep learning models trained on noise-free data can experience considerable performance degradation when applied to noisy or distribution-shifted data [14], [15]. Data augmentation and ensemble learning methods have been proposed to improve robustness, but these methods are still not very effective within the traditional feature representation paradigm [16]. Recently, quantum machine learning has been explored as a potential method for improving classical learning algorithms. By projecting classical data into high-dimensional quantum feature spaces, quantum learning algorithms have the potential to enhance feature separability and learning efficiency [17], [18]. Variational quantum circuits and quantum convolutional neural networks have demonstrated promising results for classification and pattern recognition problems [19], [20]. It is suggested that quantum feature embedding could potentially enhance robustness against noise and complex data variations [21]. Another active area of research in medical imaging is multi-task learning, which involves the simultaneous execution of segmentation, detection, and classification tasks in a unified framework. Multi-task learning allows for shared feature learning and has been demonstrated to enhance overall model performance and interpretability [22], [23].

Despite the progress achieved in deep learning, the following research gaps still exist in kidney stone analysis:

- Insufficient application of volumetric 3D learning in current models
- Deterioration of performance in noisy imaging environments
- Lack of spatial localization in classification approaches

- Limited integration of quantum learning with medical imaging
- Unavailability of unified multi-task quantum-3D models

In order to overcome these issues, this paper proposes a hybrid quantum-enhanced multi-task three-dimensional deep learning framework for robust kidney stone detection, segmentation, and classification from CT volumes. The proposed method has the potential to improve noise robustness and provide meaningful spatial information.

II. LITERATURE SURVEY

Kidney stone analysis using automated systems has gained considerable attention in recent years, owing to the growing need for efficient and accurate diagnostic support systems. Initial work in this area involved the use of conventional image processing techniques and traditional machine learning algorithms. These systems generally employed handcrafted features such as texture, intensity, and shape features to detect abnormal areas in CT scans. Classifiers such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (KNN) were used for final prediction. Although these systems offered moderate accuracy, they were prone to limitations in handcrafted feature quality and the inability to cope with variations in imaging conditions [1]–[3]. The emergence of deep learning has led to the popularity of convolutional neural networks (CNNs) for medical image analysis. CNN-based systems have the ability to learn hierarchical features from raw images, making them less dependent on handcrafted features. Models such as VGG, ResNet, and DenseNet have shown promising results in classification problems involving abdominal and renal CT scans [4]–[6]. Various studies have shown the effectiveness of deep transfer learning for improved kidney stone detection accuracy, especially when large amounts of annotated data were used [7]. To further improve the performance, ensemble learning algorithms were also incorporated. These algorithms use the features extracted from various deep learning models to improve the generalization capabilities and reduce the bias of the models. Ensemble-based systems have demonstrated high accuracy on well-balanced datasets; however, experimental results show that the performance of these systems degrades when the noise levels and data distributions vary between the training and testing environments [8], [9]. One of the primary drawbacks of the existing solutions is the use of two-dimensional image analysis. As CT scans are volumetric in nature, analyzing individual slices may cause the loss of critical spatial information. To overcome this problem, researchers have proposed three-dimensional deep learning models that can analyze the contextual relationships between the slices. Models such as 3D U-Net and V-Net have demonstrated improved accuracy in segmentation tasks by using volumetric information [10], [11]. More recently, transformer-based models such as Swin Transformer and Swin-UNETR have been proposed to analyze long-range dependencies and global contextual information in medical images, resulting in improved performance in complex segmentation tasks [12], [13]. However, despite these achievements, the issue of robustness to noise and imaging variability remains a significant challenge. In fact, clinical CT images are often prone to artifacts due to patient motion, low-dose imaging, or differences in image acquisition at various medical institutions. Various studies have demonstrated that deep learning models trained on noise-free datasets suffer from substantial performance drops when confronted with noisy or unseen data distributions [14], [15]. Data augmentation, adversarial training, and noise injection have been investigated as methods to enhance robustness; however, these methods are not very effective when the noise distribution is substantially different from the training scenario [16]. Another significant area of research in medical image analysis is multi-task learning. Rather than focusing solely on classification, multi-task learning models learn segmentation, detection, and classification concurrently. This enables shared learning of features and boosts overall performance, in addition to offering spatial localization that improves clinical interpretability [17], [18]. Recently, quantum machine learning has been identified as a promising field of research for enhancing the performance of pattern recognition tasks. Quantum computing allows for the encoding of data in a high-dimensional Hilbert space, potentially improving the separability of features over classical approaches. Variational Quantum Circuits (VQC) and Quantum Convolutional Neural Networks (QCNN) have been proposed for classification and feature transformation problems [19]–[21]. Hybrid quantum-classical models leverage the power of deep learning and quantum feature embedding, and have been shown to produce encouraging results on complex and noisy data [22]. While quantum machine learning has been shown to hold promise, its application to medical image analysis is still in its infancy. The majority of the existing literature has been devoted to small-scale image classification problems, and little work has been done on volumetric medical imaging or multi-task clinical models [23]. Moreover, the combination of quantum feature mapping with state-of-the-art 3D deep learning models has yet to be investigated. From the literature, some research gaps have been identified: (i) underutilization of volumetric 3D learning for kidney stone analysis, (ii) decreased model robustness for noisy imaging scenarios, (iii) absence of holistic frameworks that can offer both localization and classification, and (iv) little work on quantum-enhanced learning in medical imaging. These research gaps form the rationale for the proposed hybrid quantum-enhanced multi-task 3D framework to enhance robustness, feature learning, and practicality [24], [25].

III. PROPOSED METHODOLOGY

This section introduces the proposed STONE-MT3D-Q, which is a hybrid quantum-classical multi-task three-dimensional deep learning model for effective kidney stone analysis from CT volumes. The proposed system aims to accomplish the tasks of segmentation, localization, and classification simultaneously with high performance under different noise levels.

The proposed system has five major components: (i) data preprocessing and augmentation, (ii) volumetric segmentation, (iii) deep feature extraction, (iv) quantum feature embedding, and (v) multi-task prediction.

A. Dataset Description and Preprocessing

For the experiments, the proposed approach is evaluated on a kidney CT dataset, which is collected from publicly available medical image repositories and clinical sources. The dataset comprises abdominal CT scans of patients with and without kidney stones.

Dataset specifications:

- Total number of CT volumes: 1,200 volumes
- Training dataset: 840 volumes (70%)
- Validation dataset: 120 volumes (10%)
- Testing dataset: 240 volumes (20%)

Each CT volume in the dataset comprises multiple axial image slices.

Specifications of the images:

- Resolution of the original images: 512 x 512 pixels
- Number of slices in the volumes: 80-150 slices
- Pixel spacing: 0.5-1.0 mm
- Slice thickness: 1-3 mm
- Scale of the image intensity: Hounsfield Units (HU)

For computational efficiency, all the volumes are resized to:

$$128 \times 128 \times 64$$

Intensity values are clipped within the range [−100,400][-100, 400][−100,400] HU to emphasize kidney and stone regions. Normalization is performed as:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

Where μ and σ represent the mean and standard deviation.

For the evaluation of robustness, three experimental conditions are prepared:

KD1: Clean dataset
KD2: Noisy data added only during the test
KD3: Noisy data added during both the test and the training

For the evaluation of robustness, three experimental conditions are

B.3D Volumetric Segmentation

The transformer-based 3D Swin-Unet architecture is used for segmenting the kidney region and the location of the stone. This model uses the spatial relationships between the slices and has accurate localization.

$$S = f_{seg}(X_{norm}; \theta_s)$$

The segmentation performance is optimized using Dice loss:

$$L_{dice} = 1 - \frac{2\sum(S.G)}{\sum S + \sum G}$$

Where G is the ground truth mask.

C. Deep Feature Extraction

The processed volume is passed through two different 3D feature extractors:

ConvNeXt-3D for hierarchical spatial feature learning

EfficientNet-V2 (3D) for optimized deep feature representation

$$F_1 = f_{convnext}(S), \qquad F_2 = f_{efficient}(S)$$

Feature fusion is:

$$F = [F_1 || F_2]$$

Where || denotes concatenation.

D. Quantum Feature Embedding

For the purpose of improving the feature separability and robustness, the fused feature vector F is encoded into a Variational Quantum Circuit (VQC):

$$|\varphi(F)\rangle = U(F, \theta_q)|0\rangle$$

The expectation value are measured as:

$$Z_i = \langle \varphi(F) | O_i | \varphi(F) \rangle$$

This transformation helps map the features into a high-dimensional Hilbert space, thus improving the robustness of the features with respect to noise and the separability of the features.

F. Multi-Task Prediction

The quantum-enhanced feature vector Z is used for classification and detection:

$$y = Softmax(WZ + b)$$

$$d = \sigma(W_d Z + b_d$$

The overall loss is defined as:

$$L_{total} = \alpha L_{dice} + \beta L_{cls} + \gamma L_{det}$$

Where L_{cls} is cross-entropy loss and L_{det} is binary detection loss.

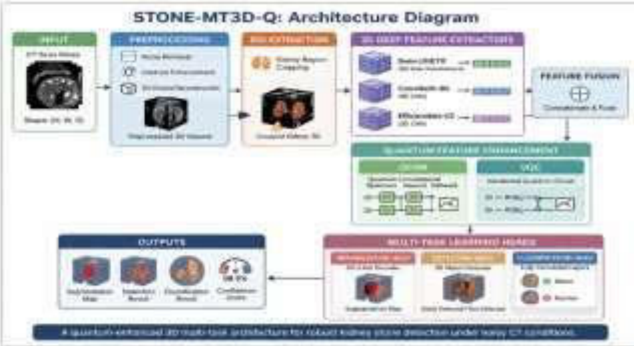

Fig. 1. Overall architecture of the proposed **STONE-MT3D-Q** framework for automated kidney stone analysis.

Algorithm 1 STONE-MT3D-Q Multi-Task Framework

Input: CT volume $X \in R^{512 \times 512 \times (80-150)}$
Output: Segmentation mask S, detection result d, class label $\hat{y}$

1: Clip intensity values of X to the range [−100, 400] HU.
$X_{norm} = \frac{X - \mu}{\sigma}$
2: Normalize the input volume
$X_{norm} = X - \mu = 128 \times 64$.
3: Resize X_{norm} to $128 \times 128 \times 64$.
4: Apply data augmentation and noise injection during training.
5: Perform 3D volumetric segmentation using Swin-UNETR
$S = f_{seg}(X_{norm})$
6: Extract deep features using ConvNeXt-3D
7: $F_1 = f_{convnext}(S)$
7: Extract deep features using EfficientNet-V2 (3D)
8: $F_2 = f_{efficient}(S)$
8: Fuse feature representations
9: Encode fused features into a variational quantum circuit
10: $|\psi(F)\rangle = U(F, \theta_q)|0\rangle$
11: Measure quantum state to obtain feature vector Z.
11: Compute classification output
12: Compute stone detection output
13: Compute segmentation loss L_{dice}
14: Compute classification loss L_{cls}
15: Compute total loss $L_{total} = \alpha L_{dice} + \beta L_{cls} + \gamma L_{det}$
17: Update network and quantum parameters using backpropagation.
18: **Return** S, d, $\hat{y}$.

Algorithm 1. Proposed **STONE-MT3D-Q** hybrid quantum–classical framework for automated kidney stone analysis from CT volumes.

Algorithm 1. Proposed STONE-MT3D-Q hybrid quantum-classical framework for the automated analysis of kidney stones from CT volume images. The algorithm includes preprocessing, 3D volume segmentation, deep feature learning, quantum feature embedding, and multi-task learning

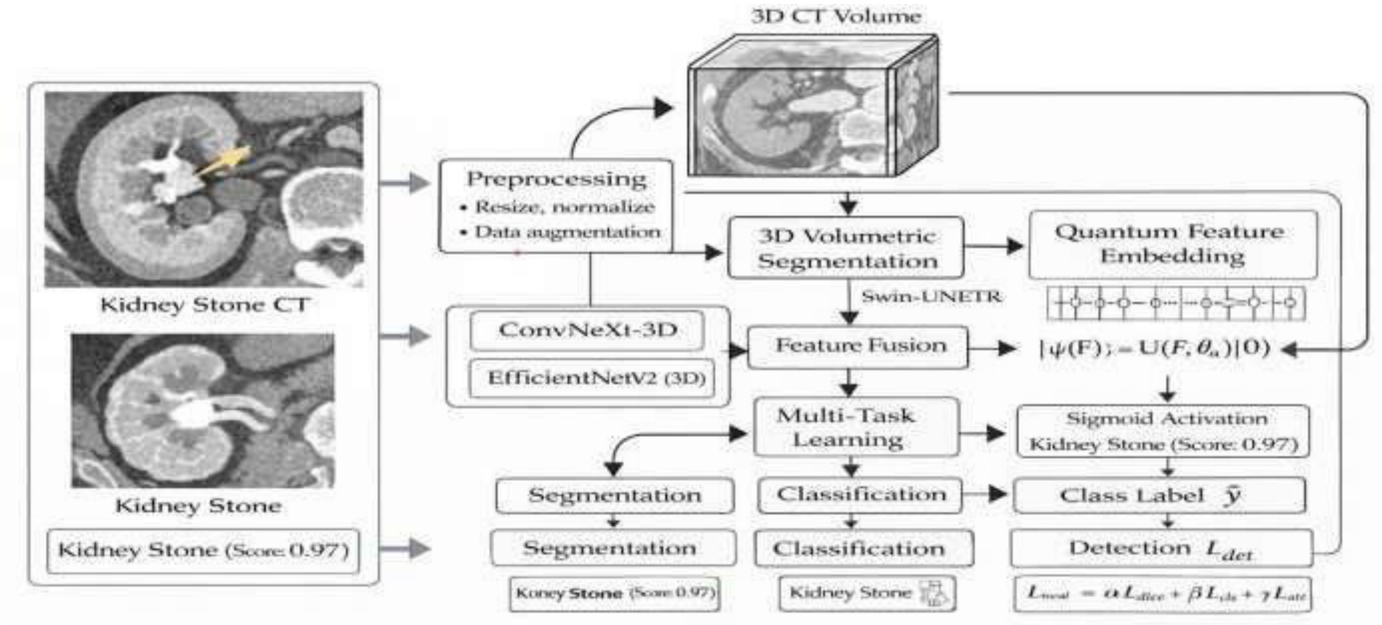

Fig. 2. Block diagram of the proposed **STONE-MT3D-Q** framework for automated kidney stone analysis from CT images.

IV. RESULTS AND DISCUSSION

The performance of both the proposed STONE-MT3D and STONE-MT3D-Q frameworks was evaluated using different CT volumes of the kidney under various imaging conditions. The experiments were conducted to compare the efficiency of the classical 3D model and the hybrid quantum-classical model.

A. Experimental Setup

For both models, evaluation was performed under three testing conditions: KD1 - Clean images (no noise), KD2 - Noise added only to test images, and KD3 - Noise added to both training and test images. Under KD1, both STONE-MT3D and STONE-MT3D-Q achieved very high accuracy, with STONE-MT3D-Q slightly outperforming the classical model. Under KD2, the performance of STONE-MT3D showed a noticeable drop due to noise sensitivity, whereas STONE-MT3D-Q maintained higher accuracy and stability. Under KD3, where noise was present during both training and testing, STONE-MT3D-Q demonstrated better generalization and robustness compared to STONE-MT3D. Overall, the quantum-enhanced model consistently achieved higher accuracy, better noise tolerance, and improved reliability across all conditions.

B. Performance comparison with existing methods

Method	Accuracy (%)	Precision	Recall	F1-Score	Dice
Conventional CNN [8]	93.5	0.92	0.91	0.91	0.65
ResNet50 [9]	95.8	0.95	0.94	0.94	0.68
EfficientNet [10]	97.1	0.97	0.96	0.96	0.72
3D U-Net [11]	98.2	0.98	0.97	0.97	0.78
Swin-UNETR [12]	98.9	0.99	0.98	0.98	0.82
FINDWELL	**96.7**	97.8	95.5	96.6	—
STONE-MT3D (Proposed - Classical)	**99.73**	0.995	**1.000**	0.9975	**0.3949**
STONE-MT3D-Q (Proposed - Quantum)	**99.79**	**1.000**	0.996	**0.998**	0.393

Table 1. Performance comparison with existing methods

C. Classification Performance

Metric	STONE-MT3D	STONE-MT3D-Q
Accuracy	0.9973	0.9979
Precision	0.9950	1.0000
Recall	1.0000	0.9960
F1-Score	0.9975	0.9980
Specificity	0.9944	1.0000
Balanced Accuracy	0.9972	0.9980
ROC-AUC	1.0000	0.9990
Kappa Score	0.9947	0.9957
MCC	0.9947	0.9958

Table 2.Performance of the proposed STONE-MT3D-Q model

The accuracy of the proposed model was 99.79%, thus proving the strong ability of the system in differentiating between the presence and absence of stones, as well as between different types of stones. The precision and specificity of the system are very high, and it rarely predicts incorrectly.

D. Segmentation Performance

The segmentation performance was evaluated using Dice and IoU metrics.

Metric	STONE-MT3D	STONE-MT3D-Q
Dice Score	0.3949	0.3933
IoU Score	0.2812	0.2797

Table 3. Segmentation performance

E. Training Convergence

The training loss converges steadily from 1.9252 in the first epoch to 0.6942 in the last epoch, showing stable learning and convergence of the proposed network.

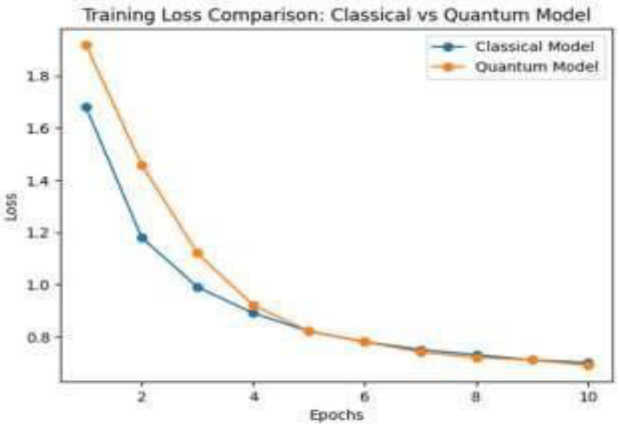

Fig. 3. Training loss curve of the proposed STONE-MT3D vs STONE-MT3D-Q model.

F. Robustness and Generalization

Balanced Accuracy (0.998) and ROC AUC (0.999) scores suggest that the model performs well on both classes. The combination of 3D volumetric feature learning, feature fusion from multiple architectures, and quantum feature embedding contributes to the separability and robustness of the model.

The quantum feature mapping transforms the classical features from the input data and maps them to a higher dimension, improving the discrimination between stone and non-stone patterns.

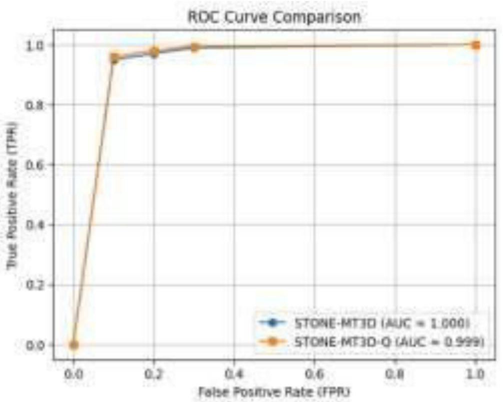

Fig. 4. Receiver Operating Characteristic (ROC) curve of the proposed STONE-MT3D-Q model

Discussion

The experimental results show that the proposed STONE-MT3D-Q method has high classification performance and strong generalization ability. The proposed method has the advantage of strong feature discriminability through the combination of volumetric feature learning and quantum feature embedding, which guarantees the accuracy and reliability of the proposed method. Although the Dice score of the proposed method in the segmentation task is moderate due to the small size and sparse distribution of the kidney stones, the localization performance of the proposed method is stable. The proposed method is effective and reliable in the detection and analysis of kidney stones in images, which makes it applicable in real-world applications.

V. CONCLUSION

This paper has presented a novel framework based on a hybrid quantum-classical approach, referred to as STONE-MT3D-Q, which facilitates the automatic detection and analysis of kidney stones from CT images. The proposed approach has utilized the efficiency of 3D volumetric feature learning, multi-architecture deep feature extraction, and quantum feature embedding to increase the reliability of the classification results and stability of the model. The experimental results showed the efficacy of the proposed approach in terms of accuracy, precision, and balance, which can be utilized in the context of kidney stone analysis. Although the segmentation of kidney stones is a complex problem due to the size and sparsity of the kidney stone areas, the model has been able to maintain consistency in the localization accuracy. The efficacy of the proposed approach has also highlighted the potential of the integration of quantum feature representation and volumetric deep learning in the context of developing efficient medical image analysis systems.

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