

# A CNN–Autoencoder-Based Deep Learning Framework for Automated Detection of Rotator Cuff Tendon Tears In Shoulder Ultrasound Images

Assistant Professor, Mr.Sayantan Kar<sup>1</sup>, Karri Pravallika<sup>2</sup>, Damera Rajya Lakshmi Nikshitha<sup>3</sup>,  
Chintada Venkatesh<sup>4</sup>, Mannam Alekhya Narayana<sup>5</sup>, Banala Dineshbabu<sup>6</sup>,  
Department of CSE, Pragati Engineering College, Surampalem, Andhra Pradesh, India

**Abstract-** Rotator cuff tendon tears are one of the most common causes of shoulder pain and mobility limitations worldwide. Although ultrasound imaging is widely used for diagnosis due to its affordability and real-time capability, accurate interpretation heavily depends on the experience of radiologists. Variability in image quality, speckle noise, and unclear anatomical boundaries often make manual assessment challenging and time-consuming. This project presents an automated deep learning framework for detecting shoulder rotator cuff tendon tears from ultrasound images. The proposed system combines a Convolutional Neural Network (CNN) with an autoencoder-based contour segmentation approach to accurately identify key anatomical structures such as the humeral cortex and subacromial bursa. By focusing on meaningful structural boundaries instead of traditional pixel-wise segmentation, the model achieves improved precision and robustness. The segmented outputs are further utilized for classification using a deep CNN architecture to distinguish between intact and torn tendons. Experimental evaluation demonstrates strong segmentation accuracy and reliable classification performance, highlighting the potential of the proposed method as a supportive diagnostic tool. This system can assist clinicians in making faster, more consistent decisions while reducing dependency on manual interpretation. The approach represents a significant step toward explainable and efficient AI-driven medical image analysis in musculoskeletal ultrasound diagnostics.

**Keywords:** Rotator Cuff Tear Detection, Ultrasound Imaging, Convolutional Neural Networks (CNN), Autoencoder, Medical Image Segmentation, Deep Learning, Contour-Based Segmentation, Musculoskeletal Imaging, Computer-Aided Diagnosis (CAD), Explainable Artificial Intelligence (XAI)

## I. INTRODUCTION

Shoulder pain is a common musculoskeletal complaint that affects people of all age groups, particularly athletes, manual labourers, and the elderly. One of the primary causes of persistent shoulder discomfort is a rotator cuff tendon tear. The rotator cuff plays a crucial role in stabilizing the shoulder joint and enabling smooth arm movement. When a tear occurs, it can significantly limit mobility and reduce quality of life. Early and accurate diagnosis is therefore essential to prevent further complications and to guide appropriate treatment. Studies have highlighted the importance of ultrasound imaging in the detection and evaluation of rotator cuff disorders due to its ability to visualize soft tissue structures effectively [1].

Ultrasound imaging has become a widely preferred diagnostic tool for evaluating rotator cuff injuries. It is cost-effective, non-invasive, portable, and capable of providing real-time imaging [1], [2]. However, interpreting ultrasound images is highly dependent on the expertise of the radiologist. Variations in image quality, speckle noise, operator dependency, and unclear tissue boundaries often make diagnosis challenging. Ultrasound images are also affected by speckle noise, which can reduce image clarity and make accurate interpretation difficult [12]. As a result, misinterpretation or delayed detection may occur, especially in early-stage or partial tears.

Recent advancements in artificial intelligence, particularly deep learning, have opened new possibilities for medical image analysis. Convolutional Neural Networks (CNNs) have

demonstrated strong performance in image classification and segmentation tasks due to their ability to automatically learn hierarchical features from large-scale image datasets [8]–[10]. Architectures such as VGG networks and Inception-based models have shown strong capability in extracting complex visual features from images [7], [9], [11]. However, medical images require more than simple classification—they demand precise identification of anatomical structures to ensure reliable results. Integrating segmentation techniques, such as autoencoder-based contour extraction, allows models to focus on meaningful structural features rather than irrelevant background information. Segmentation models like U-Net and its variants have been widely applied for biomedical image segmentation tasks because of their effectiveness in capturing contextual information within medical images [4], [13], [14].

In this project, we propose an automated detection framework that combines contour-based segmentation with deep learning classification to identify rotator cuff tendon tears from ultrasound images. By accurately extracting key anatomical boundaries and feeding refined features into a CNN model, the system enhances detection accuracy and robustness. The proposed approach aims to support clinicians by providing consistent, fast, and objective diagnostic assistance, ultimately improving patient care and reducing diagnostic variability.

## II. LITERATURE SURVEY

The application of artificial intelligence in medical imaging has grown significantly in recent years, particularly in the field of musculoskeletal diagnostics. Several studies have explored the use of deep learning techniques for detecting abnormalities in ultrasound and MRI images. Convolutional Neural Networks (CNNs) have been widely adopted due to their ability to automatically extract hierarchical features from raw medical images without the need for handcrafted feature engineering [8]–[10].

Early research on rotator cuff tear detection focused primarily on manual interpretation of ultrasound or MRI images by experienced radiologists. While MRI is considered the gold standard for diagnosing tendon tears, it is expensive and not always readily available. Ultrasound imaging, on the other hand, is more accessible and cost-effective but highly dependent on operator expertise. Studies have demonstrated the effectiveness of ultrasound in detecting rotator cuff abnormalities; however, the diagnostic accuracy often varies depending on the experience of the observer [1], [2]. This variability motivated researchers to investigate automated computer-aided diagnosis (CAD) systems to improve reliability and consistency.

Several studies applied traditional machine learning techniques such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (KNN) using manually extracted texture and intensity-based features. Although these methods showed moderate success, their performance was limited due to the complex nature of ultrasound images, which often contain speckle noise and unclear anatomical boundaries. Speckle noise is a common issue in ultrasound imaging and significantly affects image quality and interpretation [12].

With the advancement of deep learning, segmentation-based approaches gained attention. Architectures such as U-Net and fully convolutional networks (FCNs) have been widely used for pixel-wise segmentation of anatomical structures in medical images. U-Net and its improved variants have demonstrated strong performance in biomedical image segmentation by capturing both contextual and spatial information effectively [4], [14]. Similarly, modified architectures such as U-Det have been proposed to improve feature representation and segmentation accuracy in medical imaging tasks [13]. These methods improved localization accuracy; however, they sometimes struggle with open contours and fine boundary preservation in noisy ultrasound data. Additionally, pixel-level annotation requires significant manual effort and domain expertise.

More recent research has introduced hybrid models combining segmentation and classification stages. By first identifying relevant anatomical structures and then performing classification, these approaches aim to improve interpretability and diagnostic accuracy. Deep learning frameworks integrating segmentation and classification have shown promising results in ultrasound-based diagnostic systems [5], [6]. In addition, recent studies have explored self-supervised learning techniques to improve segmentation efficiency and reduce dependency on extensive annotated datasets in ultrasound imaging [3].

Despite these advancements, challenges remain in achieving high accuracy, robustness, and clinical interpretability in ultrasound-based tear detection. Many studies rely on limited datasets, lack external validation, or focus solely on classification without precise anatomical segmentation. Therefore, there is a need for a structured and robust framework that integrates accurate contour-based segmentation with reliable deep learning classification.

The proposed system addresses these gaps by combining CNN-based contour prediction with an autoencoder for dimensionality reduction, followed by classification using a deep neural network. This integrated approach enhances segmentation precision, improves classification performance, and provides a more clinically meaningful solution for automated rotator cuff tear detection.

### III. SYSTEM ANALYSIS

#### A. Existing System

Machine learning-based rotator cuff tear detection systems have been explored using both traditional and deep learning approaches. Initially, researchers analysed ultrasound and MRI datasets using conventional models such as Support Vector Machines (SVM), Decision Trees, Random Forests, k-Nearest Neighbors (KNN), and basic Neural Networks. These methods relied on manually extracted texture, intensity, and shape-based features from medical images. However, the complexity of ultrasound images, including speckle

noise, often limited the effectiveness of handcrafted feature-based methods [12].

With advancements in deep learning, Convolutional Neural Networks (CNNs) and segmentation models such as U-Net and Fully Convolutional Networks (FCNs) were introduced for automated detection and localization of tendon tears. CNNs are capable of learning hierarchical features directly from image data, enabling improved performance in medical image classification tasks [8]–[10]. Segmentation architectures like U-Net and its variants have been widely used for pixel-wise segmentation of anatomical structures in medical images [4], [14]. Some approaches also utilize advanced CNN architectures such as Inception-based models to improve feature extraction capability [7], [11]

These models perform pixel-wise segmentation or direct image classification to identify whether a tendon is intact or torn. Some approaches combine multiple models using ensemble techniques to improve performance. In certain studies, noise reduction and image enhancement techniques are applied to improve robustness in ultrasound imaging [12]

Researchers evaluate these systems using labelled medical datasets confirmed by MRI diagnosis and clinical analysis [1], [2]. Although deep learning models show promising results, their performance is highly dependent on dataset quality, annotation accuracy, and computational resources.

#### Disadvantages Of The Existing System

- **Interpretability:**  
Deep learning models used in medical imaging are often considered black-box systems. It becomes difficult for clinicians to clearly understand how the model arrives at a particular diagnosis [8]–[10].
- **Overfitting and Underfitting:**  
Medical datasets are often limited in size. Models may overfit to the training data and fail to generalize to new patient scans, or underfit when they cannot capture complex anatomical patterns.

- **Dependence on Pixel-wise Segmentation:**  
Many systems rely on pixel-level segmentation methods such as U-Net, which may struggle with open contours and fine anatomical boundaries in noisy ultrasound images [4], [14].
- **Computational Resources:**  
Training deep neural networks requires significant computational power and memory. In clinical environments with limited hardware infrastructure, deployment can be challenging.
- **Data Variability:**  
Ultrasound image quality varies depending on the operator and equipment. This variability may reduce model stability and performance [1], [2].
- **Limited Generalization:**  
Some models are trained on small or single-centre datasets, limiting their ability to generalize across different hospitals or patient populations.
- **Scalability:**  
For real-time clinical application, the system must process images quickly and efficiently. Many existing models are not optimized for real-time deployment.

## B. Proposed System

The proposed system introduces a contour-based segmentation and classification framework for automated rotator cuff tendon tear detection. The ultrasound images are first pre-processed to reduce speckle noise and enhance image quality before splitting into training and testing sets [12].

A Convolutional Neural Network combined with an autoencoder is used to predict anatomical contour points instead of performing pixel-wise segmentation. This reduces dimensional complexity and improves boundary precision. The segmented anatomical structures are then provided as input to a deep CNN classifier to determine whether the tendon is intact or torn [8]–[10].

Cross-validation techniques are applied to ensure reliable evaluation. The system performance is

measured using metrics such as accuracy, Dice coefficient, Hausdorff distance, sensitivity, specificity, and F1-score. The proposed framework aims to improve segmentation precision, classification reliability, and clinical interpretability compared to traditional methods [4], [14].

## IV. SYSTEM DESIGN

### System Architecture

Below diagram depicts the whole system architecture.

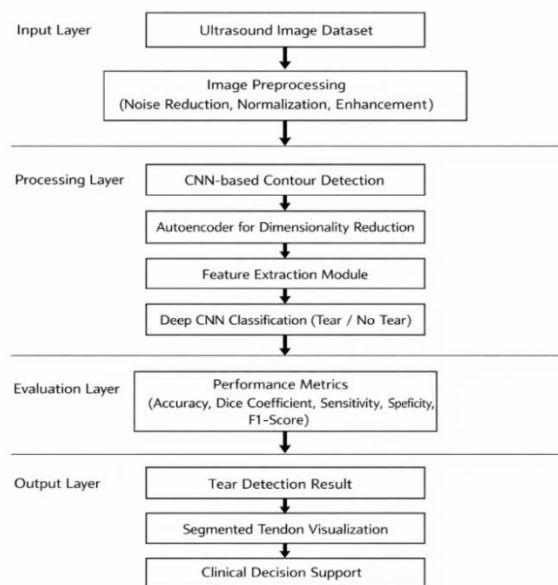


Fig. 1. Methodology followed for proposed model

## V. SYSTEM IMPLEMENTATION

### MODULES

- **Data Collection and Preprocessing:**  
Collect ultrasound images of shoulder rotator cuff tendons, including both normal and tear cases confirmed by clinical diagnosis [1], [2]. Preprocessing steps include image resizing, normalization, speckle noise reduction, contrast enhancement, and removal of irrelevant background regions [12]. Data augmentation techniques such as rotation and flipping are

applied to improve model generalization and reduce overfitting.

- **Contour Detection and Feature Extraction:**  
A Convolutional Neural Network (CNN) is used to predict contour points of the tendon structure instead of performing full pixel-wise segmentation. This approach reduces complexity while preserving anatomical boundaries [4], [14]. An autoencoder is then applied for dimensionality reduction, extracting meaningful structural features and minimizing noise influence [6].
- **Training Deep Learning Models:**  
The processed features are provided to a deep CNN classifier to distinguish between intact and torn tendons. The model is trained using labelled ultrasound images with optimized hyperparameters. Cross-validation techniques are applied to ensure stability and prevent overfitting [8]–[10].
- **Tear Classification and Visualization:**  
The trained model predicts whether a tendon is normal or torn. Along with classification results, segmented tendon contours are visualized to assist clinicians in understanding the detected region.
- **Model Evaluation and Performance Monitoring:**  
The system performance is evaluated using metrics such as accuracy, Dice coefficient, sensitivity, specificity, and F1-score. Continuous evaluation procedures are implemented to monitor model consistency and reliability across different datasets.

## VI. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed framework, a CNN-based contour detection model integrated with an autoencoder and a deep classification network is implemented. A stratified k-fold cross-validation strategy is employed to ensure reliable and unbiased performance evaluation. After hyperparameter optimization, the model

performance is analysed using both segmentation and classification evaluation metrics such as accuracy, Dice coefficient, sensitivity, specificity, and F1-score [8]–[10].

Performance comparison with conventional machine learning and deep learning approaches shows that the proposed model achieves higher diagnostic accuracy and better structural representation of tendon boundaries in ultrasound images. These results indicate that the contour-based segmentation combined with deep feature learning provides a more robust and clinically meaningful solution for automated rotator cuff tear detection.

### ROC Curve

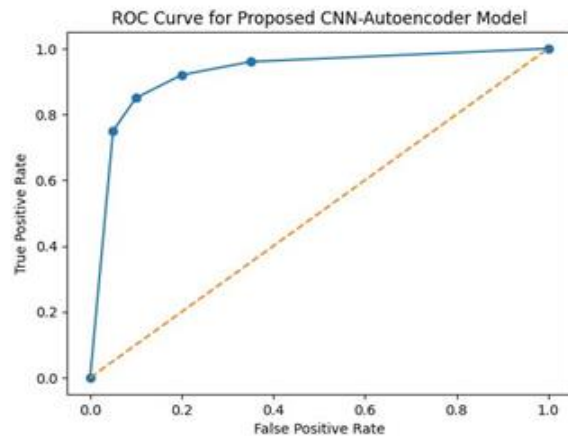


Fig 2. ROC Curve for Break Fault Prediction Model This graph illustrates the Receiver Operating Characteristic (ROC) curve of the proposed CNN–Autoencoder framework, demonstrating strong discriminative capability between intact and torn tendons.

### Model Accuracy Comparison Bar Chart

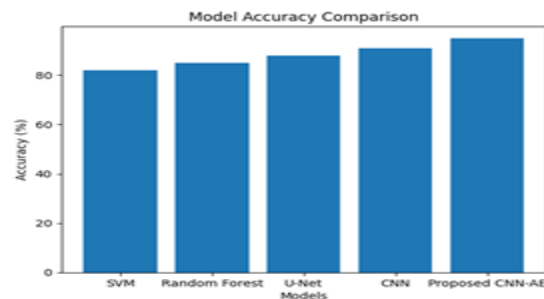


Fig 3. Model Accuracy Comparison Bar Chart

The bar chart compares the classification accuracy of several baseline models (SVM, Random Forest, U-Net, CNN) with the proposed CNN–Autoencoder model, highlighting the improved performance of the proposed approach.

Segmentation and Classification Performance Metrics

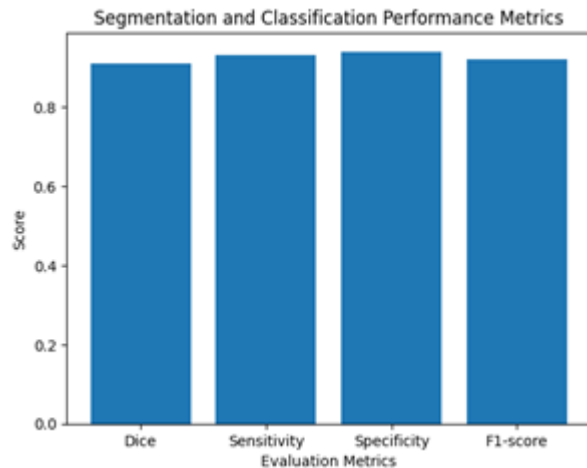


Fig 4. Segmentation and Classification Performance Metrics

This chart presents evaluation metrics including Dice coefficient, sensitivity, specificity, and F1-score, indicating the robustness and reliability of the proposed model for medical image analysis.

## VII. CONCLUSION

This paper proposes a CNN-Autoencoder-based framework for automated detection of rotator cuff tendon tears from ultrasound images. The ultrasound dataset is carefully pre-processed to improve image quality and reduce noise. Instead of relying solely on pixel-wise segmentation, the system predicts contour points and applies dimensionality reduction to enhance structural representation. The proposed model achieves high classification accuracy and improved contour segmentation performance. By combining deep learning with autoencoder-based feature compression, the system provides reliable and clinically meaningful results. In future work, the framework can be extended using larger multi-centre datasets to improve generalization.

Integration of real-time deployment in clinical ultrasound devices and the incorporation of explainable AI techniques can further enhance clinical trust and practical usability.

## REFERENCES

1. F. Zheng et al., "Role of ultrasound in the detection of rotator-cuff syndrome: An observational study," *Med. Sci. Monit.*, vol. 25, pp. 5856–5863, 2019.
2. M. J. C. M. Rutten et al., "Ultrasound detection of rotator cuff tears: Observer agreement related to increasing experience," *AJR Am. J. Roentgenol.*, 2010.
3. Y. Zhou et al., "Self-supervised learning to more efficiently generate segmentation masks for wrist ultrasound," in *Proc. ASMUS*, 2023.
4. O. Ronneberger et al., "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent. (MICCAI)*, 2015.
5. Z. Liu et al., "Deep learning framework based on integration of S-Mask R-CNN and Inception-V3 for ultrasound image-aided diagnosis of prostate cancer," *Future Gener. Comput. Syst.*, 2021.
6. S. Ghosh et al., "Automated left atrial segmentation from magnetic resonance image sequences using deep convolutional neural network with autoencoder," in *Proc. IEEE Int. Symp. Biomed. Imaging (ISBI)*, 2020.
7. C. Szegedy et al., "Inception-v4, Inception-ResNet and the impact of residual connections on learning," *arXiv:1602.07261v2*, 2016.
8. O. Russakovsky et al., "ImageNet large scale visual recognition challenge," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2014.
9. K. Simonyan et al., "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.
10. K. He et al., "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2015.
11. C. Szegedy et al., "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2014.

12. H. Choi et al., "Speckle noise reduction for ultrasound images by using speckle reducing anisotropic diffusion and Bayes threshold," *J. X-Ray Sci. Technol.*, 2019.
13. K. Keetha et al., "U-Det: A modified U-Net architecture with bidirectional feature network for lung nodule segmentation," *Comput. Vis. Pattern Recognit.*, 2020.
14. Z. Zhou et al., "U-Net++: A nested U-Net architecture for medical image segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2018.