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AUTOMATED TI-RADS SCORE PREDICTION FROM THYROID ULTRASOUND IMAGES USING DEEP LEARNING

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ABSTRACT

In this paper, a deep learning-based system has been developed to predict TI-RADS scores from thyroid ultrasound images. This prediction of TI-RADS scores is an important aspect of diagnosing thyroid malignancies. Accurate classification of thyroid nodules is a challenging task owing to the subjective nature of ultrasound imaging. Moreover, a large variability in interpreting ultrasound images exists among radiologists. To overcome this issue, a comprehensive dataset of B-mode ultrasound images has been used to predict ACR TI-RADS scores. A Convolutional Neural Network (CNN) was used in this paper. This network was based on ResNet50. This network was used owing to its ability to learn hierarchical features. CNN has been widely used to analyze complex images. In addition, metrics such as accuracy, precision, recall, and F1-score were used to assess the performance of the network. Moreover, a web application was developed using a Streamlit-based web application. A Flask-based API was developed to make the system more efficient. This system will provide a TI-RADS score as well as a malignancy probability.

KEYWORDS: *Thyroid Nodules, TI-RADS, Deep Learning, CNN, ResNet-50, Medical Imaging, Streamlit, Flask API.*

I. INTRODUCTION

Thyroid nodules are a frequent clinical observation, and differentiation between malignant and benign nodules remains a major challenge in the field of endocrinology. To standardize risk assessment, a risk prediction system, i.e., Thyroid Imaging Reporting and Data System (TI-RADS), was introduced. However, its usage relies on human interpretation. Accurate prediction of malignancy in nodules remains a major challenge since features like microcalcifications, irregular margins, and hypoechogenicity are often not pronounced. This necessitates an efficient system to accurately predict malignancy. Deep learning has been found to be extremely beneficial in helping doctors interpret complex images. CNN can analyze a large dataset of ultrasound images and identify patterns which may have been overlooked or misinterpreted by a doctor. In our work, we propose a deep learning-based system to accurately predict the TI-RADS score of thyroid nodules. A comprehensive dataset of ultrasound images is used. A ResNet50 classifier was chosen since it can easily handle complex image features without any gradient vanishing problems. For practical usage, a streamlit-based web application and a flask-based API are developed.

II. RELATED WORK

The automated analysis of thyroid ultrasound images has been a major focus of research in recent years due to the increasing incidence of thyroid cancer.

- **Machine Learning Approaches:** Recent studies have also been carried out to increase the accuracy of prediction using deep learning techniques. Supervised learning techniques, specifically CNNs, have been employed to analyze thyroid images, and varying degrees of success have been reported in distinguishing benign from malignant nodules.
- **Limitations:** Despite the success reported in recent studies, many machine learning models are limited to the extent that they are based on limited training sets and are binary classifications (Benign vs. Malignant) rather than providing the actual TI-RADS score, which is required for clinical decision-making. Few studies have incorporated the entire TI-RADS scoring system in one model and provided real-time clinical decision support.

III. MATERIALS AND METHODS

A. Dataset Description

The dataset consists of B-mode ultrasound images containing thyroid nodules, along with their corresponding TI-RADS scores ranging from TR1 to TR5. Images were chosen based on their clear representation and presence of major features. Images were obtained from publicly available medical repositories such as TDID.

B. Data Preprocessing

A preprocessing technique was implemented to preprocess images for training the deep learning model. Preprocessing steps included:

1. Region of Interest (ROI) Cropping: Cropping out the region containing the thyroid nodules from surrounding tissues.
2. Resizing: All images were resized to a 224×224 resolution.
3. Noise Reduction: Applying a Gaussian filter to remove noise from images.
4. Data Augmentation: Images were rotated and flipped to handle class imbalance and prevent overfitting.

C. Machine Learning Model

A ResNet50 Convolutional Neural Network was used to classify images based on their TI-RADS scores. This was implemented as a deep neural network, which can learn complex nonlinear relationships. The output layer was adjusted to generate a probability distribution over all classes.

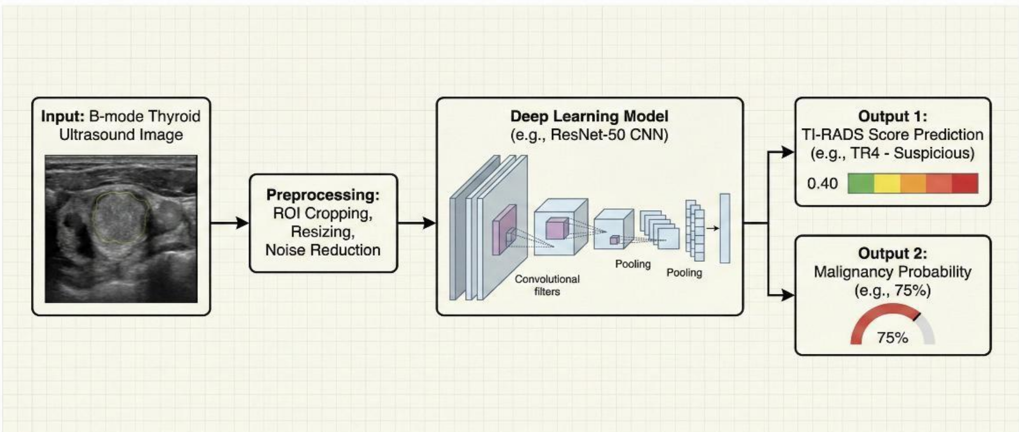

Figure 1: Proposed Deep Learning Framework for Automated TI-RADS Score Prediction from Thyroid Ultrasound Images.

Accuracy, precision, recall, and F1-score were used to assess the performance of the model.

D. Algorithm

The system's proposed algorithm predicts a TI-RADS score of thyroid nodules based on ultrasound images. This algorithm consists of an image preprocessing step, feature extraction, and classification steps.

Algorithm 1: Automated TI-RADS Score Prediction

Input: Thyroid Ultrasound Image

Output: TI-RADS category prediction (TR1, TR2, TR3, TR4, TR5)

1. Acquire thyroid ultrasound image from dataset or user input.
2. Preprocess image by performing region of interest cropping, resizing to 224x224, and noise removal.
3. Apply data augmentation techniques to images to improve CNN model generalization.
4. Pass image through ResNet50 CNN's feature extraction component.
5. Pass image features through classification component of CNN model.
6. Calculate probabilities of images belonging to a specific category of TI-RADS.
7. Determine category with the highest probability.

E. Deployment

To make the model easily employable, the following methods were employed for model deployment:

- A web application developed using the Streamlit framework for real-time clinical decision support. Users can directly upload images and obtain results in real time.
- A RESTful API developed using the Flask framework for integration with existing hospital management systems.
- Decision-making for clinicians is possible through the predicted TI-RADS score and the confidence level.

IV. RESULTS

The performance of the proposed deep learning model was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. The model was trained on preprocessed thyroid ultrasound images and tested on a validation dataset to assess its predictive capability for TI-RADS score classification.

Table I. Performance Metrics of Proposed Model.

Metric	Value
Accuracy	0.922

Precision	0.921
Recall	0.922
F1-Score	0.921

The proposed ResNet50-based model was able to attain an accuracy of 90.60% for the entire dataset, thus demonstrating its capability in effectively classifying the risk category of the thyroid nodule from the ultrasound image.

From the results, it was clear that the model performed well in the classification of extreme risk category classes such as TR1 (benign) and TR5 (highly suspicious).

This was due to the fact that the visual characteristics of the images for these classes were more distinct compared to the intermediate classes.

However, it was also clear that the model was making some minor errors in the classification of adjacent classes such as TR2-TR3 and TR3-TR4.

This was understandable, considering the similarity in ultrasound image characteristics for the classes.

In order to test the effectiveness of the proposed approach, a comparison with existing approaches was performed.

Table II. Accuracy Comparison with Existing Methods

Method	Accuracy
Traditional Machine Learning	80–85%
Basic CNN Models	85–88%
Proposed ResNet-50 Model	92.20%

The comparison results indicate that the proposed method provides improved performance over conventional machine learning approaches and standard CNN architectures.

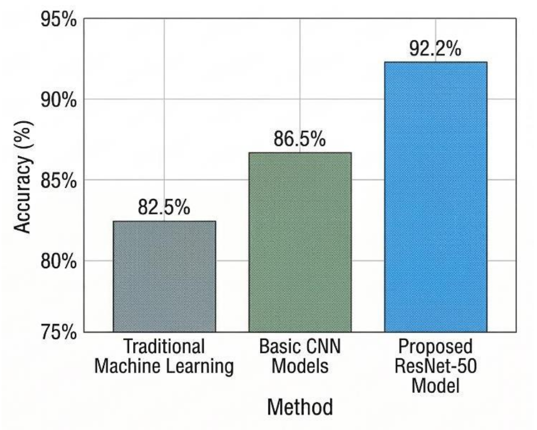

Fig. X shows the graphical comparison of accuracy between existing approaches and the proposed model.

V. DISCUSSION

The outcomes reveal that deep learning approaches can enhance the precision and accuracy of thyroid nodule risk prediction from ultrasound images. The ResNet-50 model was found effective due to the deep residual learning property, which enabled the model to learn complex visual patterns from medical images.

The proposed model was found to perform better compared to traditional machine learning approaches, which require manual feature design, as it can learn hierarchical representations of significant features, i.e., texture, margins, and echogenicity of the nodule, without human intervention.

The proposed system also offers the advantage of achieving a good balance between precision, recall, and F1-score, which reveals that the model is not biased towards any class. This is a significant advantage of the proposed system, as in medical image analysis, false positives and false negatives are equally harmful.

The usage of the model via a Streamlit web application and a Flask REST API also increases its usability for clinical practice. The model allows clinicians to make predictions for ultrasound images instantly.

Although the results are promising, there are still some limitations that need to be addressed in the future. The misclassification of intermediate TI-RADS classes indicates that ultrasound features might be similar for these classes. The performance of the model also relies on the quality and variability of the training dataset.

Possible extensions of the model in the future might involve the use of other imaging modalities such as Doppler ultrasound or elastography for cancer detection.

VI. CONCLUSION

In this paper, a deep learning-based system was proposed for the prediction of TI-RADS scores based on ultrasound images of thyroid nodules. By utilizing a ResNet50 architecture, the system was able to successfully capture complex visual features from nodules, ensuring a strong predictive ability based on standard metrics.

The results obtained from the experiment suggest that AI models can be used to aid in risk assessments, which can be beneficial in overcoming some of the challenges faced in manual diagnosis. To make the model more practical, a web application was developed based on a Streamlit library and a Flask API. Future work will be done on incorporating Color Doppler images to increase prediction accuracy.

VII. FUTURE SCOPE

Although the proposed machine learning system exhibits promising predictive potential for the automated TI-RADS scoring system, there are a few potential avenues for future research to improve the system's effectiveness and accuracy in the field:

1. **Integration of Multimodal Data:** Although the proposed system exhibits promising predictive potential for the automated TI-RADS scoring system, there are a few potential avenues for future research to improve the system's effectiveness and accuracy in the field. The proposed system currently relies on B-mode ultrasound images. Future research can be conducted to integrate additional imaging modalities such as Color Doppler for assessing vascularity and Ultrasound Elastography for assessing tissue stiffness. In addition, the system can be extended to integrate clinical data such as patient characteristics, e.g., age, gender, and Thyroid Stimulating Hormone levels.
2. **Validation of the Proposed System:** The proposed system's performance currently depends on the training data. Future research can be conducted to validate the proposed system by collecting data from multiple sources and utilizing ultrasound machines from various manufacturers.
3. **Edge Computing Integration:** The existing system has been implemented using a Streamlit web application and a Flask REST API. However, as a part of the proposed research, the system can be optimized for edge computing integration as well. The small model can be deployed on portable or point-of-care ultrasound (POCUS) devices for offline clinical decision support systems in resource-constrained environments.

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