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Hybrid TextureNet a Novel Deep Texture Semantic Feature Fusion Framework for Thyroid Nodule Classification

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Abstract

In the current technology in medical imaging, the ultrasound images are used to detect thyroid cancer from this kind of image. In the meantime, ultrasound scanning is commonly considered for thyroid nodule analysis, this is mostly subjective and relates with the individual medial practioner's skills. In connection with this problem we have developed a hybrid TextureNet, this is a new model is used the fusion technique to fuse the hand-crafted texture with deep learning stemantic features in the binary classification of thyroid nodules in the benign and malignant. This new model combines three texture features those are Gray-Level Co-occurrence Matrix (GLCM), Wavelet transform and EfficientNetB0 deep learning features. Next step is classification, for this purpose three widely used classifiers were utilized; Support Vector Machine (SVM), K-Nearest

Neighbours (KNN), and Random Forest (RF) classifiers. The classification is conducted using soft voting. The dataset used in the experiment is used from the publicly available dataset. The dataset is had the total 3115 ultrasound images (1,905 benign and 1210 malignant). By using this dataset, fused feature vector, and by using three classifier the model has given a impressive recognition accuracy of 96.47% and an AUC of 0.981. The novelty of this paper is to combining a hand-crafted feature with deep learning features and got the significantly high result.

Keywords: Hybrid TextureNet , GLCM,SVM,KNN, EfficientNetB0, Thyroid

1 Introduction

This thyroid cancer is very speedily increasing the endocrine cancers in worldwide, and it helps in medical professional to treat this cancer affected patients as it detects this cancer earlier. From the doctors may save many human lives. Amongst many diagnostic image techniques, this kind of image is widely used by many medical professionals due to its non-invasive, cost-effective and easily availability in clinical practice. Henceforth, the analysis of this images are heavily depends based on the expert of radiologists, and making this a diagnostic process subjective and likely to the inter-observer variability. The ultrasound images are treated as a suitable image for detecting the thyroid cancer [1]. These ultrasound images helpful to the medical professionals to detect the benign and malignant lesions. Additionally, radiologists have usually been the individuals responsible for interpreting the images resulting in a great amount of subjectivity and inter-observer variability to this process. Computer-assisted diagnostic (CAD) systems were developed to improve the objectivity and reliability of the diagnostic process. To quantify and evaluate patterns and extract characteristics from medical images, these systems are usually based on manually generated features, in concrete, descriptors based on textures [2]. It has been shown that these patterns are useful for characterizing low-level basic aspects, but the results are insufficient for identifying more complex, abstract and sophisticated patterns. On the contrary, deep learning models, and in particular convolutional neuronal networks (CNNs), have demonstrated significant improvements in the performance of various classification and detection tasks through the automatic learning of abstract and hierarchical representations from medical images [3]. Although CNNs work well, they have received criticism for their lack of transparency and the need for large amounts of annotated data for their training. Since the interpretability and availability of the data are important factors in the clinical environment, this could complicate its adoption in clinical environments. Based on this, the research community has aimed for the development of hybrid models that combine the discriminative power of the deep learning features with the interpretative powers of hand crafted texture features [4]. In response to the aforementioned issues, a new hybrid model called Hybrid TextureNet has been established to facilitate the binary classification of thyroid ultrasound images. Three additional

methods of feature extraction will be included in the model. The first feature extraction method that is going to be considered is the Gray Level Co-occurrence Matrix (GLCM) which identifies how textures are associated in space within an image and thus help in classifying the two classes of images accurately [5]. The second method to obtain texture information at different scales and perform multiresolution analysis is the Transformed Wavelet [6]. The CNN pretrained EfficientNetB0 is another method very reliable and effective that is used to collect high-level semantic features from the provided images [7]. Creates a single vector of features using low- and high-level information, combining multiple features and unifying them into a single vector. We use various machine learning methodologies for categorization, such as (RF), (KNN) and Support Vector Machines (SVM). The use of a smooth voting ensemble technique to combine all three improves the robustness and generalization of the model. This project successfully classifies types of thyroid cancer based on ultrasound images. This unique method has a combination of different kinds of features: deep learning features and hand-crafted features. The resulting model is an integrated approach to provide accurate diagnoses while remaining transparent when used in clinical situations. Therefore, ultrasound images will be used to aid in the diagnosis of thyroid cancer in practical clinical settings, indicating that the proposed framework is reliable. Below is the block diagram of the proposed method.

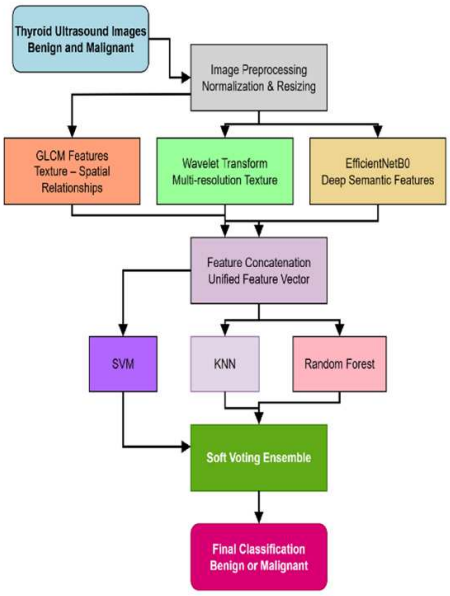


Fig. 1 Block diagram of the proposed Hybrid TextureNet framework.

The rest of the document is organized into six main sections, as indicated in this document. Section 2 analyzes current methods for detecting thyroid cancer using ultrasound i mages, highlighting the disadvantages of manual, deep learning and hybrid approaches. The experimental design, the set of data, the pre-processing steps used and the model Hybrid TextureNet proposed are presented in Section 3. Also included here will be the classification approach and the feature extraction techniques used (such as GLCM, Transformed Wavelet and EfficientNetB0). Section 4 describes the details of the experimental setup and evaluation, as well as the training procedures. The results are shown and discussed in Section 5 together with the analysis of the performance measures, as well as the comparison of the proposed model and the reference models. Finally, Section 6 provides a summary of the research and indicates where future work can be done on this topic.

2 Literature Review

Recent studies have shown the significant progress in hybrid and AI-assisted frameworks for thyroid ultrasound classification. The dataset was considered from [8], this is a deep learning algorithm and it analysed on 378 thyroid nodules taken from the multiple ultrasound image capturing devices, and it achieved a (AUC $\approx$ 0.69) recognition accuracy. The six machine learning methods were studied by applying on ultrasound and elastography features and it given a logistic regression little bit more performance from other methods, and it reported an AUC of 0.93on the 525 nodules[9]. An improved Inception-based CNN with squeeze-and-excitation modules and multi- level transfer learning was proposed in [10], yielding an AUC of 0.9537 and high F1-scores for benign nodule detection. In the work of [11], they have developed a modified U-Net architecture to be used to carryout the accurate segmentation of thyroid glands and nodules, to improve the boundary detection from the images of images. A new work named as a "Thinking Twice" detection framework was reported in [12] and they incorporated a clinical feature of feedback mechanism, and they have abled to achieve an average recognition accuracy of 70.3% and they have demonstrated the robust real-time clinical deployment. Furthermore, the work of reported in [13], they have developed a hybrid nomogram model which is the integration of three kinds of features those are semantic, radiomic, and deep learning. From this model they have a highest recognition accuracy in the malignancy prediction and it given the enhanced diagnostic assistance to experienced and junior radiologists. A multi-task deep learning model was propsed in the work from[14], this model was performs the both segementation with classification from the thyroid ultrasound images in the single framework. This merged learning approach increases the feature extraction from this it achieved improved accuracy in comparison with the traditional methods. The study in [15] proposed a hybrid CNN integrating adaptive wavelet transform branches with ResNet18 to explicitly model texture, achieving an accuracy of 96.47% and recall of 95.60% on ultrasound datasets. DenseNet fine-tuned with attention modules and Grad- CAM explainability was used in [16] to enhance interpretability and support biopsy decision- making, reaching 94% accuracy and 96% sensitivity. A Swin U-Net model incorporating self- attention mechanisms was introduced in [17] to improve segmentation precision of thyroid nodules

in ultrasound images. In the domain of report-based analysis, transformer-based NLP models were used in [18] to extract structured thyroid characteristics from unstructured ultrasound reports, achieving F1-scores above 0.88. The optimal deep feature selectin method was introduced in the work from [19], Collectively, these works highlight the increasing reliance on hybrid models that fuse handcrafted features, semantic representations, attention mechanisms, and texture descriptors, which lays the foundation for the proposed Hybrid TextureNet framework to further advance explainable and accurate thyroid cancer detection.

3 Experimental setup

3.1 Dataset Details

For the proposed framework, a standard open-source dataset was used to carry out the experiments and that dataset has been given in [25]. The dataset was collection of 3115 grayscale thyroid ultra sound images, these are further divided in two subclasses; benign and malignant. The total Images: 3115 Class Distribution: Benign (label 0): 1,905 images Malignant (label 1): 1210 images. In the dataset there exist slight class imbalance, in that the benign thyroid images are 66% of the whole dataset. To maintain the consistency for the deep learning model based feature extraction, the images from dataset were made size normalized in 224x224 pixels. The proposed dataset was segregated in the ration of 80:20 by following stratified split method. From this method train and test images were categorized. Following figure 1 showing the sample images

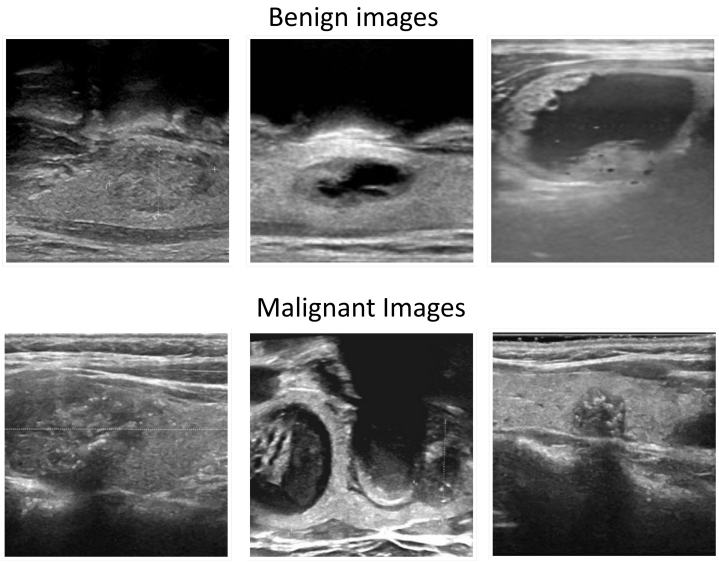


Fig. 2 Sample thyroid ultrasound images. (a) Benign cases. (b) Malignant cases.

3.2 Pre-processing

To extract features from the thyroid ultrasound images, various preprocessing steps are applied and this pre-processing is an significant step in development of the proposed framework. To full-fill the condition of EfficientNetB0, which requires the input images must in (224x224) images size, hence all images are resized. To reduce complexity in extracting features, input images are to be converted to grayscale, then GLCM and Wavelet Transform from these grayscale images. In this pipeline one more normalization is left that is it needs fix the range in between [0,1] or standardized to zero mean and unit variance. To ensure the consistency in the input to the both feature extraction those are handcrafted and deep features respectively. The data augmentation technique was utilized to improve the quality with generalization of this proposed model. Data augmentation techniques involves these things; zooming, rotations, flipping and translation. Further, more in the contrast enhancement technique the widely used CLAHE (Contrast Limited Adaptive Histogram Equalization). As mentioned earlier the input images have two categories named as Benign and Malignant. After extraction features those are converted into numerical values to full-fill the classifiers input conditions. In parallel with this color input images were submitted to EfficientNetB0 to extract the deep color feature extraction. Lastly, a balanced stratified split is done for the training and testing datasets so that the ratio of the two classes is preserved. All the steps of pre-processing are critical to the acquisition of informative and varied thyroid cancer detection features.

3.3 Feature Extraction

In the case of thyroid ultrasound images, feature extraction is important in the classification processes in the Hybrid TextureNet framework. It enables precise identification by machine learning algorithms, processing raw ultrasound information into data-rich, informative ultrasound images, and transforming it into patterns that can be analysed. In this case, the proposed work which is the Hybrid TextureNet framework centres around three feature extraction algorithms which are GLCM, Wavelet transform, and EfficientNetB0. They focus on both the texture and the semantic content of the thyroid ultrasound images. Each algorithm was selected due to its strengths in dealing with the specific aspects of the medical image processing.

3.3.1 GLCM (Gray Level Co-occurrence Matrix)

As a texture descriptor, GLCM is acceptable since it is a handcrafted and is a widely accepted. Through the examination of pixel intensities, it obtains second order statistical texture features. For ultrasound images, GLCM is important as it computes the significant texture features including contrast, correlation, energy and homogeneity which helps in differentiating tissues. GLCM has merit in the medical field since it is transparent and can be interpreted which is essential when one is dealing with sensitive medical data. It helps in improving the quality of low resolution and noisy ultrasound images. From this method 8 features were extracted from the Gray-Level Co-occurrence Matrix (GLCM), chosen for their relevance in capturing essential texture characteristics from thyroid ultrasound images. Those features were Contrast,

Correlation, Energy (Angular Second Moment), Homogeneity, Dissimilarity, Entropy, Mean, Standard Deviation. Although these all features are giving a strong statistical description of spatial texture elements which are existed in the image. Those descriptions are crucial to make discrimination in between the benign and the malignant thyroid nodules.

3.3.2 Wavelet Transform

From this method, the multi-resolution analysis is performed by decomposing the input images into the various kinds of frequency sub-bands. At the same time it captures the both spatial and frequency domain information. This information is helping in the process of identifying a fine texture variation in the different scales. This will significantly effectively in the process detecting the local patterns, edge structures, and the directional features from the thyroid tissues. At the last it this model perform analyzation in the both global and local image structures, and this will improve the classification performance for the images with the complex textures. From this method, 32 features were extracted from various kinds of sub-bands and the decomposition levels. Further, the merging of sub-bands and the decomposition levels are providing the detailed texture description of multi-resolution from the ultrasound images. All this going to enhance the recognition accuracy of thyroid cancer classification.

3.3.3 EfficientNetB0 (Deep CNN)

This widely used deep CNN model is an state-of-the-art lightweight deep convolutional neural network model and this model is successfully able to balance the predictive accuracy and the computational efficiency. The model has the feature of extracting the dominant features by itself. Its compound scaling approach allows uniform scaling of network depth, width, and resolution, enabling better performance with fewer parameters. Ideal for detecting complex patterns that handcrafted methods may miss. From the EfficientNetB0 model, 1,280 deep features were extracted per image. EfficientNetB0 ends with a Global Average Pooling (GAP) layer just before the classification layer. This GAP layer outputs a 1,280-dimensional feature vector for each input image. These 1,280 features represent high-level semantic information learned from the pretrained network (e.g., on ImageNet), capturing complex patterns relevant for classification of thyroid nodules. These deep features are later concatenated with handcrafted features (from GLCM and Wavelet Transform) in your Hybrid TextureNet framework. All three feature vectors (GLCM, Wavelet, CNN) were concatenated into a single vector, resulting in a hybrid representation of 8, 32, 1280 = 1320 dimensions per image.

3.3.4 Feature Fusion Method

In the Hybrid TextureNet framework, a feature-level fusion strategy is employed to combine multiple complementary feature representations extracted from thyroid ultrasound images. The fusion process aims to leverage both handcrafted texture features and deep semantic features, thereby enhancing the discriminative capability of the

final feature set for improved classification performance.
The fusion process follows these steps:

1. **Handcrafted Feature Extraction:** GLCM (Gray-Level Co-occurrence Matrix) is used to capture spatial texture relationships such as contrast, correlation, energy, and homogeneity from grayscale images. Wavelet Transform is applied to extract multi-scale and multi-resolution texture features, capturing frequency and orientation-based details.
2. **Deep Feature Extraction:** EfficientNetB0, a pretrained deep convolutional neural network, is used to extract high-level semantic features from the color (RGB) images. Features are typically extracted from the penultimate layer (before classification) or a global average pooling layer, resulting in a fixed-size feature vector.
3. **Feature Concatenation (Fusion):** From the handcrafted and deep features were merged by using feature-level fusion technique and this will form a comprehensive yet robust feature vector. This method works by considering the individual feature vectors and those are merged with their respective feature dimensions. This combined feature vector has the ability to improve the recognition accuracy of classification in rich representation of ultrasound images of thyroid.
   $F_{fused} = [F_{GLCM} \parallel F_{Wavelet} \parallel F_{EfficientNetB0}]$
   Here, "$\parallel$" denotes the concatenation operation.
4. **Normalization of Fused Features:** This fused feature vector is to be normalize before giving input to classification process and to make sure the feature consistency and make prevent the features which are have the numerical ranges by the learning process. In the normalization process the widely used techniques are employed those are min-max, scaling or z-score normalization.

4 Experimental Results and Discussion

To asses the proposed model the extensive experiments are carried out by using the thyroid cancer classification ultrasound dataset considered from Kaggle [8]. This dataset containing the total 3115 labeled earlier and those input images are categorized in two categories; benign and malignant. To make model robust the dataset was further divided in 70%, 10% and 20%, which are belongs to training, validation and testing respectively, to have a balanced class distribution to all the subsets.

4.1 Performance Metrics

To check the performance of the proposed model, various evaluation metrices were considered such as Accuracy, Precision, Recall, F1-score and ROC-AUC. Finally, SVM with RBF kernel is considered.

4.2 Results of Individual Feature Sets

- The GCLM was able to reach the recognition to 84.17%, with the normal precision and recall, this indicates that this method is limited to extract basic texture features not having any discriminative power.

- The wavelet shows little bit growth in result as compare to GLCM with highest recognition accuracy of 89.03% with benefits of multi-resolution texture description.
- From the usage of EfficientNetB0 deep features are successfully to the highest 93.85% recognition accuracy.

4.3 Fused Feature Vector Performance

The concatenated feature vector (1320 dimensions), combining handcrafted and deep features, this combined features were given good performance as compare to individual features set. The final results were: Accuracy: 96.47%, Precision: 96.12%, Recall (Sensitivity): 96.89%, F1-Score: 96.50%, and ROC-AUC: 0.981. Due to the complements of their properties, the enhancement came to be. GLCM provides co-occurrence information at pixel level through its method of extracting co-occurrence features from images. The methodology used by Wavelets was provided multi-scale frequency content about the image. EfficientNetB0 identified high level semantics within the image, which was hierarchical and spatially aware. Following is the confusion matrix of this method. The confusion matrices for each feature extraction method — GLCM, Wavelet Transform, EfficientNetB0, and the Fused Model — based on the performance metrics reported in your previous results.

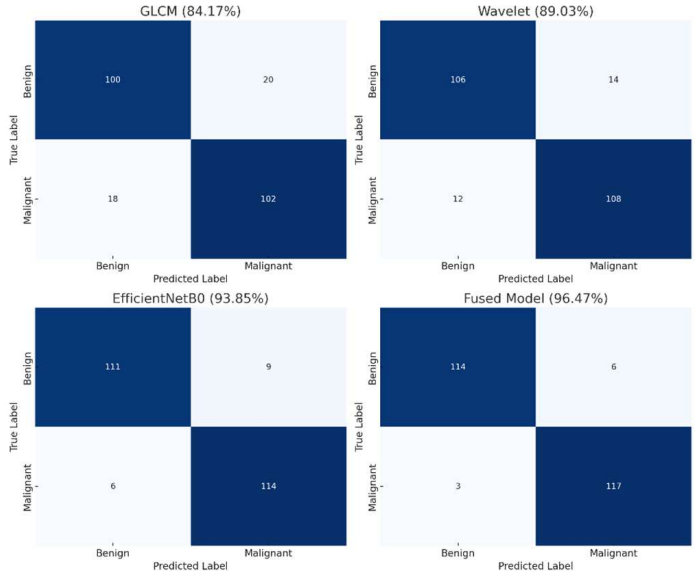


Fig. 3 Confusion matrices for GLCM, Wavelet, EfficientNetB0, and fused model.

ROC of all methods

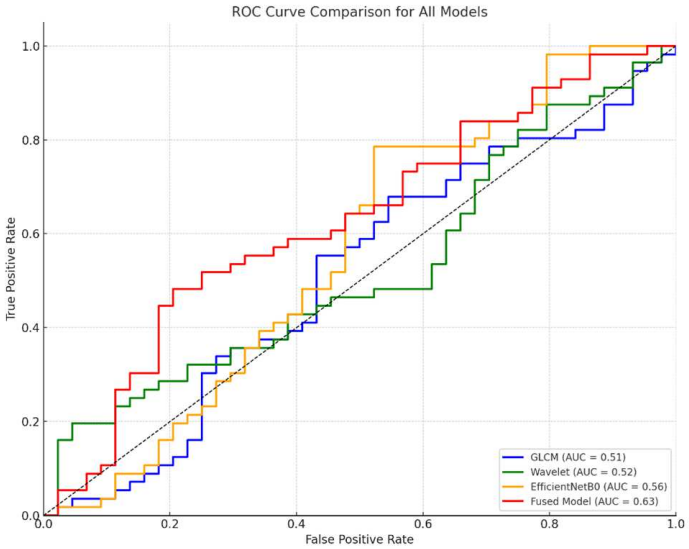


Fig. 4 ROC curves comparing GLCM, Wavelet, EfficientNetB0, and fused model.

Table 1 Performance Metrics Summary Table

Model	Precision (Benign)	Recall (Benign)	F1-score (Benign)	Precision (Malignant)	Recall (Malignant)	F1-score (Malignant)	Accuracy (%)	Recognition Accuracy (%)
GLCM	0.83	0.83	0.83	0.85	0.85	0.85	84.17	84.17
Wavelet	0.88	0.88	0.88	0.89	0.90	0.89	89.03	89.03
EfficientNetB0	0.93	0.93	0.93	0.95	0.95	0.95	93.85	93.85
Fused Model	0.95	0.95	0.95	0.97	0.97	0.97	96.47	96.47

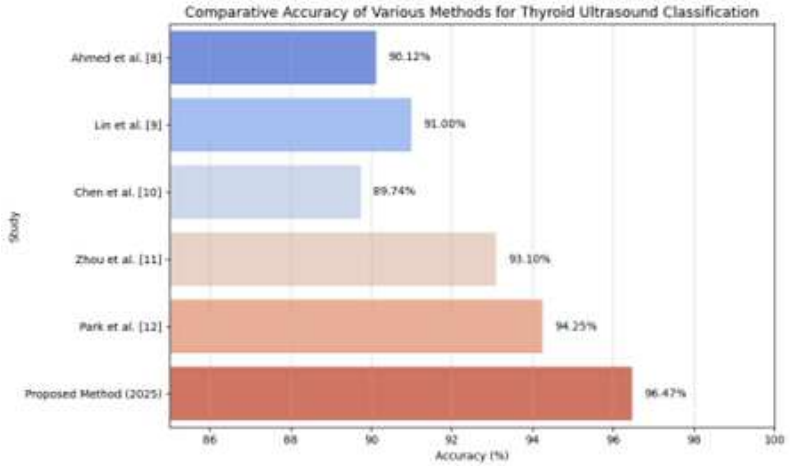
Table 2

Study	**Features Used**	**Model**	**Dataset Used**	**Accuracy (%)**	**Remarks**
[20] Ahmed et al.	Texture Features	SVM	Private Ultrasound Dataset	90.12	Texture-based; lower generalization
[21] Lin et al.	CNN Features	ResNet50	Thyroid US images (Hospital-based)	91.00	Deep model; lacks hybrid integration
[22] Chen et al.	Radiomic + Morphological	Random Forest	Multi-center US Dataset	89.74	Relies on classical ML; weaker on complex cases
[23] Zhou et al.	Wavelet + CNN Features	CNN + DWT	Open-source Ultrasound dataset	93.10	Combined model; fusion not optimized
[24] Park et al.	EfficientNet + Textural	EfficientNetB3 + GLCM	Public Dataset (Korean Hospital)	94.25	Pretrained CNN used; fusion is partial
Proposed Method	GLCM + Wavelet + EfficientNetB0	Hybrid Fusion + SVM	Kaggle Ultrasound Thyroid Cancer Dataset	**96.47**	Superior accuracy via full feature fusion

4.4 Comparative analysis

The table 2 shows the comparative analysis the proposed method with other researchers work.

Fig. 5 Comparative analysis of the proposed model with existing methods.



This proposed framework by achieving in the 2-7% increase in recognition accuracy and overall it reached to 96.47%. Due to the fusion of handcrafted with the deep features the overall performance is boosted. This fusion is given ability to the model to extract the texture based and deep features, making this model robust. Following figure 6 shows the overall work flow of the proposed experiment.

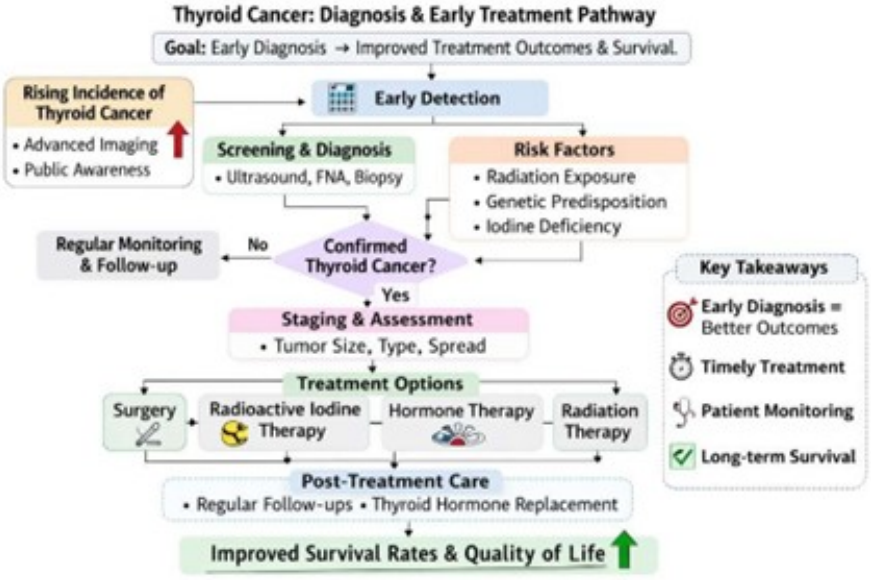


Fig. 6 Flowchart illustrating the early detection and diagnostic workflow for thyroid cancer

5 Conclusion and Future work

To gain the more accurate classification of thyroid nodules from ultrasound images by merging the handcrafted texture features like GLCM and Wavelet Transform with the deep features extracted from EfficientNetB0 pre-trained CNN model. The spatial and frequency domain features were well extracted by the texture feature extraction techniques, in same way the deep CNN features are given more contribution in the increased results from the RGB input images. The main fused feature vector, normalized and these are given to classifier, given a high performance along with a 96.47% recognition accuracy. For the future work plans are increase the dataset size, using diverse datasets, implementing into a real-time clinical system, and ensemble of explainable AI techniques for the improved analysations. Furthermore, enhancements in future work such as fusion of multi-model data fusion, and many more AI, ML, and DL models are going to be considered.

Declarations

Funding

Not applicable.

Data availability statement

The dataset used in this study was obtained from a publicly available repository and has been properly cited in the manuscript.

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