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# Hybrid deep learning and ensemble learning approach for high-accuracy thyroid disease classification

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**ABSTRACT**

Thyroid disease is a common endocrine disorder affecting the thyroid gland, a small butterfly-shaped organ at the base of the neck. According to the World Health Organization (WHO), nearly one billion people worldwide are affected by thyroid-related conditions. Conventional diagnostic methods, such as thyroid scans and function tests, are often costly, time-consuming, and complex for clinicians to interpret. To overcome these limitations, this study introduces a novel temporal conditional-Markov random field (TC-MRF) framework for early detection and classification of thyroid disease. The multi-modality images computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US) are collected from the ImageNet database and preprocessed using contrast stretching adaptive Gaussian star (CSAGS) filter to improve image clarity. The enhanced images are then processed over a convolutional neural network (CNN) for feature extraction. These features are classified using a random forest (RF) model to determine whether the thyroid condition is normal or abnormal. The proposed TC-MRF achieves a classification accuracy of 98.27% and F1-score of 96.05%. The TC-MRF enhances the total accuracy range of 6.30%, 4.11%, and 5.36% better than naive Bayes, multilayer perceptron (MLP), and decision tree, respectively.



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## 1. INTRODUCTION

Thyroid disorders, including hypothyroidism and hyperthyroidism, are among the most common endocrine abnormalities worldwide, second only to diabetes [1]. The thyroid gland is essential for regulating blood pressure, heart rate, metabolism, and body temperature because it produces hormones such as thyroxine (T4) and triiodothyronine (T3) [2]. Dysfunction in the thyroid or related organs such as the pituitary and hypothalamus can disrupt hormonal balance, leading to serious health complications [3]. Hypothyroidism can result in fatigue, weight gain, depression, and cognitive impairment, whereas hyperthyroidism may cause anxiety, weight loss, palpitations, and cardiovascular issues [4]. Early and accurate diagnosis of these conditions is crucial to prevent complications and ensure effective treatment, highlighting the need for improved diagnostic approaches [5]. Traditional diagnostic methods, including laboratory blood tests and imaging techniques such as ultrasound (US), computed tomography (CT), and magnetic resonance imaging (MRI), are widely used to detect thyroid abnormalities [6].

Blood tests assess hormone levels to determine thyroid function, while imaging provides insights into structural anomalies [7]. However, these methods are often dependent on human expertise and interpretation, which can result in inconsistent outcomes and increased diagnostic errors [8]. Recent developments in deep learning (DL) [9] and machine learning (ML) [10] have demonstrated promise in tackling these issues by facilitating automated, data-driven interpretation of medical imagery and patient data [11]. Algorithms such as support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN) [12] can extract patterns from complex datasets, offering higher accuracy, efficiency, and objectivity compared to traditional methods [13]. Nevertheless, current models often focus either on feature extraction or classification alone and may fail to integrate both optimally, limiting their performance in real-world clinical scenarios [14]. To address these challenges, this study proposes a novel temporal conditional-Markov random field (TC-MRF) for thyroid disorder detection. The key contributions of this research are multi-modality images were obtained from the ImageNet dataset. ImageNet is a large-scale annotated database that provides high-quality, full-resolution images across diverse categories. Using this dataset ensures variability and richness in input samples, thereby enhancing the generalization ability of the proposed TC-MRF framework. The multi-modality images are preprocessed by CSAGS filter to enhance the image quality and reduce the noise artifacts. In order to extract multi-level discriminative features from low-level texture and edge patterns to high-level semantic representations of thyroid abnormalities, the denoised images are fed into a CNN. Based on the extracted features, the RF classifies thyroid disease into four classes: normal, hypothyroidism, hyperthyroidism, and thyroid nodules. In comparison to single classifiers, it improves accuracy, robustness, and generalization by constructing several decision trees and combining their outputs by majority voting. The efficiency of the proposed TC-MRF model was evaluated based on the criteria, includes F1-score, precision, recall, specificity, and accuracy.

This structure of the paper is organized as follows: section 2 explains the literature survey in detail. Section 3 explains the proposed TC-MRF method. Section 4 explains the results and discussion. Section 5 explains the conclusion and future work.

## 2. LITERATURE SURVEY

In recent years, several researchers have proposed diverse frameworks aimed at enhancing the precision of thyroid disease classification in patients. This section provides a concise analysis of some of these approaches.

i) Topsir *et al.* [15] suggested a sophisticated ML method that combines Kolmogorov-Arnold networks (KANs) for classification with generative adversarial networks for data augmentation. Multilayer perceptrons (MLP), logistic regression (LR), RF, SVM, and KANs were among the ML models that were trained and assessed. In particular, the KAN model outperformed CNN applications with an AC of 98.68% and an RF F1-score of 98.00%.

ii) Sharma *et al.* [16] suggested that a pre-trained model like Mixer-MLP, DeiT, and Swin Transformer is utilized for feature extraction. To solve problems with class imbalance, the proposed method combines an ensemble model with stratified over-sampling. The optimal values are 92.83%, 87.76%, 97.66%, 88.89%, 0.9551, and 0.9357 for accuracy, precision, recall, specificity, F1-score, and ROC-AUC score.

iii) Xiang *et al.* [17] suggested a multi-attention guided UNet (MAUNet) for segmenting thyroid nodules. It uses a multi-scale cross attention (MSCA) module for the initial visual feature extraction step. The model is trained utilizing the federal learning approach to protect privacy. The model Dice scores on the three center datasets are 0.908, 0.912, and 0.887, respectively, based on the experimental findings.

iv) Raza *et al.* [18] suggested an artificial intelligence-based method for thyroid disease early detection. In order to diagnose thyroid disease and address issues with class imbalance, this study used a fine-tuned light gradient booster machine technique and the nominal continuous synthetic minority oversampling strategy for data balancing. In comparison to the state-of-the-art technology, the proposed synthetic minority over-sampling technique-nominal and continuous-light gradient boosting machine (SMOTE-NC-LGBM) methodology achieved high accuracy performance ratings of 0.96.

v) Uddin *et al.* [19] suggested a hybrid feature selection technique for thyroid disease prediction that is based on ensemble ML. To choose the best thyroid prediction outcome, we used five ML models in addition to the Ensemble ML classifier. Using the extreme gradient boosting (XGBoost) and SelectKBest feature selection methods, the ensemble ML classifier achieves the best results on hard voting on RF and DT with 100% recall and 99.71% accuracy.

vi) Akter and Mustafa [20] suggested a method for feature significance analysis and model explanation that has been investigated both locally and globally utilizing explainable artificial intelligence (XAI) tools.

Lastly, the domain experts confirm the XAI results. According to experimental data, our suggested mechanism may accurately explain the models and is useful in detecting thyroid illness.

vii) Kesavulu and Kannadasan [21] proposed a better bio-inspired method for thyroid prediction using ML. In order to increase the accuracy of thyroid disease prediction, this work explores the use of several ML and DL techniques, including RF, decision tree, SVM, and KNN. The RF with particle snake swarm optimization (PSSO) model achieved 98.7% accuracy, 98.47% F1-score, 98.51% precision, 98.7% recall, and 98% specificity.

viii) Banerjee *et al.* [22] proposed a hybrid DL strategy that combines statistical validation with deep feature attention to improve thyroid US segmentation. TATHA is a novel DL architecture that the researchers created by the goal of increasing the accuracy of thyroid US image segmentation. The results validate that TATHA is now a vital tool for thyroid imaging and clinical applications for researchers and physicians.

Based on the reviewed literature, various DL and ML approaches have been developed for thyroid disease classification. However, these methods still face several limitations, such as high computational complexity, dependency on synthetic data augmentation that may not fully represent real-world cases, persistent class imbalance issues despite oversampling strategies, restricted generalizability due to limited or single-center datasets, and challenges in clinical integration caused by a lack of interpretability. To address these shortcomings, the TC-MRF model is proposed as a more effective and reliable solution for thyroid disease classification.

## 3. PROPOSED METHOD

In this section, the TC-MRF model is utilized to classify thyroid disease. Figure 1 displays the general structure of this proposed TC-MRF model. The model enables effective classification through its integrated framework.

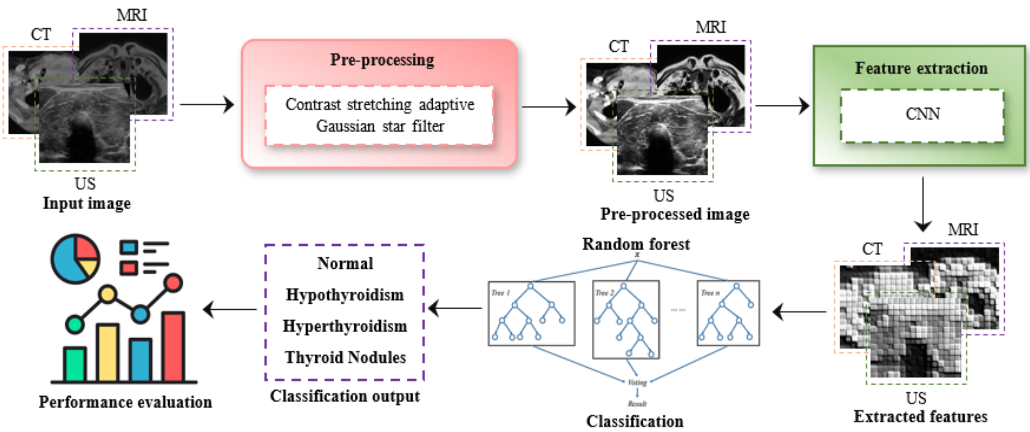



Figure 1. Proposed TC-MRF model

### 3.1. Dataset description

Images are represented by the ImageNet ontology based on the WordNet model. The goal of ImageNet is to add 500-1,000 high-quality, full-resolution images on average to each of the 80,000 subsets of WordNet. This will result in millions of annotated images arranged in WordNet semantic hierarchy. Gathering patient images for every subset is the initial step in ImageNet. Eventually, ImageNet provides 500-1,000 clean images. Consequently, it gathers a big collection of patient images.

### 3.2. Data pre-processing

Medical images are improved by pre-processing by lowering noise and adjusting highlighting. A straightforward method for enhancing images is called contrast stretching, which increases an image's contrast by widening its range of intensity values. This is particularly useful for images with low contrast, which can result from poor illumination or other acquisition problems. It indicates the image's lowest and maximum intensity values. Mathematically, for pixel intensity $I$ as in (1).

$$I_{new} = \frac{I - I_{min}}{I_{max} - I_{min}} \times (I_{new-max} - I_{new-min}) + I_{new-min} \quad (1)$$

The term adaptive Gaussian star filter combine the concepts of adaptive filtering, Gaussian filtering, and star filtering. This filter adaptively applies Gaussian smoothing to enhance star-like features in an image.

### 3.3. Feature extraction

CNN [23] is used to extract the feature of the image. CNN, with its capacity to automatically analyze and extract complicated information from medical images, for identifying thyroid disease. In the CNN architecture, a convolution layer is a basic element that usually combines linear and nonlinear operations. In this application, a collection of thyroid images, such as US, CT, or MRI images, that had labelled with particular thyroid diseases, is used to train CNNs. The network architecture typically includes a large number of convolutional layers to capture spatial hierarchies in the data, pooling layers to reduce dimensionality while preserving crucial information, and fully connected layers to produce final predictions, as shown in Figure 2. In the training phase, the CNN picks up on characteristics and patterns that points the various thyroid diseases, such as nodules, hypothyroidism, and hyperthyroidism. Convolution layers employ filters to extract local features from images, including edges, textures, and other patterns. Maps are parameterized by the number of convolutional layers. An image is classified using a CNN based on features extracted from raw pixel data using filters. ML classifiers such as RF are used to enhance the performance of this feature extraction process.

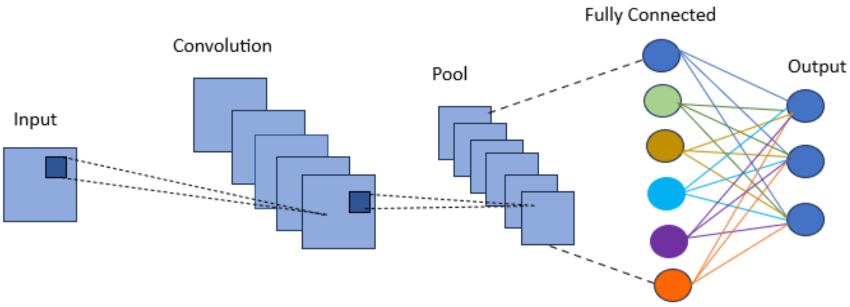



Figure 2. Structure of CNN

### 3.4. Classification

RF [24] combines several decision trees to produce more accurate predictions. Thyroid illness detection with ML works well with RF. It is possible to train RF with features that are retrieved from images, like shape descriptors, texture attributes, and color histograms. A thyroid disease detection process begins with the collection and preprocessing of relevant data, including thyroid hormone levels and US features. This data is then separated into training and testing sets in order to build and evaluate the RF model. During training, the model learns to classify thyroid conditions by analyzing various features, with hyperparameters such as the quantity and depth of trees being optimized. After training, the performance is evaluated to understand its impact on predictions. RF offers benefits such as high accuracy and robustness against noisy data, though they can be computationally demanding and complex to interpret. Final prediction $\hat{y}$ is determined by majority as in (2).

$$\hat{y} = mode(y_{1'} \ldots y_r) \quad (2)$$

The average of the predictions produced by each individual tree is the final prediction in regression. The equation is given in (3).

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} y_t \quad (3)$$

Where $y_t$ is the prediction made by the t-th tree. $T$ represents the forest's total tree count. The majority vote determines the final anticipated class label, $\hat{y}$. To address the challenges outlined in the Introduction, the proposed methodology employs advanced pre-processing with Gaussian–median filtering, optimized feature extraction using InceptionResNet, and classification through an interpretable generalized additive neural network. These components improve data quality, capture discriminative features, and ensure robust, transparent decision-making, as demonstrated by superior accuracy and reliability in disease prediction.

## 4. RESULTS

The proposed TC-MRF is evaluated using the gathered datasets in order to determine its specificity, precision, recall, accuracy, and F1-score, among other metrics. Performance of TC-MRF and the overall accuracy rate, which is specifically defined and assessed, are included in the benchmark.

Figure 3 shows the outcome of the proposed TC-MRF with a sample of three different imaging modality such as CT, MRI, and US, for identifying the thyroid classification. From the collected ImageNet dataset, the medical image is preprocessed by contrast stretching, adapted to eliminate the unwanted distortions. The preprocessed images are then sent through a CNN. Classification results from the CNN might be further refined or complemented by using an RF classifier. The output images are captured and used as input for TC-MRF to classify the thyroid disease.

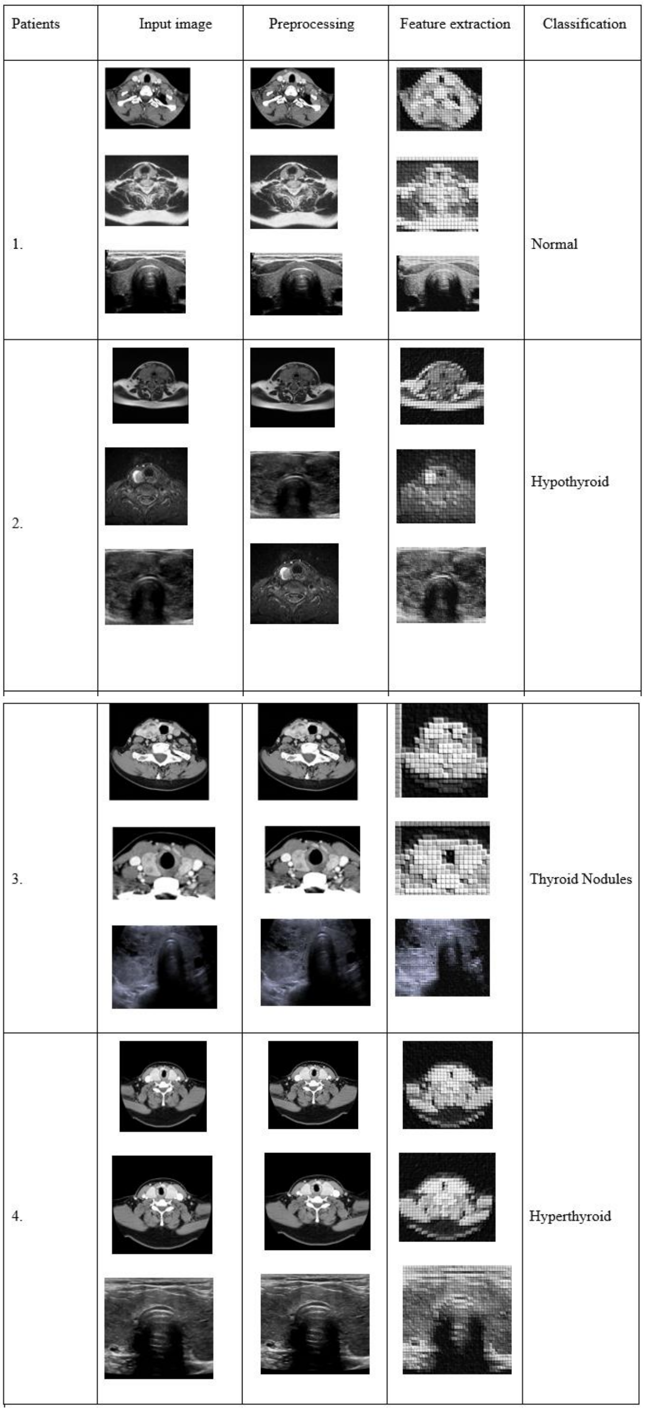



Figure 3. Experimental result of TC-MRF model

### 4.1. Performance analysis

The proposed TC-MRF model efficiency can be evaluated utilizing the evaluation metrics of F1-score, precision, specificity, accuracy, and recall of TC-MRF.

$$Specificity = \frac{T_{neg}}{T_{neg} + F_{pos}} \tag{4}$$

$$Precision = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{5}$$

$$Recall = \frac{T_{pos}}{T_{pos}+ F_{neg}} \tag{6}$$

$$Accuracy = \frac{T_{pos}+T_{neg}}{Total\ no.\ of\ samples} \tag{7}$$

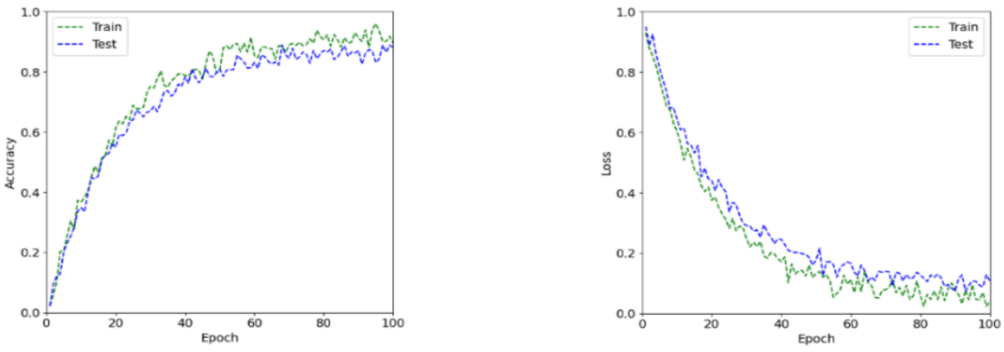
$$F1 - score = 2(\frac{precision*recall}{precision+recall}) \tag{8}$$

Where $T_{pos}$ and $T_{neg}$ represents the actual positives as well as negatives of one of the images. Negatives and false positives for the sample images are indicated by $F_{Pos}$ and $F_{neg}$. The performance outcome obtained by the proposed TC-MRF for categorizing several thyroid disease detection classes, i.e., hypothyroidism, hyperthyroidism, thyroid nodules, and normal are exposed in Table 1. Proposed TC-MRF achieves 95.19% recall, 96.67% specificity, 95.87% precision, and 96.05% F1-score, respectively.

Figure 4 illustrates the overall performance of the TC-MRF model during training and testing, presented through the accuracy and loss curves plotted against the number of epochs. Figure 4(a) shows the accuracy of the testing and training, which also displays the epochs on the x- and y-axes. Based on accuracy of its testing and training curves, TC-MRF's accuracy level is 98.27%. The loss curve plotted against epochs is shown in Figure 4(b), showing that the loss reduces with increasing epochs. The proposed procedure yields an accurate result with a reasonably low loss of 1.73%. Tested and trained, TC-MRF exhibits good performance.

Table 1. Performance assessment of the TC-MRF model

| Types | Accuracy | Specificity | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| Normal | 98.41 | 95.12 | 96.24 | 96.25 | 96.19 |
| Hypothyroidism | 99.23 | 94.27 | 96.12 | 95.48 | 95.48 |
| Hyperthyroidism | 97.13 | 96.24 | 97.28 | 96.08 | 96.52 |
| Thyroid nodules | 98.32 | 95.15 | 97.05 | 96.12 | 96.02 |




(a) (b)

Figure 4. Training and testing graph of the TC-MRF model of (a) accuracy curve and (b) loss curve

### 4.2. Comparative analysis

The effectiveness of ML network was determined in order to verify that the TC-MRF had a high level of accuracy. The TC-MRF with LR, DT, and NB was compared and evaluated. With 98.27% accuracy rate, the TC-MRF outperformed the traditional ML networks.

Table 2 presents the performance comparison of several standalone models using metrics such as accuracy, specificity, precision, recall, and F1-score. The proposed TC-MRF outperforms all other models, achieving the highest overall accuracy of 98.27%. Compared to standalone models, TC-MRF improves accuracy by 8.92%, 7.19%, 2.10%, 5.00%, and 0.82% over DT, NB, LR, RF, and CNN, respectively, demonstrating the benefit of combining CNN feature extraction with RF classification. Similar hybrid CNN-RF and transfer-learning approaches have also shown improved diagnostic accuracy and robustness in medical imaging, validating the superior performance and reliability of the TC-MRF.

Table 2. Performance comparison of standalone models and the proposed TC-MRF hybrid model

| Networks | Accuracy | Specificity | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| DT [25] | 89.53 | 88.75 | 86.25 | 85.30 | 85.70 |
| NB [26] | 91.26 | 89.26 | 87.57 | 84.63 | 86.53 |
| LR [27] | 95.22 | 92.13 | 90.62 | 90.85 | 94.18 |
| RF [28] | 93.27 | 92.18 | 94.67 | 92.87 | 93.05 |
| CNN [29] | 97.45 | 94.34 | 93.13 | 94.62 | 95.23 |
| TC-MRF (ours) | 98.27 | 95.19 | 96.67 | 95.87 | 96.05 |

Table 3 shows the number of experimental images taken during the process of testing various methods to determine their accuracy. The proposed TC-MRF improves the overall accuracy by 6.30%, 4.11%, and 5.36%, better than NB, MLP, and DT, respectively. Comparing the proposed network to the existing technique, TC-MRF performs much better than the other methods. As a result, the proposed TC-MRF offers high reliability for detecting thyroid disease.

Table 3. Comparative analysis of existing vs proposed TC-MRF model

| Authors | Methods | Accuracy (%) |
|---|---|---|
| Mir *et al.* [30] | NB | 92.07 |
| Pal. *et al*. [31] | MLP | 94.23 |
| Yadav and Pal [32] | DT | 93 |
| Proposed | TC-MRF | 98.27 |

Figure 5 shows the practical deployment of the proposed TC-MRF model within a clinical workflow. The multi-modality thyroid images from patients are processed through the TC-MRF model for accurate disease classification. The classified results are then communicated to hospital diagnostic systems to assist clinicians in decision-making. This automated process minimizes human error, reduces diagnosis time, and enhances reliability.

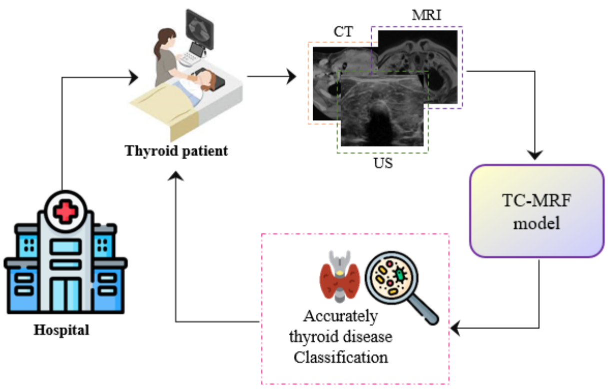



Figure 5. Real-world deployment of TC-MRF in clinical workflow

## 5. DISCUSSION

The findings reveal that the proposed TC-MRF model, which integrates CNN-based feature extraction with RF classification, achieves an accuracy of 98.27%, precision of 96.67%, and F1-score of 96.05%. These results demonstrate its superiority over conventional models such as DT, NB, and LR, showing improvements of up to 8% in accuracy. The hybrid DL ensemble approach effectively captures both spatial and contextual features from multimodal images, ensuring robust and reliable thyroid disease classification. This enhanced performance suggests strong potential for clinical decision support, enabling early detection, reducing diagnostic errors, and supporting radiologists in routine diagnosis. The model could also support telemedicine by enabling remote diagnosis, facilitating early screening, and integrating with electronic health record systems for streamlined reporting and clinical decision-making. Furthermore, careful consideration of ethical implications, data privacy, and clinical validation is essential to ensure unbiased predictions, protect patient data, and validate the model across diverse populations. Incorporating explainable AI and federated learning in the future can further enhance interpretability, privacy, and scalability for telemedicine applications.

## 6. CONCLUSION

In this research, the TC-MRF model is proposed for classifying thyroid diseases. The input images are gathered from the ImageNet datasets. To remove noise artifacts from the input images, a contrast-stretching adaptive Gaussian star filter is applied during pre-processing. To extract the feature, the preprocessed image is fed into a CNN. The extracted feature from CNN is used to classify the thyroid disease. To evaluate the effectiveness of the parameters, such as recall, F1-score, accuracy, precision, and specificity, TC-MRF is utilized. Proposed RF increases the overall accuracy by 8.1%, 7.15%, and 2.1% of decision trees, naive Bayes, and LR. As a result of experimental results, the proposed approach detects thyroid illness within an accuracy range of 98.27%. The proposed TC-MRF improves the overall accuracy by 6.30%, 4.11%, and 5.36%, better than DT, NB, and LR, respectively. In the future the proposed TC-MRF increase its accuracy and detect the grades of thyroid disease.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

**ETHICAL APPROVAL**

My research guide reviewed and ethically approved this manuscript for publication in this journal.

**DATA AVAILABILITY**

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

**REFERENCES**

[1] D.-M. Tilici *et al.*, “The intricate relationship between thyroid disorders and type 2 diabetes—a narrative review,” *Diabetology*, vol. 6, no. 5, May 2025, doi: 10.3390/diabetology6050041.
[2] L. Sabatino and C. Vassalle, “Thyroid hormones and metabolism regulation: which role on brown adipose tissue and browning process?,” *Biomolecules*, vol. 15, no. 3, Mar. 2025, doi: 10.3390/biom15030361.
[3] Udi, “Sleep, neuroendocrine disorders, and the bidirectional relationship between the hypothalamic-pituitary-adrenal axis: a mini-review,” *Journal of Applied Sciences and Environmental Management*, vol. 29, no. 4, pp. 1217–1227, 2025, doi: https://doi.org/10.4314/jasem.v29i4.25.
[4] N. S.-Gutaj, N. Zawalna, P. Gut, and M. Ruchała, “Relationship between thyroid hormones and central nervous system metabolism in physiological and pathological conditions,” *Pharmacological Reports*, vol. 74, no. 5, pp. 847–858, Oct. 2022, doi: 10.1007/s43440-022-00377-w.
[5] Y. AbdulRaheem, “Unveiling the significance and challenges of integrating prevention levels in healthcare practice,” *Journal of Primary Care & Community Health*, vol. 14, Jan. 2023, doi: 10.1177/21501319231186500.
[6] J. Huang and J. Zhao, “Quantitative diagnosis progress of ultrasound imaging technology in thyroid diffuse diseases,” *Diagnostics*, vol. 13, no. 4, Feb. 2023, doi: 10.3390/diagnostics13040700.
[7] M. Vineela, G. D. S. Reddy, G. Karthik, N. Muthukumaran, and S. H. Al Deen, “Classification of leukemia white blood cell cancer,” in *2024 International Conference on Inventive Computation Technologies (ICICT)*, Apr. 2024, pp. 1233–1236, doi: 10.1109/ICICT60155.2024.10544978.
[8] R. A. Taylor *et al.*, “Leveraging artificial intelligence to reduce diagnostic errors in emergency medicine: Challenges, opportunities, and future directions,” *Academic Emergency Medicine*, vol. 32, no. 3, pp. 327–339, Mar. 2025, doi: 10.1111/acem.15066.
[9] R. Tharani and C. Jasphin, “Gastric cancer detection via deep learning in image processing,” *International Journal of System Design and Computing*, vol. 2, no. 1, pp. 7–13, 2024.
[10] R. Sundarasekar and A. Appathurai, “Automatic brain tumor detection and classification based on IoT and machine learning techniques,” *Fluctuation and Noise Letters*, vol. 21, no. 03, Jun. 2022, doi: 10.1142/S0219477522500304.
[11] A. V. Supramanian, “Big data and machine learning in healthcare: revolutionizing patient outcomes through advanced analytics,” *International Journal of Advanced Research in Engineering and Technology*, vol. 16, no. 2, pp. 228–254, Mar. 2025, doi: 10.34218/IJARET_16_02_014.
[12] J. B. Madavarapu, “CAB-IDS: IoT-based intrusion detection using bacteria foraging optimized BiGRU-CNN network,” *International Journal of Computer and Engineering Optimization*, vol. 1, no. 2, pp. 63–68, 2023.
[13] M. C. Guerrero, J. S. Parada, and H. E. Espitia, “EEG signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks,” *Heliyon*, vol. 7, no. 6, Jun. 2021, doi: 10.1016/j.heliyon.2021.e07258.
[14] F. Liu and D. Panagiotakos, “Real-world data: a brief review of the methods, applications, challenges and opportunities,” *BMC Medical Research Methodology*, vol. 22, no. 1, Nov. 2022, doi: 10.1186/s12874-022-01768-6.
[15] A. Topşir, F. Güler, E. Çetin, M. F. Burak, and M. Ağraz, “Thyroid disease classification using generative adversarial networks and Kolmogorov-Arnold network for three-class classification,” *BMC Medical Informatics and Decision Making*, vol. 25, no. 1, Jul. 2025, doi: 10.1186/s12911-025-03014-7.
[16] R. Sharma, G. K. Mahanti, C. Chakraborty, G. Panda, and A. Rath, “An IoT and deep learning-based smart healthcare framework for thyroid cancer detection,” *ACM Transactions on Internet Technology*, Dec. 2023, doi: 10.1145/3637062.
[17] Z. Xiang *et al.*, “Federated learning via multi-attention guided UNet for thyroid nodule segmentation of ultrasound images,” *Neural Networks*, vol. 181, Jan. 2025, doi: 10.1016/j.neunet.2024.106754.
[18] A. Raza, F. Eid, E. C. Montero, I. D. Noya, and I. Ashraf, “Enhanced interpretable thyroid disease diagnosis by leveraging synthetic oversampling and machine learning models,” *BMC Medical Informatics and Decision Making*, vol. 24, no. 1, Nov. 2024, doi: 10.1186/s12911-024-02780-0.
[19] K. M. M. Uddin, A. Al Mamun, A. Chakrabarti, and R. Mostafiz, “An ensemble machine learning-based approach to predict thyroid disease using hybrid feature selection,” *Biomedical Analysis*, vol. 1, no. 3, pp. 229–239, Sep. 2024, doi: 10.1016/j.bioana.2024.08.001.
[20] S. Akter and H. A. Mustafa, “Analysis and interpretability of machine learning models to classify thyroid disease,” *PLOS ONE*, vol. 19, no. 5, May 2024, doi: 10.1371/journal.pone.0300670.
[21] D. Kesavulu and R. Kannadasan, “Improved bio-inspired with machine learning computing approach for thyroid prediction,” *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-03299-8.
[22] T. Banerjee, D. P. Singh, D. Swain, S. Mahajan, S. Kadry, and J. Kim, “A novel hybrid deep learning approach combining deep feature attention and statistical validation for enhanced thyroid ultrasound segmentation,” *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-12602-6.
[23] D. Yang, T. Li, L. Li, S. Chen, and X. Li, “Multi-modal convolutional neural network-based thyroid cytology classification and diagnosis,” *Human Pathology*, vol. 161, Jul. 2025, doi: 10.1016/j.humpath.2025.105868.
[24] R. N. P. Pratama, S. Winarno, and T. N. O. Wijaya, “Thyroid disease prediction using random forest with KNNImputer for missing values,” *Sinkron*, vol. 9, no. 1, pp. 160–166, Jan. 2025, doi: 10.33395/sinkron.v9i1.14334.
[25] S. Ouartani, N. Taleb, and B. Ayoub, “Integrating ontology and machine learning for enhanced decision support in thyroid disease prediction,” in *2023 International Conference on Decision Aid Sciences and Applications (DASA)*, Sep. 2023, pp. 208–212. doi: 10.1109/DASA59624.2023.10286675.

[26] V. Brindha and A. Muthukumaravel, “Efficacy of the decision tree as an alternative to the naïve Bayes model for the prediction of thyroid disease classification,” in *Optimizing Patient Outcomes Through Multi-Source Data Analysis in Healthcare*, IGI Global, 2025, pp. 133–148. doi: 10.4018/979-8-3693-9420-5.ch009.

[27] S. R. Darawsheh, A. S. Al-Shaar, F. A. Haziemeh, and M. T. Alshurideh, “Classification thyroid disease using multinomial logistic regressions (LR),” in *The Effect of Information Technology on Business and Marketing Intelligence Systems*, 2023, pp. 645–659. doi: 10.1007/978-3-031-12382-5_34.

[28] S. R. J, S. K S, and S. S. T K, “Predictive modeling for thyroid disease using gradient boosting and random forest algorithms,” in *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)*, Dec. 2024, pp. 1–6. doi: 10.1109/SCOPES64467.2024.10990454.

[29] P. T. Rajan. B and N. Muthukumaran, “Optimized CNN and adaptive RBFNN for channel estimation and hybrid precoding approaches for multi user millimeter wave massive MIMO,” *International Journal of Electronics*, vol. 112, no. 7, pp. 1295–1318, Jul. 2025, doi: 10.1080/00207217.2024.2372060.

[30] Y. I. Mir, S. Mittal, and M. Shuja, “An insight of thyroid disease prediction using data mining techniques,” *SSRN Electronic Journal*, vol. 9, no. 2, pp. 2868–2874, 2020, doi: 10.2139/ssrn.3554226.

[31] M. Pal, S. Parija, and G. Panda, “Enhanced prediction of thyroid disease using machine learning method,” in *2022 IEEE VLSI Device Circuit and System (VLSI DCS)*, Feb. 2022, pp. 199–204. doi: 10.1109/VLSIDCS53788.2022.9811472.

[32] D. C. Yadav and S. Pal, “Prediction of thyroid disease using decision tree ensemble method,” *Human-Intelligent Systems Integration*, vol. 2, no. 1–4, pp. 89–95, Dec. 2020, doi: 10.1007/s42454-020-00006-y.


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