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An AI Based Multi-Modal System for Thyroid Disease Using Xgboost and Resnet18

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Abstract
Thyroid disease are common disorders requiring timely diagnosis. This project presents a multi-modal AI system combining XGBoost for structured clinical data and ResNet18 for thyroid imaging to classify and predict thyroid disease accurately. The system integrates predictions using a fusion module and provides medicine suggestions, automated medical reports, and an AI chatbot to guide patients on whether to visit a hospital. Experimental results show improved accuracy over single-model approaches, offering a reliable, real-time and interpretable solution to assist clinicians in early detection, treatment planning, and better patient outcomes.
Keywords: *Thyroid Disease Prediction, Multi-Modal Artificial Intelligence.*

1. Introduction
Research is a systematic process of collecting, analysing and interpreting data to develop new knowledge or improve existing systems. In thyroid disease detection, research focuses on using machine learning and deep learning techniques to improve the accuracy of diagnosis using clinical data and medical images [1].Recent research in thyroid disease detection uses machine learning algorithms such as XGBoost to analyze structured clinical data like Thyroid-Stimulating Hormone(TSH), Triiodothronine(T3), and Thyroxine (T4) levels for predicting thyroid disorders [1]. Deep learning models such as ResNet18 are also widely used for analysing thyroid ultrasound images to automatically detect thyroid nodules and abnormalities with high accuracy [2]. AI- based thyroid disease detection systems are applied in clinical decision support systems to assist doctors in early diagnosis and treatment planning [3]. These systems can also be used for automated medical report generation, patient guidance and intelligence healthcare applications, improving the efficiency and reliability of thyroid disease diagnosis [4].

2. Related Works
The total number of articles published on the topic of thyroid disease prediction and detection using machine learning and deep learning over the last five years is more than 300 papers in Google Scholar, around 120 papers in IEEE Xplore, and approximately 100 papers in Academia.edu. Machine learning and deep learning techniques are increasingly applied for thyroid disease prediction and diagnosis, Early studies focused on using traditional machine learning algorithms to analyze clinical parameters such as TSH, T3, T4, and patient symptoms to classify thyroid disorders with improved accuracy compared to manual diagnosis methods (Sennan et al. 2022)[1]. Deep learning approaches have also been widely explored for thyroid ultrasound image analysis, where convolutional neural networks such as ResNet-based architectures help automatically detect thyroid nodules and classify them as benign or malignant information to build multimodal diagnostic systems, improving prediction performance and reducing misclassification rates (Li, Zhang, and Zhang 2025) [3]. Recent works also emphasize the use AI- assisted healthcare frameworks, where intelligent models assist clinicians in early diagnosis, treatment

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planning, and patient monitoring (Yao et al. 2025) [4].Deep learning techniques have further been applied to detect thyroid micro nodules and abnormalities from ultrasound images with higher sensitivity and reliability (Rho et al. 2025) [5]. Other studies explore algorithms such as Support Vector Machines, Random Forest, and Artificial Neural Networks to improve classification accuracy and reduce diagnosis errors in thyroid disease detection (Gupta and Kumar 2021) [6], (Singh et al. 2020) [7]. Furthermore, ensemble learning techniques combining multiple machine learning models have demonstrated better performance in thyroid disease prediction compared to single models (Patel et al. 2022) [8]. Recent research also highlights the use of hybrid AI systems integrating machine learning, deep learning, and medical imaging analysis to provide automated diagnostic reports and clinical decision support systems for thyroid disorder management (Chen et al. 2024) [9], (Hassan et al. 2023) [10]. From the previous findings, it is concluded that the single–model methods may fail to capture the complementary information from both clinical and imaging data, reducing the effectiveness of early detection and personalized patient care. The aims to support clinicians, improve early detection, reduce human error, and promote timely, efficient, and personalized patient care.

3. Materials and Methods

The present study focuses on the prediction of thyroid disease using artificial intelligence techniques. The experimental work carried out in the Artificial Intelligence and Machine Learning laboratory at KSRCE. For this study, the dataset was obtained from Kaggle.com, which includes patient clinical attributes such as TSH, T3,T4 levels, age, and other related medical parameters used for thyroid disease diagnosis. The dataset size and experimental design were determined based on previously published research studies on thyroid disease prediction (Sennan et al., 2022). The proposed system was implemented using Python programming with machine learning and deep learning. Algorithm such as XGBoost was applied for structured clinical data analysis and ResNet18 for processing thyroid ultrasound images. The performance of the model was evaluated using standard metrics including accuracy, precision, recall, and F1-score, with a confidence level of 95% and significance threshold of 0.05 to ensure reliable experimental results. In the current research, thyroid disease detection is mainly performed through manual evaluation of laboratory test result and ultrasound images by healthcare professionals. This process typically involves analysing clinical parameters such as TSH, T3, T4 levels along with patient symptoms to determine thyroid prediction. Some methods rely on the single machine learning model that processes either structured clinical datasets or medical images independently. These approaches were failed to utilize the both data modalities, which reduce the overall diagnostic performance [1], [2]. The proposed system is designed to work on both clinical data and ultrasound imaging with combing the algorithms of XGBoost and ResNet18. These can be designed using the below Equations. (1) The sigmoid function converts prediction values into probabilities between 0 and 1.

$$\sigma(x)=1/(1+e^{(-x)}) \quad (1)$$

- Here, ‘x’ is the input value, ‘e’ is the exponential constant and the output range will be 0 to 1.
- The Extreme Gradient Boosting means each new tree improves the previous prediction.

$$F_m(x)=F_{(m-1)}(x)+h_m(x) \quad (2)$$

Here, ‘Fm(x)’ is the final prediction, ‘Fm-1(x)’ is the previous model prediction and ‘hm(x)’ is the new tree correcting previous errors.

- Residual Network 18 used to convolution to extract features from images and helps to detect edges, textures and patterns thyroid ultrasound images.

$$\mathbf{S(i,j)} = \sum_{\mathbf{m}}\sum_{\mathbf{n}} \mathbf{I(m,n)K(i-m,j-n)} \quad (3)$$

Here, ‘I’ will be the input images, ‘K’ will be kernel/filter and S (i,j) is the output feature.

- Accuracy measures how well the model predicts thyroid disease.

$$\mathbf{Accuracy=(TP+TN)/(TP+TN+FP+FN)} \quad (4)$$

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Here, 'TP' is the true positive, 'TN' is the true negative, 'FP' is the False Positive and 'FN' is the false negative.

- Accuracy measures how well the model predicts thyroid disease.

$$\textbf{Accuracy} = \frac{\textbf{TP} + \textbf{TN}}{\textbf{TP} + \textbf{TN} + \textbf{FP} + \textbf{FN}} \qquad (4)$$

Here, 'TP' is the true positive, 'TN' is the true negative, 'FP' is the False Positive and 'FN' is the false negative.

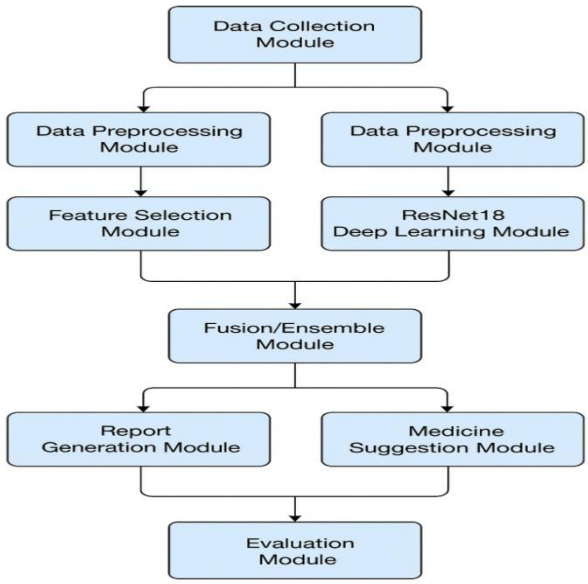

Figure 1 Workflow of the ResNet18-Based Fusion Ensemble Model

The Testing setup and simulation of a specific frequency is given below. The system configuration is the intel i5 core processor, 10 GB Ram, 1 TB hard disk and also HTML, CSS, flask as framework as software.

4. Result

The experimental results demonstrates that the proposed multimodal fusion framework outer performs individual models trained on single data modalities. The XGBoost model achieved strong performance on clinical data due to its capability to model complex feature interactions. The ResNet 18 model effectively classified ultrasound images by extracting deep spatial features. However, the fusion based approach consistently produced compared to individual models. The fusion model achieved the highest accuracy and F1-score, indicating its effectiveness in combing and imaging information. Improved recall values show better detection of thyroid disease cases, which is critical in medical diagnosis where missed cases may lead to delayed treatment. Overall, the results validate the multimodal integration enhances diagnostics reability and reduces misclassification compared to unimodal approaches.

TABLE 1 The performance results table compares the prediction performance of XGBoost, ResNet-18, and the fusion model using evaluation metrics such as aacuracy, precision, recall, and F1-score. These metrics measure how correctly the models identify thyroid disease cases

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
XGBoost	92.4	91.8	90.6	91.2
ResNet 18	93.7	92.9	92.1	92.5
Fusion Model (XGBoost+ResNet18)	96.3	95.8	95.2	95.5

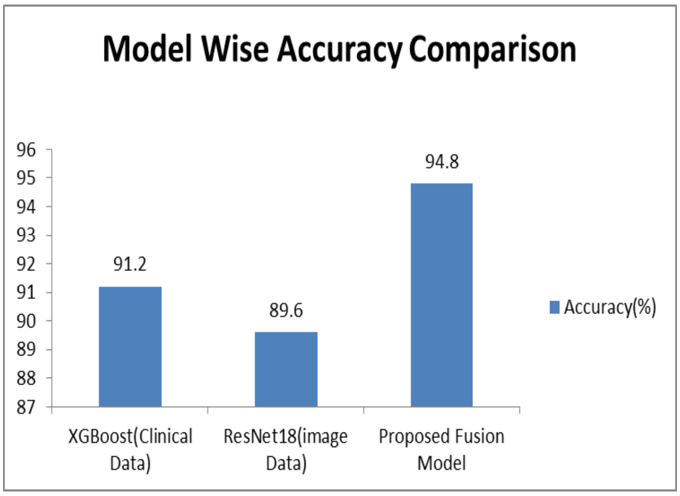

Figure 2 Model wise Accuracy comparison

Fig. 2. Model Wise Accuracy Compares overall classification accuracy of the XGboost model, the ResNet 18 model and the proposed fusion based framework. The barchart clearly shows that while both individual models achieve the competitive accuracy using using clinical and imaging data separately the fusion model achieves the highest accuracy.

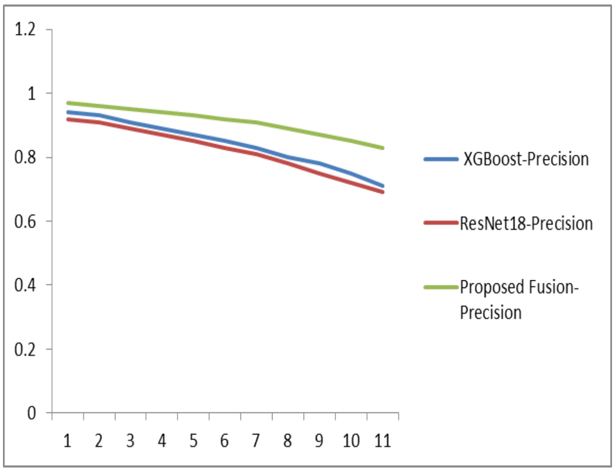

Figure 3 Precision Comparison

Fig. 3. The precision-recall curve the balance between precision and recall under class imbalance conditions. The fusion model maintains higher precision across a wider recall range than individual models. This reduces false positive and false negatives, which is important in healthcare applications. Hence, the proposed approach provides reliable disease detection with high prediction confidence.

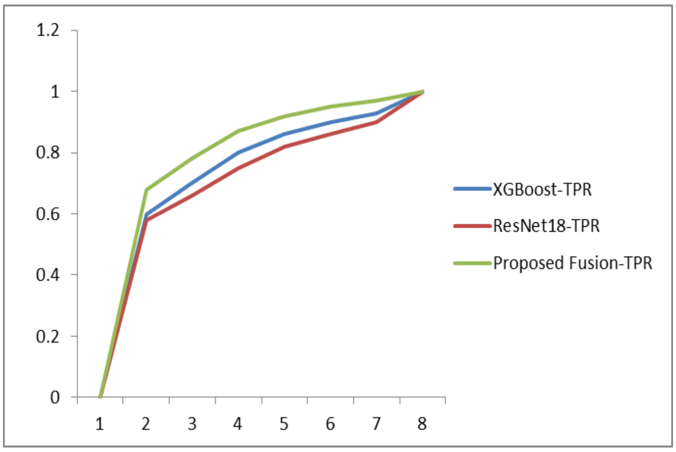

Figure 4 TRP Comparison

Fig. 4. The ROC-AUC curve shows the trade-off between the true positive rate and false positive rate at different thresholds. The proposed fusion model achieves a higher AUC compared to individual models. This indicates better ability to distinguish between normal, hypothyroid, and hyperthyroid cases. The higher AUC confirms consistent performance across different threshold values, which is important for medical diagnosis.

5. Discussion

The experimental result demonstrates that the proposed multimodal framework significantly improves thyroid disease prediction by combining structured clinical data and ultrasound imaging. The fusion of XGBoost and ResNet18 allows the system to leverage complementary information from both data modalities, resulting in higher accuracy and improved class wise performance class performances compared to single model approaches. The higher Matthews Correlation Coefficient further indicates that the model under class imbalance conditions, a common issue in healthcare datasets [6], [8]. Graphical analysis using accuracy comparison charts, ROC-AUC curves, and precision recall plots supports these findings by visually highlighting the consistent performance gain of the fusion-based approach[6], [9]. Despite its strong performance, proposed framework has the certain limitations [6]. The increased computational complexity due to multimodal fusion and deep learning is one challenge [7], [9]. Additionally, model performance may vary depending on data quality and availability [6]. However these limitations are outweighed by the significant improvement in diagnostic reliability [6], [9]. Overall, the discussion highlights that multimodal learning is a promising direction for accurate and practical thyroid disease prediction systems [6], [9]. Although the proposed framework demonstrates strong performance, several extensions can further enhance its applicability and robustness. Including additional clinical such as patient history, genetic markers, and lifestyle factors may further strengthen predictive performance. Advanced fusion strategies, such as attention- based or transformer based multimodal learning techniques, can be explored to improve interaction between clinical and imaging feature. In addition, explainable artificial intelligence methods can be integrated to provide transparent and interpretable predictions, thereby increasing clinical trust and adoption.

Conclusion

This study presented an effective multimodal framework for thyroid disease prediction by integrating structured clinical data and thyroid disease prediction by integrating structured clinical data and thyroid ultrasound images. The proposed approach combines the strengths of XGBoost for handling tabular laboratory data and ResNes18 for extracting deep spatial features from medical images. By fusing predictions from both models, the system overcomes the limitations of single modality methods and achieves improved diagnostic accuracy and reliability. Extensive experimental evaluation confirmed that the fusion-based model consistently outerformed individual classifiers across all standard performance metrics. Overall, the proposed system offers a reliable and scalable solution for automated thyroid disease detection. Its modular design allows easy integration into clinical decision-support systems and supports early screening with minimal manual intervention. The experimental and visual analysis strongly suggest that the proposed multimodal fusion framework can assist healthcare professionals in improving diagnosis and reducing misclassification errors.

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