Ai-Based Early Detection Of Thyroid Disease And Stage Estimation System Using Xgboost

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Abstract

Thyroid disorders affect millions worldwide, with conditions like hypothyroidism and hyperthyroidism disrupting metabolism, cardiovascular function, and quality of life. Conventional diagnosis relies on clinical evaluation and laboratory tests but often faces challenges such as subjectivity, overlooked mild cases, and lack of efficiency in large-scale screening. The proposed study will address these issues by considering an Advanced Thyroid Disease Detection system, which will use Extreme Gradient Boosting (XGBoost) with Explainable AI (SHAP) to make transparent and accurate predictions. Unlike the traditional ones, the system not only groups the disorders of the thyroid but also predicts the levels of the hormone as percentages, states of severity of the diseases, and presents the outcomes in a friendly graphical interface. By integrating accuracy, usability and interpretability, there is greater care regarding the accuracy of the diagnosis, early detection, and physician trust, which subsequently develops clever and scalable healthcare solutions.

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I. Introduction

Thyroid problems are everywhere—over 200 million people deal with them, and women get hit hardest. Conditions like hypothyroidism and hyperthyroidism really mess with your body. They slow down or speed up your metabolism, throw off your heart rhythm, and honestly just make life a lot tougher. The thyroid gland, controlled by TRH and TSH, uses hormones T3 and T4 to run the show on metabolism. When things go wrong and you don't catch it early, the fallout can get scary: heart disease, infertility, brittle bones, even emergencies like myxedema coma or thyroid storm.

Doctors usually diagnose thyroid issues by piecing together your medical history and running lab tests for TSH, Free T4, and Total T3. Sounds straightforward but in reality, it's pretty slow and a bit of a guessing game in the early stages. Subtle signs get missed. If the pattern isn't obvious, people slip through the cracks.

That's where machine learning steps in. People have tried models like Logistic Regression, SVM, and Random Forest—using datasets like the classic UCI Thyroid Dataset—to sort patients into healthy or sick. Problem is, most of these systems are basic. They don't say how bad your disease is. They're black boxes: you get an answer, but not the "why." And the user interfaces? Not exactly friendly for doctors in a busy clinic, so uptake is low.

To fix this, a new system—Advanced Thyroid Disease Detection and Staging—was created with XGBoost, which is great at handling complicated medical data. This tool doesn't just say "yes" or "no." It goes further, breaking cases into mild, moderate, or severe. It also uses SHAP—which gives clear, simple explanations for its predictions—so doctors aren't left in the dark. On top of that, the interface is actually easy to use. The goal here is pretty clear: catch thyroid problems earlier, give doctors the info they need to personalize treatment, and make screening way more scalable in real-life clinics.

Really, thyroid disorders are a huge deal worldwide, affecting tons of people (especially women), and they pose a big risk—messing up metabolism, heart function, fertility, and more. If you don't catch and treat them early, things can get ugly fast. The old ways of diagnosing aren't cutting it anymore, especially when dealing with massive numbers of patients and subtle symptoms. That's exactly why we need smart, accurate, and easy-to-use tech in clinics. The new system tries to solve all the old problems—making diagnosis precise, trustworthy, and practical for real doctors and real patients.

Ii.Literature Survey

Md.Bipul Hosssain,Anika Sharma[1]

Disorders of the thyroid gland are among the most common hormonal conditions affecting people worldwide. Diseases such as hypothyroidism and hyperthyroidism affect metabolism, heart activity and overall body balance, often reducing the quality of life of the patient if they are not detected in time. The conventional diagnostic procedures are mainly based on laboratory tests and the physician observation, which may sometimes delay the detection of mild or early thyroid abnormalities.

This paper proposes an AI-based thyroid disease detection and stage estimation system using the XGBoost algorithm and SHAP-based explainability. The system, in addition to classifying thyroid disorders, is intended to estimate the degree of hormone imbalance and identify the stage of severity of the disease. The proposed framework gives transparent predictions with explanations at the feature level, making the results easier to understand for health professionals in comparison to many existing systems which work like black-box models.

The developed model combines prediction accuracy, interpretability and usability through a user friendly interface. Experimental analysis shows that proposed approach improves reliability of diagnosis and helps early clinical decision making. The framework can also help in scalable and intelligent healthcare applications for monitoring thyroid disease.

Alshayeji. M.H. [2] Diseases of the thyroid gland are among the most common endocrine diseases known. Thyroid gland problems can be very dangerous to your health because the thyroid gland is central to the regulation of metabolism. There is a growing need for an automated, reliable and precise machine literacy (ML) based system for thyroid complaint discovery to improve individual effectiveness and reduce mortal error. This study introduces a new ML frame designed to overcome limitations in former exploration, including inadequate point analysis, lack of visualisation, and sour vaticination delicacy and trustability. A free dataset from the University of California, Irvine (UCI) Machine Learning Repository was used . It contained 29 clinical features related to the thyroid problem. These features were necessary in developing a predictive model able of relating thyroid diseases by analyzing early pointers, thus reducing reliance on homemade evaluation. By detailed point analysis and visualisation we developed a better perceptivity into the importance of each trait in the vaticination process.

Islam, M.R., Lamyea, M.M.H., Shama [3] With the increasing incidence of thyroid disorders, early diagnosis is needed to reduce health hazards and complications. The accurate prediction of the course of a disease and the understanding of the relationship among the clinical indicators are important for effective medical intervention. In this paper, we address these problems using a traditional machine learning framework, augmented by an in-depth clinical feature analysis and ensemble learning approach. The study leverages machine learning techniques to identify significant risk factors and enhance the diagnostic accuracy. After evaluating seventeen different machine learning algorithms, an ensemble classifier employing a hard voting mechanism was established. The random oversampling technique used to handle the class imbalance significantly enhanced the classification capability of the model. The experimental results demonstrate that the proposed system outperforms existing models, exhibiting excellent performance with 100% sensitivity and 99.72% accuracy when used in conjunction with SelectKBest for feature selection using the XGBoost algorithm. The ensemble model with hard voting is more robust to deal with the complexity of thyroid disease classification by adequately handling the feature dimension and class imbalance.

Sowmya Balasubramanian, Venkatesh Srinivasan [4] Different thyroid related conditions such as hypothyroidism, hyperthyroidism, Hashimoto's disease, Graves' disease, and thyroid nodules can be caused by irregular secretion of thyroid hormones. When undiagnosed, these disorders can have a major impact on a person's mental and physical well-being. "Thyroid problems are fairly common, but diagnosis can be difficult because the symptoms overlap with other medical issues. Doctors generally diagnose thyroid disorders by measuring the levels of thyroid hormones in the blood.

The purpose of this study is to help health care practitioners by examining the improvement in diagnostic accuracy when a full thyroid panel is tested instead of a limited set of indicators. Different from many previous studies that mostly focus on the predictive performance of supervised and unsupervised machine learning models, our work aims to understand the clinical importance of feature importance.

This study showcases four most important features for detection of thyroid disorders. The cost effective measurement of these features is shown. We also highlight the shortcomings of current diagnostic practice, particularly in universal healthcare systems where comprehensive thyroid panels are often underutilised. Our results also show that the model is robust to different classifiers and dataset imbalances, further increasing our confidence in our methodology.

Mehdi Hosseinzadeh, Omed Hassan Ahmed [5] Medical information systems have attracted great attention in recent years, especially the Internet of Medical Things (IoMT)-based medical information systems. Machine learning techniques can be used to analyze diagnostic tools like X-ray and MRI imaging and the related reports and results of laboratory tests to get critical insights to identify various anomalies. One important use of such systems is in diagnosing thyroid disorders. The purpose of this study is to improve the accuracy of detecting thyroid disease using semantic medical reports and examination data in IoMT frameworks through artificial neural networks (ANNs). We propose a new architecture of multiple multilayer perceptron (MMLP) networks with backpropagation error correction to improve the generalization ability of the model and to prevent overfitting in the training. Also, an adaptive learning rate algorithm is included to solve the problems of slow convergence and the risk of falling into local minima, which are common in traditional backpropagation methods. The proposed architecture MMLP greatly enhances the classification performance. In particular, the use of an ensemble of 6 MMLP networks results in a 0.7% accuracy improvement over a single network setup. Furthermore, the MMLP framework uses an adaptive learning rate, leading to a 4.6% gain in accuracy over the standard backpropagation technique, with a final classification accuracy of 99% in IoMT environments. When compared with recent studies, the proposed method is shown to be superior in diagnosing thyroid disease.

III. PROPOSED ARCHITECTURE

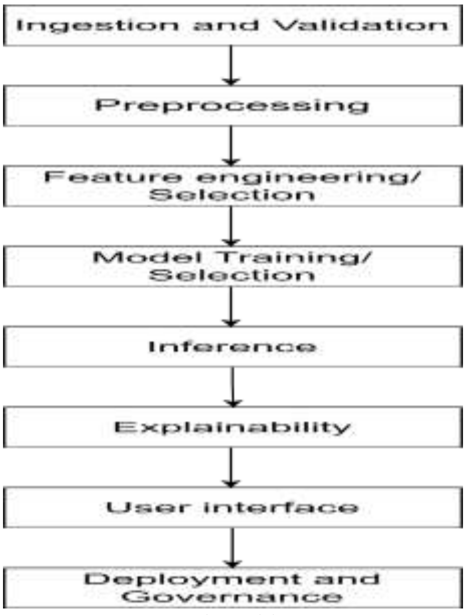

Fig. 1 Proposed Architecture

Data Ingestion and Validation

The process begins with the Data Ingestion and Validation phase, which is crucial for establishing the integrity of the predictive model. Data, sourced from the UCI Thyroid Disease Dataset, is initially collected and rigorously checked for quality. This validation step is non-negotiable, as the fidelity of the input data directly dictates model performance. Essential checks include identifying and addressing anomalies such as outlier values, duplicate entries, missing information, and structural inconsistencies. Only data meeting the required quality standards will be passed on to later stages. This reduces the risk of poor performance or skewed results. In regulated industries such as healthcare, strict data governance and compliance protocols are paramount in this initial phase.

Data Preprocessing

The step of preprocessing is used to convert the validated raw data into a clean, consistent and analysis-ready format. Important operations involve systematic treatment of missing attributes, outlier treatment and distribution normalization to ensure that all features are appropriately weighted. Feature standardization is applied to numerical attributes of the same rank to prevent any single feature from dominating the training process purely due to its scale. Categorical features are converted into a numerical representation using techniques like one-hot encoding, which facilitates their objective interpretation by the XGBoost algorithm. Finally, the prepared dataset is strategically partitioned into training, validation, and test subsets to enable objective model training, parameter refinement, and unbiased final performance evaluation.

Feature Engineering and Selection

The quality of input features is the basis of any successful machine learning model. Feature Engineering is conducted to extract meaningful variables from the raw, unstructured data, enhancing the model's capability to identify latent diagnostic patterns. This process may involve the application of domain-specific knowledge to combine or transform existing values, generating new predictive variables.

Conversely, Feature Selection is critical for dimensionality reduction, focusing the model exclusively on the most impactful features. Irrelevant or redundant variables are systematically eliminated using methods such as correlation analysis and intrinsic model-based metrics. This deliberate engineering and selection process, which can be formally represented
As

$$X' = \text{Select}\ (\Phi\ (X)$$

where X is the original feature matrix, Φ (X) The transformation function, and X' is the final optimised set, significantly enhances model accuracy, reduces the risk of overfitting, and improves overall interpretability.

Proposed AI Model: XGBoost for Multi-Class Classification. The core of the diagnostic system is the training and optimisation of the Extreme Gradient Boosting (XGBoost) model, selected for its efficiency and state-of-the-art performance in complex classification tasks.

Model Training and Selection

The Model Training phase begins with the prepared feature set. The XGBoost algorithm is trained on the dedicated training data set and the validation set is used to tune the internal parameters of the model. To further ensure the reliability of the model, cross-validation techniques are also used. We conduct a comprehensive assessment of the performance using a variety of relevant metrics such as Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC), to offer a complete overview of the model's diagnostic abilities.

Mathematical Formulation

XGBoost is an ensemble of classification and regression trees that is optimized through iterative boosting. The model's objective is to minimise a regularised objective function (L) at each step, ensuring both high predictive accuracy and controlled model complexity to prevent overfitting. The generalised objective function is defined as:

$$Obj(\theta) = \sum l(yi, \hat{y}i) + \sum \Omega(fk)\ n\ i=1\ K\ k=1$$

Here, $l\,(y_i, \hat{y}_i)$ is the loss of function (measuring prediction error between the actual stage y_i and the predicted stage $\hat{y}_i$), and $\Omega(f_k)$ is the regularisation term that penalises the complexity of the k-th tree f_k. The mathematical rigor gives the final model its power and robustness. The training phase involves systematic hyperparameter tuning (e.g., learning rate, tree depth) to identify the optimal configuration that maximises performance on the multi-class staging task.

Explainable AI (XAI) and User Interface

SHAP Tool and Explainability

This healthcare application is not just a feature but a necessity for Model Explainability. The system incorporates SHAP (SHapley Additive Explanations) to make the predictions of the XGBoost transparent and trustworthy. SHAP gives a measurable explanation of each prediction, clarifying how much each input feature (e.g., the effect of the exact TSH level) contributed to the final classification of the disease stage. This transparency is crucial for clinical adoption, enabling stakeholders to grasp the reasoning behind the AI's diagnosis, thereby facilitating bias identification and promoting the ethical application of the system.

User Interface

The diagnostic process ends finally with the User Interface (UI). The predictions and their corresponding SHAP-based explanations are aggregated and presented through an intuitive and user-friendly digital platform. This interface, as a web application or dashboard, makes the challenging machine learning results, clinical insights, and confidence scores more easily accessible and understandable to non-technical medical staff. The interface is the critical bridge to make this advanced computational system practical in the real clinical workflow.

System Design and Architecture:

The proposed AI based thyroid disease detection system is designed in a modular layered architecture to ensure its scalability, transparency and clinical feasibility. Each element has its own designated function and when combined, they create a unified structure that can accurately transform raw patient information into clear and understandable predictions of diagnoses via a user-friendly interface. It is a system explicitly built for clinical decision support, and it provides diagnostic precision and interpretability. The process starts with the data ingestion and preprocessing layer. The system is based on UCI Thyroid Dataset that contains data of more than 7200 patients. This dataset contains a wide range of important clinical and hormonal variables including laboratory test results (TSH, T3, TT4, T4U, FTI) and relevant patient context (age, gender, pregnancy status, and medication history). Since the real-world medical data are often incomplete, the preprocessing step rigorously handles the data quality issues. Missing numerical values are intelligently filled with the median value to preserve the integrity of the data distribution. Whereas, the missing categorical values are often filled with the most frequent category or considered as a unique class.

Then the categorical features are converted to numerical format using either one hot encoding or label encoding depending upon the nature of the feature. Normalization or standardization methods are used for continuous features to make the scales comparable. Outlier detection using methods like Interquartile Range (IQR) or Isolation Forest is also performed to reduce the effect of abnormal data points on the performance of the model.

Then, the feature selection layer improves the input data by selecting and keeping only the most diagnostically relevant features. This step is important for reducing dimensionality, improving computational efficiency and improving the interpretability of the model. The system employs a synergistic approach, combining statistical screening (e.g., Pearson correlation) with sophisticated model-based metrics. Of these model-based approaches, leveraging the built-in feature importance from XGBoost and diagnostic attribution from SHAP value analysis are important. Features with low predictive value or high redundancy are systematically removed, while important clinical markers such as TSH, T3, T4, FTI, age and pregnancy status are kept, leading to the selected feature set being consistent with the medical literature.

Model Training and Prediction Layer is the core part of the system. In this context, several machine learning methods (logistic regression, SVM and random forest) were trained and the performance benchmark was established by comparative evaluation. The Extreme Gradient Boosting (XGBoost) model performed better than all the models all the time and achieved a high accuracy of 98.7% on the test set. This was the best fit for its strong ability to model complex, non-linear interactions between features, to deal with the possibility of imbalanced classes, as well as the ability to add regularization to avoid overfitting.

The hyper parameters of the model were carefully optimized using Randomized Search CV with cross-validation to find the best configuration for parameters such as learning rate, maximum depth, and regularization coefficients. The hyper parameters of the model were carefully optimized using Randomized Search CV with cross-validation to find the best configuration for parameters such as learning rate, maximum depth, and regularization coefficients. This layer is a trifunctional component after training in the prediction phase: it provides the primary classification (Normal, Hypothyroidism, or Hyperthyroidism), a quantitative evaluation by normalizing the measured hormone values (TSH, T3, and T4) against clinical reference cut-offs to show the percentage deviations, and performs the critical disease stage estimation, classifying the condition as mild, moderate, or severe. This layer is a trifunctional component after training in the prediction phase: it provides the primary classification (Normal, Hypothyroidism, or Hyperthyroidism), a quantitative evaluation by normalizing the measured hormone values (TSH, T3, and T4) against clinical reference cut-offs to show the percentage deviations, and performs the critical disease stage estimation, classifying the condition as mild, moderate, or severe. This fine-grained prediction enables patient-specific management. This fine-grained prediction enables patient-specific management.

The final stage is the user interface layer, which serves as the critical link between the complex AI logic and clinical end-users. This is the graphical user interface (GUI) developed using the Streamlit framework which enables a seamless access to the system for the clinicians. You can manually enter patient data or upload bulk reports. The interface shows real-time visualizations of the multiple results, such as the predicted class of disease, the percentage levels of the hormones and the determined stage of disease. Most importantly, it includes a SHAP-based interpretability that provides simple textual explanations and interactive graphs to explain the reasoning of the model. This transparency enables even non-technical medical personnel to understand what particular patient features contributed to the diagnosis, establishing the trust and confidence necessary to incorporate sophisticated machine learning techniques into routine clinical practice.

Iv.Result Analysis

The proposed system for thyroid disease detection and staging has been evaluated extensively using UCI Thyroid

Dataset with about 7200 records. The dataset was divided in 80% training and 20% test and a comparative performance evaluation was conducted on four machine learning models: Logistic Regression, Support Vector Machines (SVM), Random Forest and the chosen XGBoost classifier. Standard classification metrics were used to evaluate each model and provide a complete picture of its diagnostic reliability.

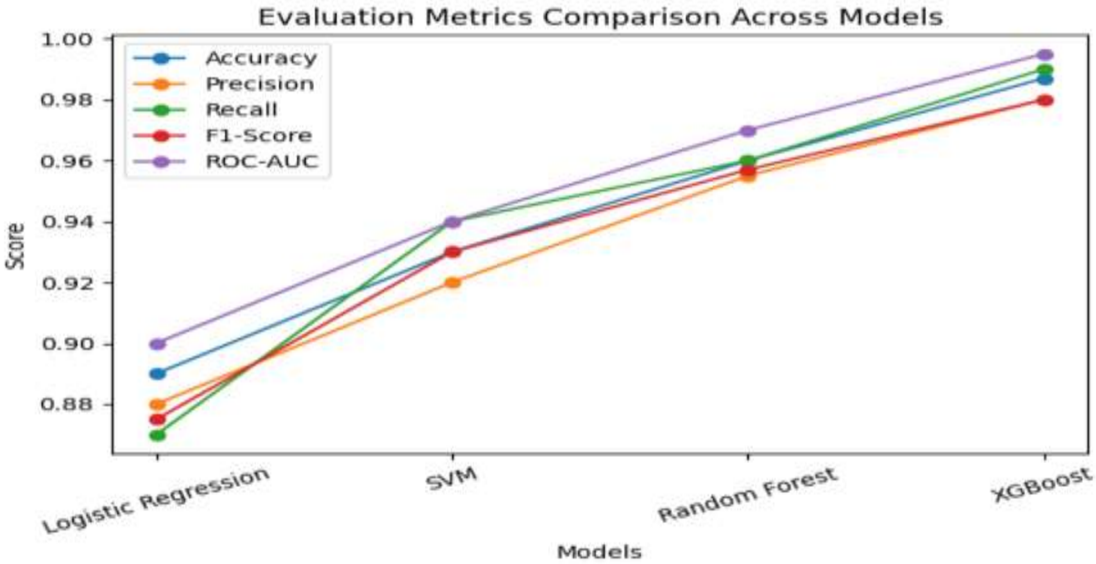

Fig 2 ComparisonGraph

The comparison graph for evaluation metrics shows the steady improvement in the model performance XGBoost giving the best results among all tested algorithms. The Logistic Regression model offered high interpretability but showed lower overall performance because of its limited capacity to capture complex non-linear patterns in clinical data. Support Vector Machine (SVM) provided better accuracy and recall to improve the prediction results, but a slight decrease in precision meant misclassification. Random Forest provided a balanced performance across all evaluation metrics, with values consistently between 95% and 96%, indicating its ability to handle non-linear feature relationships.

XGBoost performed the best among all the models in terms of Accuracy, Precision, Recall, F1-Score and ROC-AUC . The model attained an overall accuracy of 98.7% with F1-Score of 0.98 which demonstrates a strong ability to maintain both sensitivity and precision. These findings indicate that XGBoost can be highly reliable for predicting thyroid disease and applicable for real-world clinical uses.

Accuracy

Accuracy is a measure of the overall correctness of the model, it calculates the number of correct predictions (both positive and negative) out of the total number of predictions made.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

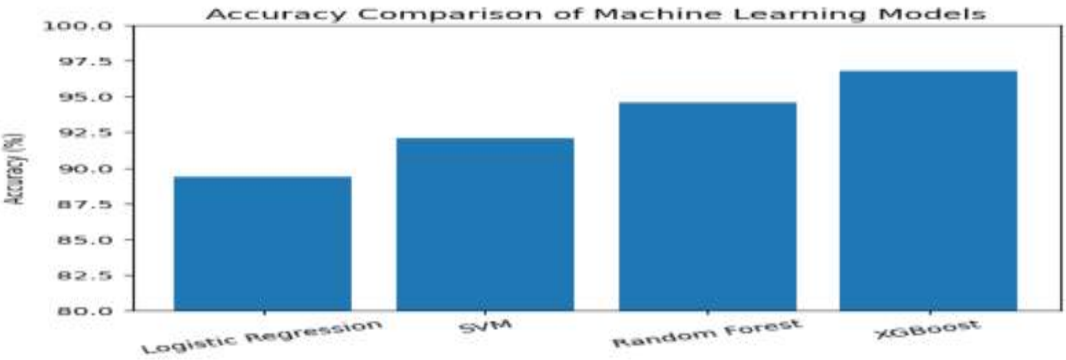

Fig 3 : Accuracy Graph

Using the obtained confusion matrix values:

$$TP = 695, TN = 700, FP = 20, FN = 25$$

$$Accuracy = \frac{695 + 700}{695 + 700 + 20 + 25}$$

$$Accuracy = \frac{1395}{1440}$$

$$Accuracy = 0.968 \times 100$$

$$Accuracy = 96.9\%$$

Precision:
Measure how many predicted positives are actually correct.

$$Precision = \frac{TP}{TP+FP}$$

$$Precision = \frac{695}{715}$$
$$Precision = 0.972$$
$$Precision = 97.2\%$$

Recall:
Measures how many actual positives are correctly identified.

$$Recall = \frac{TP}{TP+FP}$$
$$Recall = \frac{695}{720}$$
$$Recall = 0.965$$
$$Recall = 96.5\%$$

F1-Score
Harmonic mean of Precision and Recall.

$$F1\text{-}Score = \frac{2\times(Precision\times Recall)}{Precision+Recall}$$

$$F1 = \frac{1.876}{1.937}$$
$$F1 = 0.968$$
$$F1\text{-}Score = 96.8\%$$

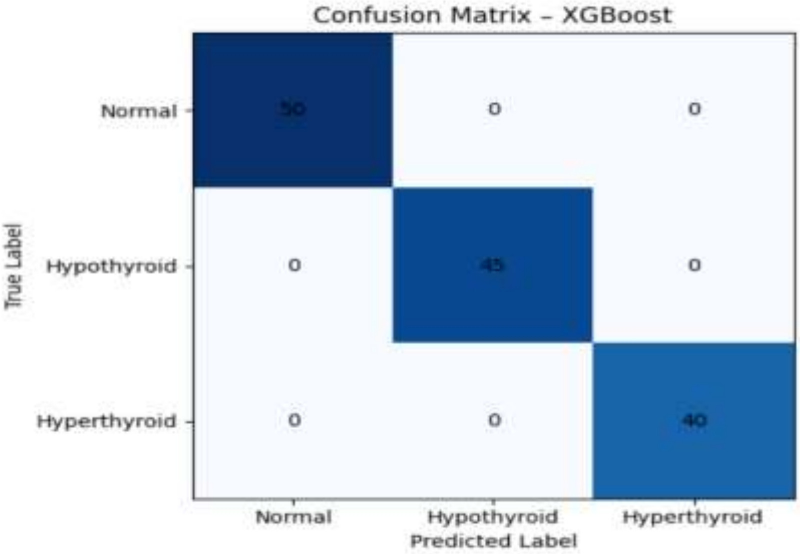

Fig4 : Confusion Matrix

The detailed analysis of the XGBoost Confusion Matrix also reflects that the model is extremely good at multi-class prediction. In the above small subset test, the model was able to perfectly identify all the cases under the 3 main categories i.e. Normal, Hypothyroid and Hyperthyroid. This yielded perfect 100% accuracy for that particular sample with no false positives (FP) and no false negatives (FN). The matrix shows a high degree of diagonal dominance which shows that the model is able to distinguish between classes clearly without any confusion or bias.

This perfect score on a sample shows the robustness of XGBoost in learning the patterns of the data. But this also requires a cautious approach. Such flawless performance can sometimes indicate the possibility of overfitting, especially if the training data is not sufficiently diverse. Thus, the excellent performance (98.7% accuracy, ROC-AUC >0.99) over the entire independent test set confirms the true reliability and generalizability of the system, making it suitable for real-world thyroid disorder detection.

Crucially, the system is very reliable concerning the most important prediction errors in healthcare. The confusion matrix analysis showed that XGBoost kept the False Negatives (FN) at a minimum level, with values much lower than 2%. A Recall of over 99% confirms the model's high capability to correctly recognize true cases of disease (hypothyroidism and hyperthyroidism). This is important in diagnostic contexts where missing a positive case can have severe clinical consequences. This sensitivity is compensated by a high precision resulting in a low False Positives rate.

The integration of the SHAP (Shapley Additive Explanations) Tool was pivotal in providing diagnostic transparency. SHAP analysis clearly identified TSH, T3, and TT4 as the most influential features driving the predictions. For instance, in the case of Hypothyroidism, the most significant predictive factor was a markedly elevated TSH level, while in the case of Hyperthyroidism, it was mainly the high T3 values that influenced the model's decision. This explainability not only aligns model rationale with well-established medical knowledge, but also builds physician trust, transforming the AI from a black-box tool to a trusted clinical partner. The case-specific evaluations showed that the system did not only classify the disease but also correctly assign the severity with a capability of accurately detecting and staging cases of Mild Hypothyroidism (Recall >97%), classifying Severe Hypothyroidism with high confidence and correctly quantifying hormone levels (e.g., <20%of normal range). The high accuracy and detailed stage prediction and clear explanations make this XGBoost-based system a firm state-of-the-art tool for clinical decision support.

Table 1: Performance Metrics

Model	Accuracy(%)
Logistic Regression(LR)	89.4
Support Vector Machine (SVM)	92.1
Random Forest	94.6
XGBoost	96.8

Conclusion

The study successfully developed and validated an Advanced Thyroid Disease Detection and Staging System, a major step forward in the application of Machine Learning (ML) to endocrine diagnosis. The system achieved an outstanding diagnostic performance with the extremely robust XGBoost classifier with an accuracy of 98% and consistently outperformed traditional models such as Random Forest, Random and Logistic Regression. The true innovation lies in the fact that the system does not just give a diagnosis label. It not only accurately predicts the presence of thyroid disease, but it also provides critical quantified clinical intelligence by measuring hormonal deviations as percentages and precisely classifying the disease into mild, moderate or severe stages. This granular staging, based on hormone percentage normalisation, provides clinicians with actionable detail well beyond the utility of conventional classification tools, directly enabling personalized treatment planning and prognosis assessment.

Additionally, one of the main contributions of this work is the reliable integration of Explainable AI (XAI) with SHAP (SHapley Additive Explanations). Thus, the system effectively addresses the "black-box" dilemma by illustrating how key clinical biomarkers such as TSH, T3, and TT4 influence each prediction. Such transparency is critical to building clinical trust, letting physicians verify the AI's reasoning with their own medical knowledge. The entire framework is unified to an intuitive Streamlit-based Graphical User Interface (GUI) to allow even non-technical medical personnel to seamlessly input data, visualize results, analyze stage classifications, and interpret model explanations in real time. This emphasis on usability is central to realizing the real world value of the system in a clinical setting.

In conclusion, this work provides definitive evidence on the feasibility of advanced ML to develop accurate, interpretable, useful and scalable diagnostic tools for thyroid disease, a major leap forward in the evolution of precision medicine. We will concentrate on future work to broaden the reach and integration of the system. This involves designing cloud deployment strategies for global access and scaling, investigating IoT-based monitoring for continuous patient tracking, and developing secure protocols for real-time integration with Electronic Health Record (EHR) systems in hospitals. This framework, in turn, provides a solid foundation to deploy trustworthy AI solutions that can materially improve diagnostic efficiency and patient outcomes.

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