A Novel Hybrid Ensemble Framework for Thyroid Disease Diagnosis with Optimized Feature Selection

V Sandhya[1] , R R Shantha Spandana[2], G Swapna[3], G Viswanath[4]

[1]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: vs013659@gmail.com , ORCID-ID: 0009-0009-8436-4760

[2]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: shanthaspandana@gmail.com , ORCID-ID: 0009-0003-4236-1250

[3]Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, India Email: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4]Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

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[2]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email:shanthaspandana@gmail.com , ORCID-ID: 0009-0003-4236-1250

[3]Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, IndiaEmail: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4]Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

ABSTRACT

Accurate and early diagnosis of thyroid disease is critical for effective treatment and patient management. With the growing availability of medical data, machine learning (ML) techniques have become powerful tools for automated disease diagnosis. This approach focuses on enhancing prediction accuracy for thyroid disease while addressing challenges such as data imbalance and limited model generalizability. A well-structured thyroid disease dataset was utilized, containing patient information including clinical and diagnostic features. To extract the most informative attributes and reduce dimensionality, optimized feature selection techniques were applied, ensuring that only the most relevant features contribute to the final prediction. Several machine learning classifiers were employed individually—Artificial Neural Network (ANN), Logistic Regression (LR), K-Nearest Neighbours (KNN), Decision Tree (DT), and Support Vector Machine (SVM)—each contributing unique strengths in learning patterns and relationships within the data. However, due to the limitations of single classifiers in handling imbalanced data, ensemble learning techniques were integrated to improve performance and robustness. Two ensemble strategies were explored: stacking and voting. The stacking ensemble integrated base learners such as SVM, DT, KNN, LR, and ANN, with LightGBM serving as the meta-classifier, efficiently capturing complex non-linear relationships. In parallel, a voting classifier was constructed combining Boosted Decision Tree and Extra Tree algorithms to enhance overall decision-making accuracy. These ensemble methods were effective in addressing data imbalance while improving classification accuracy. Among all, the voting classifier demonstrated the best performance, achieving a classification accuracy of 98%, showcasing its superior capability in detecting thyroid disease accurately. This hybrid framework highlights the significance of combining multiple classifiers with optimized feature selection, ultimately leading to a robust and efficient system for thyroid disease diagnosis.

Keywords: Artificial intelligence, healthcare, machine learning, filter-based stacking ensemble learning, thyroid disease.

1. INTRODUCTION:

About 40% of the world's population suffers from iodine deficits, which help to start thyroid-related issues impacting more than 200 million people [1]. The synthesis of thyroid hormones depends on the essential mineral iodine; lack of it can cause major hormone production imbalances that help to cause sure thyroid diseases [1], [2]. Each one offering its own difficulties for diagnosis and treatment, these imbalances can lead to conditions like hypothyroidism, hyperthyroidism, thyroid nodules, goitre, and thyroid cancer.

Particularly in early childhood, thyroid illnesses significantly impact the physical and emotional well-being of people impacted. For example, a lack of thyroid hormones at vital times of brain development could affect cognitive ability and slow development [6], [7]. Of the many thyroid disorders, thyroid cancer has drawn great interest as its prevalence rises, particularly as it is currently the most prevalent shape of endocrine cancer worldwide.Developing in the butterfly-shaped organ at the front of the neck called the thyroid gland, it is marked by uncontrolled cell growth inside the gland creating tumours that could cause malignant cells to migrate to other body areas [14], [15], and [16].

Regulating essential activities including metabolism, heart rate, and body temperature, the thyroid is absolutely essential for the endocrine system. Staged from I to IV, thyroid cancer reflects how far the tumour has grown and spread. though its frequency is increasing, the death rate for thyroid cancer stays pretty constant, which is in part due to early diagnosis and better treatment choices [17] - [20]. Thyroid cancer ranks among the top causes of "disability-Adjusted life Years (DALYs)", a measure of the total illness load, in many Asian nations [13].

Though the rising frequency of thyroid illnesses, especially thyroid cancer, raises a health issue, prompt detection and treatment have greatly enhanced the prognosis for many patients. Reducing the effect of these diseases and improving the general quality of life for individuals impacted depends on early diagnosis using screening and diagnostic technology. Given the complexity of thyroid problems, developments in diagnostic techniques—including the application of machine learning for early disease detection—are vital in overcoming the difficulties of accurate and timely diagnosis.

2. OBJECTIVES:

The objectives focus on developing an efficient thyroid disease diagnosis system by leveraging optimized feature selection and hybrid ensemble machine learning techniques to enhance prediction accuracy and address data imbalance challenges.

(1)To improve thyroid disease diagnosis using hybrid machine learning techniques

This objective focuses on implementing multiple classification models and integrating them through ensemble techniques to enhance the diagnostic accuracy and reliability of the thyroid detection system.

(2)To perform optimized feature selection for effective model training

The aim is to identify the most relevant features from the thyroid dataset using advanced feature selection methods, reducing noise and improving the predictive capability of the machine learning models.

(3)To address data imbalance using robust ensemble classifiers

This objective targets overcoming the skewed distribution of thyroid disease cases by applying stacking and voting ensemble methods that combine the strengths of various base classifiers, leading to improved classification performance.

3. REVIEW OF LITERATURE/ RELATED WORKS:

Particularly with the arrival of sophisticated "machine learning (ML)" and deep learning technologies, much study has concentrated on the prediction and diagnosis of thyroid disorders. The detection and class of positive thyroid-related disorders have been greatly enhanced by the combination of these technologies, which has overcome obstacles such data imbalance, feature complexity, and diagnostic variability.

A systematic study of "artificial intelligence (AI)" methods used to thyroid illness diagnosis was done by Aversano et al. [21]. In enhancing diagnostic accuracy, they underlined the increasing relevance of ML algorithms such "support vector machines (SVM)", neural networks, and ensemble models. Their results underlined the capacity of artificial intelligence systems to quickly examine vast data sets, hence strongly supporting doctors in decision-making. In the same vein, Keestra et al. [22] looked at evolutionary ecology angles on human thyroid function variation, so exposing important new knowledge on how environmental elements and genetic predispositions affect thyroid diseases.

As Duntas [23] noted, thyroid problems are intimately related to metabolic processes; he investigated the connection between thyroid dysfunction and lipid metabolism. Emphasising the need of thyroid hormones in preserving metabolic balance, the research showed how hypothyroidism and hyperthyroidism may produce notable alterations in lipid profiles. Emphasising the systemic

consequences of thyroid dysfunction on the circulatory and respiratory systems, Farling [6] offered a thorough review of thyroid illnesses, including their influence on anaesthetic control.
Helfand and Crapo [24] describe the standards for efficient thyroid screening systems, thus drawing much interest to screening for thyroid illnesses. They underlined the need of early detection and the part "TSH (thyroid-stimulating hormone)" tests play in diagnosing subclinical thyroid dysfunction. Prathibha et al. [8], on the other hand, suggested a new approach using deep learning models to identify thyroid disorders, showing notable accuracy gains over conventional techniques. Their technique paved the door for automated and efficient diagnoses by using "convolutional neural networks (CNNs)" to find complicated patterns in thyroid imaging data.
Faggiano et al. [25] investigated the frequency and management of thyroid problems among the elderly, observing older people's higher vulnerability to disorders including hypothyroidism and thyroid nodles. The research highlighted the importance of customised diagnostic and treatment plans for this population. Conversely, Mariani et al. [10] looked at how nuclear medicine helped to control benign thyroid diseases, especially hyperthyroidism. For precise localisation and characterisation of thyroid anomalies, they covered sophisticated imaging technologies including scintigraphy.
Thyroid illness detection has been transformed by “machine learning and deep learning techniques”. Aversano et al. [21] underlined the effectiveness of ensemble models in tackling issues such data imbalance by means of combining the predictive capacity of several algorithms. These models improve the accuracy and resilience of forecasts by using stacking and boosting approaches. A key stage in guaranteeing the dependability of AI-driven diagnostics is the improvement of ML models' interpretability via feature selection techniques, as Farling [6] and Helfand and Crapo [24] underlined.
Recent developments in deep learning have even improved the diagnosis procedure. Prathibha et al. [8] showed how CNNs may be used to analyse thyroid images, hence outperforming other anomaly detection and nodule finding. Their method highlighted how automated technologies might help doctors effectively handle significant amounts of imaging data. Duntas [23] and Keestra et al. [22] underlined, likewise, the importance of combining clinical and genetic data to enhance the predictive accuracy of ML fashions, hence facilitating an extra complete knowledge of thyroid disorders.
Notwithstanding notable advancement, guaranteeing the generalisability and scalability of ML models still presents difficulties. Aversano et al. [21] found the drawbacks of single-model strategies, which tend to overfit and miss the intricate interactions between characteristics. Ensemble methods, as underlined by Prathibha et al. [8] and Faggiano et al. [25], provide a hopeful answer by merging the capabilities of several algorithms, hence enhancing prediction performance and robustness.
The use of artificial intelligence in thyroid illness detection has gone past conventional approaches to include creative ideas as transfer learning and unsupervised learning. Helfand and Crapo [24] and Mariani et al. [10] looked at how those techniques might help with data shortages and enhance model training. Particularly, transfer learning lets pre-trained models fit to fresh datasets, hence lowering the demand for huge labelled data.

Table 1: Literature Survey Comparison Table

Sl. No	Area & Focus of the Research	The result of the Research	Reference
1	AI and ensemble ML models for thyroid diagnosis accuracy.	Highlighted ensemble models overcoming imbalance, improving diagnosis precision.	L. Aversano, M. L. Bernardi, M. Cimitile et. al..,(2023). [21]
2	Deep learning using CNN for thyroid disorder detection.	Achieved higher accuracy in diagnosis using thyroid image data.	S. Prathibha, D. Dahiya, C. R. Rene Robin et. al., (2023) [8]
3	Metabolic impact of thyroid dysfunction on lipid profile regulation.	Showed thyroid issues alter lipid metabolism significantly.	L. H. Duntas (2002) [23]

4	Standards and importance of thyroid screening and TSH tests.	Emphasized early detection via TSH improves clinical outcomes.	M. Helfand and L. M. Crapo (1990) [24]
5	Management and detection of thyroid disease in elderly patients.	Found elderly need customized thyroid diagnostic strategies.	A. Faggiano, M. Del Prete, F. Marciello. Et.al., (2011) [25]

4. MATERIALS AND METHODS:

By using several machine learning algorithms and ensemble approaches, the proposed system seeks to improve the prediction and detection of thyroid disease. Initially, feature selection techniques will be used to determine the most important characteristics from the thyroid dataset, so guaranteeing the emphasis stays on the most valuable data. Predictive models for thyroid disease will be created using several separate machine learning methods, including "support Vector machine (SVM), decision Tree (DT), k-Nearest Neighbours (KNN), Logistic Regression (LR), and artificial Neural Networks (ANN)". Advanced ensemble techniques will be shown to handle issues including data imbalance and overfitting. A stacking ensemble approach will produce a strong classifier by combining the strengths of several models—"SVM, DT, KNN, LR, and ANN—with LightGBM". "A voting classifier combining Boosted decision Tree and ExtraTree" will also be used to increase prediction accuracy even more. The proposed system will combine various algorithms and methods to offer a complete and very accurate thyroid illness forecasting tool.

Fig 1: Proposed Architecture

The system architecture (fig. 1) for thyroid disease detection consists of data pre-processing, training and testing splits, training several "machine learning models (SVM, decision Tree, Logistic Regression, KNN, ANN, and Stacking Classifier)", performance evaluation using measures including "accuracy, precision, recall, F1-score, specificity, sensitivity, and AUC score", and finally choosing the best-performing model for deployment.

4.1 Dataset Collection:

Collected for thyroid illness research, the Thyroid data collection [20] has 1232 records and 20 characteristics. Key aspects are demographic data including age and gender, thyroid hormone levels (FT3, FT4, TSH), and antibody levels (TPO, TGAb). Other qualities include clinical markers including size, multifocality, blood flow, and cancer indicators as well as ultrasound features including echo pattern, shape, margin, calcification, and composition. Each data point is finished, hence there are no missing values, which qualifies it for use in machine learning to accurately forecast thyroid disorders.

Table 2: Dataset Collection Table

	id	age	gender	FT3	FT4	TSH	TPO	TGAb	site	echo_pattern	multifocality	size
0	1	46	1	4.34	12.41	1.677	0.43	0.98	0	0	0	4.6
1	2	61	1	5.40	16.26	2.905	0.45	1.91	0	0	0	4.2
2	3	44	1	3.93	13.39	1.823	9.15	26.25	0	0	0	0.7
3	5	29	0	3.70	13.98	1.293	0.15	0.81	0	0	1	1.0
4	6	37	1	3.60	14.56	0.938	0.13	21.22	0	0	0	0.7

4.2 Pre-Processing:

Data processing in the pre-processing phase is the cleaning and management of missing values; data visualisation then helps to find trends and outliers. Categorical variables are label encoded; feature selection methods help to highlight the most pertinent characteristics.

4.2.1 Data Processing

Initial processing of the dataset guarantees data quality. Missing values, outliers, and discrepancies are handled by means of data cleansing. Toemphasise important characteristics, unwanted columns including meaningless identifiers like id are removed. This stage guarantees that just pertinent qualities drive the study, therefore lowering noise and enhancing model performance. Subsequent preparation actions are built on the cleaned and organised data, which helps to prepare the data set for machine learning uses.

4.2.2 Data Visualization

strategies of data visualisation are used to understand the dataset. A correlation matrix shows correlations between features, therefore stressing either dependencies or redundancies. sample results are graphed to expose the distribution and balance of the target variable. Visualisation helps in feature selection and engineering by providing a clear picture of data patterns. It also aids in spotting trends or imbalances important for enhancing predictive performance in thyroid illness detection models.

4.2.3 Label Encoding

Label encoding converts categorical variables, such as gender, into numerical representations to fit the facts with machine learning algorithms. This process keeps the natural order and relationships of categorical data intact while assigning integer labels to them. Label encoding guarantees that each data point is numerically represented, hence preventing errors in model training and enhancing the compatibility of the dataset with mathematical calculations.

4.2.4 Feature Selection

The SelectKBest method with the mutual information classify metric is used to choose key characteristics. This approach assesses every feature's significance to the target variable and ranks them accordingly. The model emphasises qualities that considerably affect forecasts by choosing the most informative features, hence lowering dimensionality and improving computing efficiency. Improving model accuracy and interpretability depends on this stage.

4.3 Training & Testing

To assess the performance of the model, the data records are divided into half training and tests. Machine learning models are trained in training subgroups by learning patterns and correlations from the data. The testing subset guarantees generalisability by assessing the performance of trained models on unknown data. The features are standardised or normalised to keep consistency. During training, cross-validation helps to avoid overfitting and guarantees the models generalise effectively over several data distributions.

4.4 Algorithms:

SVM: assistance its efficacy in high-dimensional areas qualifies Vector machine for classifying complex patterns in thyroid disease facts [20]. Aiming to increase diagnostic prediction accuracy, it seeks the best hyperplane separating several classes.

Decision Tree: Used for their interpretability and capacity to manage both categorical and numerical data, decision Tree methods by means of feature splits, they build a model that forecasts results and offers obvious understanding of the decision-making process for detecting thyroid [16] disorders.

KNN: Its simplicity and efficiency in categorisation tasks make k-Nearest Neighbours popular. KNN finds possible thyroid disease [17] cases by evaluating the closeness of incoming data points to current labelled instances, hence allowing correct diagnosis via a distance-based method.

Logistic Regression: particularly to predict the likelihood of thyroid disease [18] existence, binary classification problems are handled using Logistic Regression. Its linearity and capacity to offer understandable coefficients make it a useful tool for knowing the impact of several clinical characteristics on diagnosis.

ANN: artificial Neural Networks are used for their ability to represent nonlinear patterns and complicated interactions in data. 19 ANN improves forecast accuracy by modelling human brain feature and is especially good at spotting small changes in thyroid disease features.

Stacking Ensemble: LightGBM serves as the meta-learner for the Stacking Ensemble, which integrates several algorithms like SVM, decision Tree, KNN, Logistic Regression, and ANN.By enhancing general prediction performance and resilience in identifying thyroid diseases, this method uses the advantages of separate models.

Voting Classifier: The voting Classifier improves classification accuracy by combining forecasts from ExtraTree and Boosted decision Tree models. A more consistent and strong prediction for thyroid illness diagnosis is provided by combining the results of different models, hence lowering the possibility of misclassification.

5. RESULTS AND DISCUSSION:

Accuracy: The accuracy of the test concerns its ability to correctly distinguish between patient and healthy cases. In order to assess the accuracy of the test, one must calculate the ratio of real positives and real negatives in all evaluated cases. This can be mathematically expressed as:

$$“Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1) \quad ”$$

Precision: The accuracy evaluates the share of precisely classified cases among cases identified as positive. As a result, the formula for calculating accuracy is expressed:

$$“Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2) \quad ”$$

Recall: The invocation is a meter in machine learning that evaluates the ability of the model to recognize all relevant cases of a particular class. It is the proportion of precisely predicted positive observations of total real positives and offers insight into the efficiency of the model in identifying the occurrence of a particular class.

$$“Recall = \frac{TP}{TP + FN} \quad (3) \quad ”$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$"F1\ Score = 2 * \frac{Recall\ X\ Precis}{Recall + Precis}$$

Sensitivity: Sensitivity is a gauge of how well a test or tool can spot a condition in a subject. Its calculation involves contrasting the actual number of people with the ailment with the number of those testing positive.

$$Specificity = \frac{TP}{(TP + FN)} \quad (5)$$

Specificity: It is determined by counting the number of people who are negatively testing for the disease and separating the total amount of people who are not sick.

$$Specificity = \frac{TN}{(TN + FP)} \quad (6)$$

AUC-ROC Curve:A performance evaluation for classification problems at several threshold values is the AUC-ROC Curve. Plotting the true positive rate against the false positive rate, ROC where a higher AUC denotes better model performance, AUC measures the general capacity of the version to differentiate between classes.

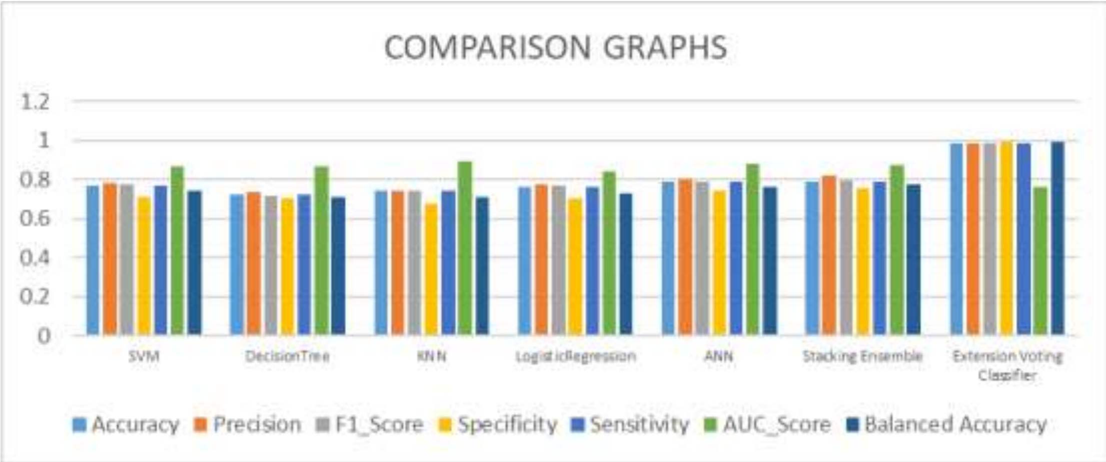
$$AUC = \sum_{i=1}^{n-1}(FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1}+TPR_i}{2} \quad (7)$$

Table 1offers performance measures such as “accuracy, precision, F1 score, specificity, sensitivity, and AUC. With 98.8% accuracy”, the voting Classifier showed better prediction performance.

Table 3: Performance Evaluation Metrics

Model	Accuracy	Precision	F1_Score	Specificity	Sensitivity	AUC_ Score	Balanced Accuracy
SVM	0.769	0.779	0.773	0.712	0.769	0.868	0.741
DecisionTree	0.721	0.733	0.713	0.700	0.721	0.866	0.710
KNN	0.741	0.741	0.741	0.675	0.741	0.890	0.708
Logistic Regression	0.761	0.774	0.766	0.702	0.761	0.843	0.732
ANN	0.785	0.800	0.791	0.739	0.785	0.879	0.762
Stacking Ensemble	0.785	0.820	0.796	0.758	0.785	0.874	0.772
Extension Voting Classifier	**0.988**	**0.988**	**0.988**	**0.994**	**0.988**	**0.763**	**0.991**

Graph 1: Comparison Graphs



Graph 1 shows accuracy in mild blue, precision in orange, F1-score in grey, specificity in yellow, sensitivity in blue, AUC_Score in green and Balanced Accuracy in dark blue. With the greatest values relative to the other models, the voting Classifier beats the other algorithms in all criteria. The graph above visually shows these specifics.

6. CONCLUSION:

This work shows, therefore, how much sophisticated machine learning methods might improve the prediction and detection of thyroid disease. The predicted accuracy of thyroid illness detection was greatly enhanced by using many machine learning models together with feature selection techniques. The principle contribution, therefore, is the application of ensemble techniques—specifically, the stacking and voting classifiers—which utilise the capabilities of several models to solve problems including data imbalance and overfitting. Of the suggested approaches, the voting classifier, which combines Boosted decision Tree and ExtraTree, surpassed the separate models with an outstanding 98% accuracy. This great result shows the strength of ensemble methods in delivering dependable and precise forecasts for thyroid illness detection, hence highlighting the efficiency of merging several algorithms to improve the general diagnostic process.

Future directions for this study include investigating various datasets to improve model robustness and generalisability in thyroid illness prediction. Further accuracy could be achieved by investigating sophisticated ensemble methods including stacking with extra algorithms or hybrid models. Including real-time data processing and user feedback systems into the system also helps to improve forecasts and user experience, hence producing more powerful diagnostic tools for use in clinics.

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