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An Improved Framework for Detecting Thyroid Disease Using Filter-Based Feature Selection and Stacking Ensemble

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Abstract: *Machine learning (ML) had become quite significant in determining what type of thyroid disease an individual has and in informing individuals that they may possess one in the last several years. Single ML models have been examined but their capability to produce accurate forecasts is usually impaired by information imbalance and model-specific constraints. These problems were addressed using a number of ML techniques applied to a thyroid dataset primarily to increase the accuracy of the predictions. The most useful features that could make a correct evaluation were found by means of feature selection methods. Some of the models used to determine thyroid disease were support vector machines (SVM), decision trees (DT), k-nearest neighbors (KNN), logistic regression (LR), and artificial neural networks (ANN). There was also the ensemble approach of stacking and voting a classifier to combine multiple models to improve performance. There were significant improvements in the stacking ensemble including LightGBM, SVM, DT, KNN, LR, ANN and vote classifier including Boosted Decision Tree and ExtraTree. The best of these was the voting predictor whose accuracy was 98% reliable. This demonstrates that ensemble techniques may be useful in addressing imbalance of data and achieve improved outcomes in the prediction of what thyroid disease a patient has.*

"Index Terms - *Artificial intelligence, healthcare, machine learning, filter-based stacking ensemble learning, thyroid disease".*

1. INTRODUCTION

Approximately 40 percent of the global population has inadequate amounts of iodine in their diets and this may cause thyroid related illnesses that afflict over 200 million persons worldwide [1]. Thyroid hormones require a lot of iodine. A lack of sufficient iodine may put hormone production in a wrong manner that can lead to many varieties of thyroid disease [1], [2]. The imbalance may cause such conditions as hyperthyroidism, hypothyroidism, goiter, thyroid nodules, and thyroid cancer. Identification and treatment of each of them is problematic.

Thyroid issues cause significant effects to the physical and psychological wellbeing of those affected and particularly in young persons. Indicatively, deficiency of thyroid hormones in significant periods of the brain development may impair learning, and halt growth [6], [7]. Thyroid cancer has gained much publicity among thyroid cancer diseases as it is the most prevalent endocrine cancer in the world and is increasingly becoming common. It is grown in the thyroid gland which is a butterfly shaped gland in the anterior neck. It is characterized by uncontrolled cell proliferations in the gland that are tumor forming. These may allow cancerous cells to proliferate to other body organs [14], [15], [16].

The thyroid has a significant role in the endocrine system in that it regulates most of the functions that are considered important such as metabolism, heart rate and body temperature. There are four stages of thyroid cancer. The stage zero to IV indicates the extent of growth and spread of the tumor. Although thyroid cancer is diagnosed more frequently, the death rate due to it did not vary significantly over the time. This is at least in part due to the fact that it is early-caught and that there are more effective means of its treatment [17]-[20]. In most Asian nations, Thyroid cancer tops the list of leading causes of Disability-Adjusted Life Years (DALYs) [13]. The overall burden of disease can be measured in terms of DALYs.

It is a healthy issue of great concern that there is an increasing number of people contracting thyroid illnesses, primarily thyroid cancer. However, most patients have had far greater success as they were diagnosed and treated in a timely manner. Screening and diagnostic technologies are very important in detecting these diseases in their early stages and reducing the impact of the diseases and overall quality of life of the affected citizens. The impossibility of understanding thyroid disorders, as well as the fact that new techniques of diagnosis like machine learning to detect diseases early are useful in addressing the issue of proper and rapid diagnosis makes it hard.

2. RELATED WORK

There has been much research to date into the process of predicting, diagnosing, and treating thyroid diseases, and with the aid of new ML and DL techniques. The combination of these technologies has indeed enhanced the capacity to discover and classify various ailments related to thyroid. It has been dealing with irregular data, complex features, and inconsistencies in diagnosis of conditions.

Aversano et al. [1] have conducted a systematic review of AI use in the discovery of thyroid diseases. They have also indicated that ML algorithms, such as SVM, neural networks, and ensemble models, are increasingly significant in terms of ensuring that the process of making a diagnosis is more accurate. They worked on the manner in which the AI systems could scan large datasets fast, which offers the doctors with solid backing whenever they require to make decisions. Similarly, Keestra et al. [3] investigated the evolutionary ecological aspect of the modified human thyroid functioning over the years. This provided us with valuable new data on the role of genetic factors and conditions of the environment on thyroid diseases.

Duntas [5] discusses the relation of thyroid diseases to metabolic processes, namely, the association of thyroid problems with lipid metabolism. The research indicated that both hypothyroidism and hyperthyroidism conditions might cause significant alterations in lipid profiles. This demonstrates that thyroid hormones play a very significant role in maintaining metabolic balance. Farling [6] provided a complete description of the thyroid diseases particularly with respect to their influence on the control of the anesthetics and the impact of thyroid issues on the heart and the breathing system.

Many individuals have been keen on thyroid screening tests and Helfand and Crapo [7] presented the guidelines on effective thyroid screening programs. They emphasized the necessity to find something at an early stage and TSH (thyroid-stimulating hormone) tests to detect subclinical thyroid failure. Meanwhile, Prathibha et al. [8]

proposed another method of identifying thyroid diseases with the help of DL models that appeared to be considerably more accurate than the old ones. They used CNNs also known as CNN in their model to identify complex patterns in thyroid imaging data. It was due to this that tests could be performed speedily and automatically.

The study by Faggiano et al. [9] investigated the prevalence of thyroid diseases in elderly individuals and the management of such diseases, which indicated that older adults have higher chances of developing ailments such as hypothyroidism and thyroid tumors. The analysis revealed that individuals of this category require unique diagnosis and treatment programs. Conversely, Mariani et al. [10] were interested in the potential of nuclear medicine in the treatment of non-cancer-related thyroid issues, particularly hyperthyroidism. The new imaging techniques such as scintigraphy that could assist in locating and characterizing thyroid issues more effectively were discussed.

It has been a breakthrough in that ML and DL have been utilized to detect thyroid diseases. According to Aversano et al. [1], ensemble models, which combine the capacity of numerous other algorithms, are suitable in addressing issues such as imbalance of data. The methods of stacking and boosting are applied in these models to ensure that the predictions are more accurate and reliable. According to Farling [6] and Helfand and Crapo [7], the reason why feature selection methods are significant is to simplify the understanding of or reduce the dimensionality of the ML models. It is a valuable measure that will ensure AI-based diagnostics is trustworthy.

Recent advancements in DL have made the diagnosis process even better. Prathibha et al. [8] demonstrated that it was possible to analyze images of the thyroid using CNNs. They were more successful in their work than using the previous methods, finding tumors and other problems. Their work demonstrated that automatic systems could prove to be a significant assist to doctors that have to work with a significant amount of imaging data. Similarly, Duntas et al. [5] and Keestra et al. [3] reported that a combination of clinical and genomic data would assist the ML models in making more accurate predictions and allow individuals to understand the thyroid conditions better.

Although much has been accomplished, it is not always easy to ensure that ML models can be applied in a wide range of scenarios and on a wide range of different data. The authors stated that single-model approaches are not effective as they tend to overfit, and fail to display the complex interactions of features with one another [1]. Ensemble methods combine the power of a number of algorithms to render them more correct and dependable and are a promising solution as stated by Prathibha et al. [8] and Faggiano et al. [9].

Old methods of finding thyroid diseases have been surpassed by the use of AI to cover other emerging approaches such as transfer learning and unsupervised learning. Helfand and Crapo [7] and Mariani et al. [10] investigated the possibility that such approaches would assist in addressing a data deficit and improving model training. Specifically, transfer learning allows models that have been previously trained to learn on new data and this implies that you do not require as many labeled data.

3. MATERIALS AND METHODS

The proposed system will be used to meet the goals of enhancing prediction and diagnosis of thyroid disease, by applying a set of ML algorithms and ensemble techniques. First of all, the most crucial features of the thyroid dataset will be identified through the feature selection methods. This will ensure that analysis remains oriented towards the information that presents the best information. The predictive models of thyroid disease will be made with the help of a number of different ML methods. These are SVM, DT, KNN, LR and ANN. Advanced ensemble techniques will be presented as solutions to such problems as data mismatch and overfitting. A stacking ensemble approach will combine the advantages of a very large number of different models, including LightGBM, SVM, DT, KNN, LR and ANN, to produce a powerful predictor. The predictions will also be made more precise with the use of a vote classifier based on Boosted DT and ExtraTree. All these algorithms and techniques will be applied to the suggested system to create a complete prediction model of thyroid disease, which will be highly accurate.

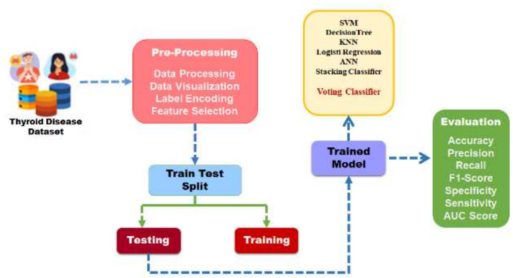


Fig.1 Proposed Architecture

The thyroid disease detection system structure is depicted in figure 1. It involves data preparation, division into a training set and a test-set, training multiple ML models (SVM, Decision Tree, Logistic Regression, KNN, ANN, and Stacking Classifier), testing each of the models on the basis of their performance metrics (accuracy, precision, recall, F1-score, specificity, sensitivity, and AUC score), and selecting the most effective model that should be used in a real-life software.

i) Dataset Collection:

The Thyroid Data dataset [20] that was compiled to examine thyroid cancer has 1232 records and 20 attributes. The most important ones include level of thyroid hormone (FT3, FT4, TSH), levels of antibodies (TPO, TGAb), and individual information (age and sex). Additional features are ultrasound signs (such as pattern of echo, form, margin, calcification, and composition) and clinical signs (such as size, multifocality, blood flow and cancer signs). Each of the data points has been filled in and thus it is ready to be used in ML apps to forecast thyroid conditions accurately.

	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

Fig.2 Dataset Collection Table

ii) Pre-Processing:

To use data, it has to be cleaned and numbers missing addressed and patterns and outliers have to be identified with the help of data visualization. Encoding of labels is applied to categorical variables, and feature selection techniques are applied to obtain the most significant features.

a) Data Processing: First processing is done to ensure that the quality of the data. Data cleaning eliminates missing data, outliers and inconsistency. Unnecessary columns are eliminated to concentrate on the most significant ones that include the useless identifiers such as the "id. This move ensures that the analysis is done using only significant characteristics. This assists the model to operate faster and with ease. The next preprocessing processes are based on the cleaned and sorted data, which prepares the information better to be used by machine learning.

b) Data Visualization: Data visualization techniques are employed to gain a more insight into an information. The feature interaction dependencies and redundancies are presented in a correlation matrix. Sample results are plotted sequentially in order to observe the dispersion and uniformity of the goal variable. Visualisation is useful in feature selection, engineering, as data trends are clearly displayed. It also aids in the discovery of trends or imbalances that are significant in the development of thyroid disease detection models.

c) Label Encoding: Label encoding converts categorical variables, such as gender into numbers in order to be able to apply it to ML algorithms. In this step, the numbering of categorical values is done in a way that does not distort their natural order and relationships. Label encoding ensures that the entire data is presented in the form of numbers. This avoids errors during the training of the model and aligns the information to the mathematical operations better.

d) Feature Selection: The most important features are selected using the Select KBest method that uses the mutual information classifier. This method ranks the features in terms of the degree of their contribution to the explanation of the goal variable. The model is concerned with features with an enormous impact on the predictions, which reduces the dimensions of dimensions and makes the calculations quicker, as it selects the most useful features. This measure is highly significant towards rendering the model more realistic and comprehensible.

iii) Training & Testing:

The dataset is separated into the training and testing groups to be able to observe the performance of the model. The training part assists ML models to determine patterns and correlations in the data. The testing subset is the how well the taught models perform on new data and this ensures that the models are more general. The traits are made the same through standardization and normalization. Cross-validation is performed during training to prevent overfitting in order to ensure the models can be used in a large variety of data types.

iv) Algorithms:

SVM: Back The SVM is used since it is efficient in high-dimensional space and thus an appropriate tool to sort complex patterns in data about thyroid diseases [20]. It aims at identifying the most optimal hyperplane that separates various groups. This aids in acquiring more precise predictions during diagnosis.

Decision Tree: Decision Tree algorithms are used by people as they are not complicated to comprehend and can process both categorical and number data. They construct a model which determines what a feature split would do. This creates a clear picture of how the decisions are arrived at when treating thyroid issues are being diagnosed [16] about the problem.

KNN: The reason why KNN is an effective method to use in job(classification) is that it is easy and effective. KNN assists in locating potential instances of thyroid disease [17] through the examination of the proximity between fresh data and examples already designated and identification of resemblances. This method that involves distance enables a right diagnosis.

Logistic Regression: Computations that Logistic Regression is employed in binary classification work include determining the probability of thyroid disease [18]. It is an effective instrument in interpreting the impact of various clinical variables on the identification as it is linear and provides coefficient values that can be easily understood.

ANN: The ANN are applied due to the ability to characterize non-linear patterns and complex relationships in the data. [19] ANN simulates the functioning of the human brain, which is why it becomes more effective in making predictions and in particular, it is apt at detecting subtle differences in the presentation of thyroid-related diseases.

Stacking Ensemble: The meta-learner in the Stacking Ensemble is LightGBM that assembles a collection of methods, including SVM, Decision Tree, KNN, Logistic Regression, and ANN. It is a way of taking advantage of the benefits of both models to improve the predictability and treatment of thyroid issues.

Voting Classifier: Voting Classifier employs the prediction of Extra tree and Boosted Decision Tree and makes the classifications more precise. The combination of the findings of these models provides a more reliable and powerful prediction of thyroid disease finding. This reduces the possibility of misdiagnosis.

4. RESULTS & DISCUSSION

Accuracy: The validity of a test involves its capability in distinguishing between the sick and the healthy cases. To know the extent of the false positive value, we should determine the percentage of true positives and true negatives of all the cases tested. Mathematically it can be expressed as.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \, (1)$$

Precision: Precision is a measure of correctly identified examples or instances among the ones identified as positive. The process of determining the accuracy is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \, (2)$$

Recall: The ML parameter that indicates the extent to which a model can locate all the pertinent instances of a given type is called recall. It is the proportion of correctly predicted positive cases of all the actual positives. This provides the information on the extent to which a model is complete in covering the cases of a particular class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \, (3)$$

F1-Score: The F1 score can be used to measure the accuracy of a ML model. It sums up the model accuracy and recall scores. Accuracy measure how many right predictions that the model made throughout the entire data.

$$F1\ Score = 2 * \frac{Recall \ \mathrm{X} \ Precision}{Recall + Precision} * 100(1)$$

Sensitivity: Sensitivity is a measure of the capability of a test or a tool to correctly identify a condition in an individual. It is calculated by determining the number of the people that test positive by dividing it with the number of people who actually have the disease.

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

Specificity: It is determined by the calculation of the number of people who tested negative and then divided it by the total number of people who did not have the condition and also included in this are those people who did not have the disease but had tested positive (Freeman par. 1).

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

AUC-ROC Curve: The AUC-ROC Curve is used to indicate the performance of the classification problem at various benchmark settings. ROC displays the ratio of true positives to the rate of false positives. AUC is the ability of the model to distinguish the difference between classes. A higher value of UCA indicates that the model is better.

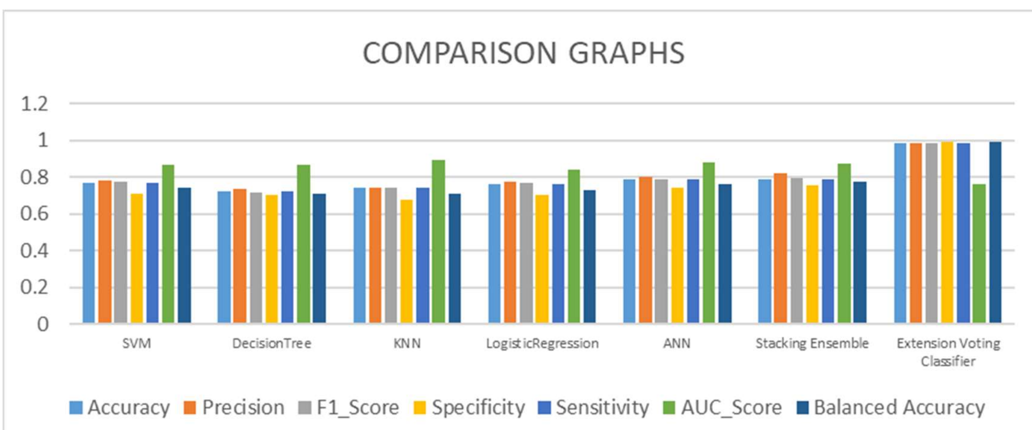
$$AUC = \sum_{i=1}^{n-1}(FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1}+TPR_i}{2} \quad (7)$$

Table 1 shows accuracy, precision, F1 score, specificity, sensitivity and AUC performance measures. The Voting Classifier was the best at guessing the result with the highest number of correct guesses, 98.8%, which depicted that it was the most accurate in its results.

"Table.1 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
LogisticRegression	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 presents the various metrics in different colors, namely light blue, which represents the accuracy, orange, which represents the precision, grey, which represents the F1-score, yellow, which represents the specificity, blue, which represents the sensitivity, green, which represents the AUC_Score, and dark blue, which represents the Balanced Accuracy. All the other models cannot compete with the Voting Classifier, it is the most scored in all the categories. These facts are visualised in the graph above.

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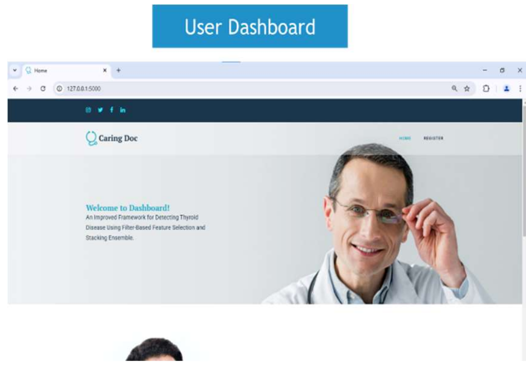

Fig.3 Home Page

This panel above enables people to navigate around pages that indicate Welcome.

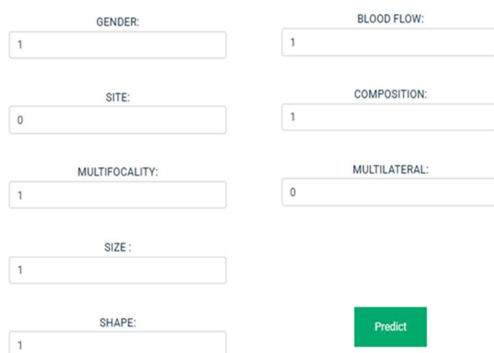

Fig.4 User input Page

In Figure 4 above, it has a page where one enters the information. Here the test data may be shared by the person who uses it.

Fig.5 Detection result

A result screen is presented in figure 5 above. This is where the user will see output after loading of raw data.

5. CONCLUSION

In conclusion, this paper demonstrates that applying the state-of-the-art ML techniques can actually assist in determining and forecasting thyroid disease. The capacity to make the right guess on the diagnosis of thyroid disease was increased significantly by applying a variety of ML models and feature selection techniques. However, ensemble techniques, such as stacking and voting classifiers, make this work very special. They integrate the strength of other models to address the issue of data imbalance and overfitting. The vote classifier, a combination of Boosted Decision Tree and ExtraTree was the best of all the recommended. It was accurate 98 percent of the times which was higher than the models applied independently. The good performance demonstrates that with the use of the ensemble approaches, one can make dependable and correct predictions which are applicable to the diagnosis of thyroid disease. This demonstrates that the application of a great number of algorithms to enhance the overall process of diagnostics is effective.

In the future, the aim of the study will be to identify alternative data to ensure that the model becomes more robust and useful in forecasting thyroid diseases. In the further development of more complex ensemble approaches, such as stacking or mixed models, it may be useful to achieve even more accurate outcomes. Predictions can be more precise with the inclusion of real-time data processing and user comments to the system, and it can enhance the user experience. Ultimately, this will lead to superior diagnostic instruments in the clinical practice.

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