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Diagnosis of Thyroid Disease: Comparison of Adaptive Neural Fuzzy Inference System and Artificial Neural Network with the Logistic Regression Model

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Abstract

Background: The development of data mining techniques and the adaptive neuro-fuzzy inference system (ANFIS) in the last few decades has made it possible to achieve accurate predictions in medical fields.
Objectives: The present study aimed to use the ANFIS model, artificial neural network (ANN), and logistic regression to predict thyroid patients.
Methods: This study aimed to predict thyroid disease using the UCI database, ANFIS and ANN models, and logistic regression. We only used four of its features as the input of the model and considered thyroid as a binary response (occurrence=1, non-occurrence=0) as the output of the model. Finally, three models were compared based on the accuracy and the area under the curve (AUC).
Results: In this study, out of the extensive UCI database, which includes 3,772 samples and over 20 features, only five specific features were utilized. Data include 1,144 males and 2,485 females. The results of multiple logistic regression analysis demonstrated that free T4 index (FTI) and thyroid stimulating hormone (TSH) had a significant effect on thyroid. The ANFIS model had a higher accuracy (99%) compared to ANN (96%) and the logistic regression model (94%) in the prediction of thyroid.
Conclusion: As evidenced by the obtained results, the forecasting performance of ANFIS is more efficient than other models. Moreover, the use of combined methods, such as ANFIS, to diagnose and predict diseases increases the accuracy of the model. Therefore, the results of this study can be used for screening programs to identify people at risk of thyroid disease.

Keywords: Adaptive neuro-fuzzy inference systems, Artificial neural network, Logistic regression, Thyroid

1. Background

The thyroid gland situated in the neck holds significant importance as one of the vital glands in the body. Its primary role is to transform iodine, which can be obtained from various food sources, into thyroid hormones known as thyroxine (T4) and triiodothyronine (T3)(1). Thyroid cells are the only cells in the body that can absorb iodine (2), and imbalances in iodine levels can lead to thyroid gland disorders (3). The thyroid gland is susceptible to various diseases, with some of the most common ones being goiters, thyroid cancer, solitary thyroid nodules, hyperthyroidism, hypothyroidism, and thyroiditis (1). An enlarged thyroid gland is termed a goiter (4), and thyroid cancer occurs when there is an uncontrolled growth and transformation of thyroid cells, leading to the development of an abnormal mass referred to as a tumor (5). The occurrence of thyroid disease is on the rise worldwide, with an annual increase in prevalence. By 2030, it is forecasted that the cost of medical treatment for thyroid disease in the US alone will reach approximately 3.5 billion dollars (6). Therefore, the growing prevalence of thyroid disease will have significant implications for the global economy and society as a whole (7).

In medical applications, the primary objective is often to anticipate the patient's outcome using the available data, commonly through classification, assigning a specific class to an observation based on the data at hand. Numerous techniques have been suggested for the prediction of outcomes in medical studies, with statistical regression methods being among the most commonly employed approaches (8). Nevertheless, the statistical methods used to analyze relationships between variables have inherent limitations and assumptions. If these assumptions are not met, it becomes impractical to use such models, resulting in significant errors. Consequently, researchers are actively looking for alternative methods with fewer limitations and assumptions, such as the Artificial Neural Network (ANN) method that, unlike traditional statistical models, does not impose any predefined assumptions regarding data distribution (9).

Some studies may have employed various techniques of machine learning to diagnose thyroid diseases. For instance, Andita et al. compared the performance of classification algorithms, including Support Vector Machine (SVM), ANN, and K-nearest Neighbor (KNN). Their objective was to determine the best algorithm based on the accuracy measure in the prediction of the target output(10). Sunila et al. conducted a comparison between the Logistic Regression and SVM algorithms. They evaluated and compared the performance of these machine learning algorithms based on several metrics, including precision, recall, and RMS error. Their study aimed to assess and compare the effectiveness of these algorithms using these evaluation measures (11). Saima et al. examined several machine learning algorithms: CatBoost, ANN, Light GBM, and KNN. The primary objective was to enhance prediction accuracy. The researchers analyzed the performance of these machine learning models using various evaluation metrics, including accuracy, prediction, recall, and F1 scores.

By assessing these metrics, they aimed to identify the algorithm that provides the most accurate and reliable predictions in their specific application context (12). Priyanka et al. conducted a comparison of three different machine learning algorithms: Naïve Bayes, SVM, and Random Forest. The objective of the study was to evaluate the performance of these algorithms in classifying a resultant set into four distinct classes: Hypo, Hyper, Sick Euthyroid, and Euthyroid. The researchers employed various feature selection techniques to select the most relevant attributes from the dataset, including univariate feature selection, recursive feature elimination, and tree-based feature selection (13). Ahmad et al. performed a study on forecasting thyroid diseases using a hybrid decision support system based on ANFIS, k-NN, and the Information Gain Method (IGN) (14).

The comparison between different models on the same dataset helps us to determine the performance and power of the models in predicting the intended event and use the optimal model in practice. In this study, according to the UCL dataset, there was no comparison in terms of the performance of logistic, ANN, and ANFIS models. In light of the aforementioned issues, the present study aimed to make a comparison between the three models to find the best model. In addition, for future studies proposed on this dataset, there exists a basis for comparison of the new model with existing models.

2. Objectives

The present study aimed to use the ANFIS model, artificial neural network (ANN), and logistic regression to predict thyroid patients.

3. Methods

This research data is from the UCI database, which includes 3,772 samples with more than 20 features (15). Among the characteristics related to this database, only five variables were considered to enter the models. The basis for choosing these variables was their importance in thyroid disease and their effect on the accuracy of the model. The occurrence and non-occurrence of thyroid are considered binary response events. The data were randomly divided into two parts, including 70% of the training set and 30% of the test set. Predictive models, including ANFIS, ANN, and logistic regression, were analyzed to predict the occurrence of the thyroid. Finally, the performance of the ANFIS model, ANN, and logistic regression (in the classification model) were compared with the accuracy and the area under the curve (AUC). Data analysis was performed using MATLAB (version 2016a) and SPSS software (version 26).

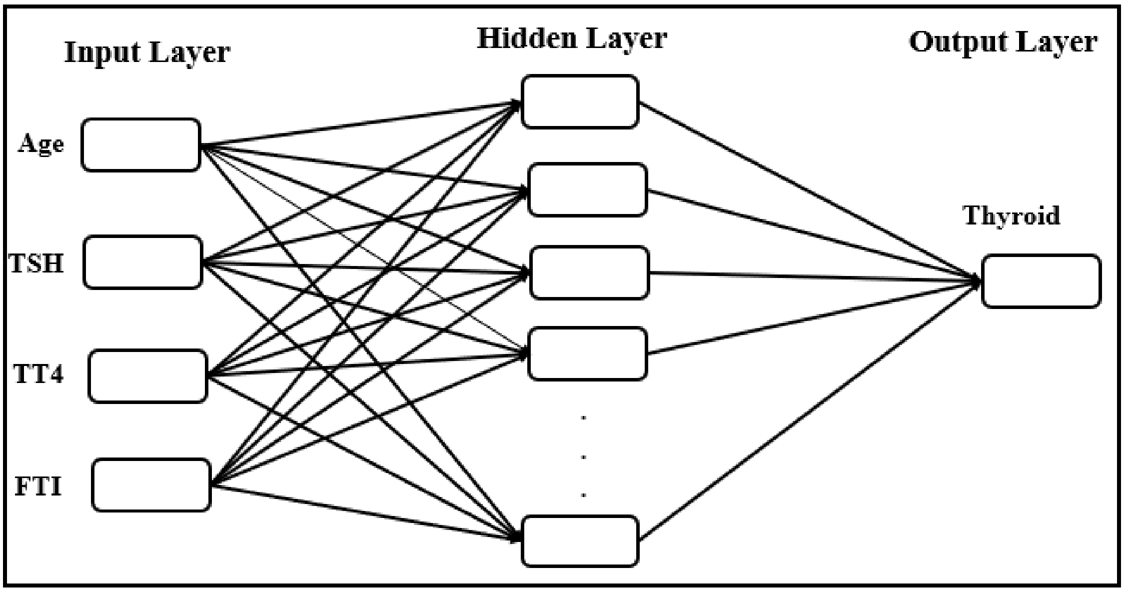

Figure 1. Proposed Structure of the artificial neural network model used in the present study

Artificial Neural Networks

The artificial neural network **(ANN)**, inspired by biological neural networks, has become a popular machine-learning technique for tackling regression and classification problems in various fields (16). Neural networks consist of several layers called the input layer, hidden layer(s), and output layer. Figure 1 illustrates the structure of a neural network with a hidden layer, where explanatory variables and response variables are located in the input layer and the output layer, respectively, and the components of the hidden layer are called neurons or nodes (17). These models excel at recognizing intricate relationships within the data and generating outputs with minimal errors (18).In this research, the gradient descent method is used to minimize the squared error between the output of the network and the desired response. Moreover, the Lunberg-Marquardt algorithm was used to update the weights due to fast convergence.

To create this network, such parameters as the number of neurons in the middle layer, which contain one type of membership function in the input and output layers, and the number of iterations (Epoch) should be optimized, which is achieved by trial and error (Table 1).

Table 1. Artificial neural network architecture and the training parameter

Training Algorithm	**Levenberg-Marquardt**
Activation Function	Middle Layer: Tansig Output Layer: purelin
The number of neurons Middle Layer	8
Error Goal	0

Adaptive Neuro-Fuzzy Inference System

Fuzzy logic and neural networks are complementary (19). Neural networks are capable of learning from data sets, although they cannot comprehend human language. On the contrary, fuzzy systems can utilize human language and incorporate human experiences and expert knowledge. These systems can effectively implement human knowledge by employing specialized language concepts and fuzzy rules that match specific condition-result relationships. Notably, the non-linearity and adaptability of fuzzy systems, along with their higher accuracy compared to other methods when dealing with limited data, are their key distinguishing features. Nevertheless, it is worth noting that despite being a robust inference system that excels in handling uncertainty, fuzzy systems are unable to learn on their own (20-22).

The ANFIS model is a type of Takagi–Sugeno (T–S) fuzzy system that relies on if-then rules. It aims to build a multi-center network with optimized parameters, such as membership type, number functions, count method, and iteration (Epoch). ANFIS combines the learning capability of artificial neural networks with the decision-making capability of fuzzy logic. By utilizing the strengths of both approaches, ANFIS can effectively handle tasks that involve learning from data and making intelligent decisions based on fuzzy reasoning. The optimization of these parameters plays a crucial role in maximizing the performance and effectiveness of the ANFIS model (23). In this research, the ANFIS model was used to predict the two-mode response, and their ability was compared with the ANN and logistic regression models.

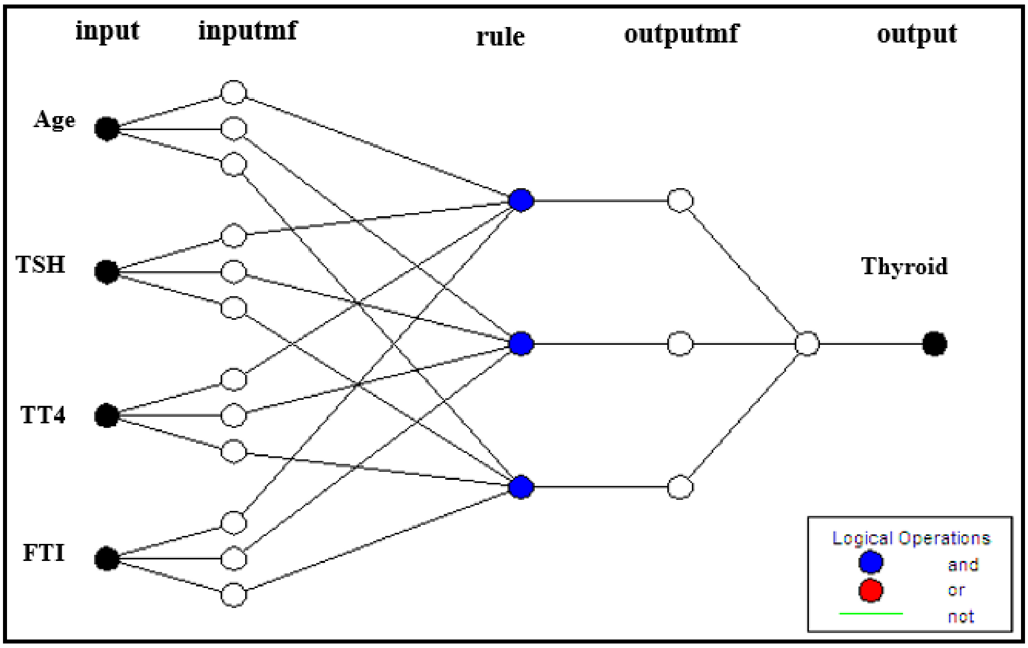

Figure 2. Proposed Structure of the adaptive neuro-fuzzy inference system model used in the present study

Table 2. Adaptive neuro-fuzzy inference system architecture and the training parameter

Sugeno	Fuzzy System
Input: Gaussian **Output: Linear**	Membership Function
backpropagation	Training Algorithm
1000	Max epoch
0.01	Initial Step Size
0.9	Step Size Decrease Rate
1.1	Step Size Increase Rate
0	Error Goal

For this study, the ANFIS structure consists of five layers (Figure 2). The first layer performs the fuzzification process. In this layer, the type of membership function and its number are defined, and all existing rules are formed. In the second layer, the effectiveness of each law is calculated, which can also be called the inference layer; moreover, rules are defined in this layer. In the third layer, the effect of each rule is normalized according to the effect of other rules. In the fourth layer, the output of each rule is obtained, calculating the weighted outputs. In the fifth layer, the outputs of the fourth layer are added together and form the fuzzy system output (24).To construct the ANFIS model, a basic FIS was constructed using the Fuzzy C-Means clustering (FCM) algorithm.

The FCM method which is for the same clustering is not available in the fuzzy toolbox and will be implemented only through the genfis3 function in the MATLAB environment. The use of this method reduces the number of adjustable rules and The adjustable parameters of the training phase of the model are shown in Table 2 (25).

The stop criteria of the ANFIS model have been considered to have an error of less than 0.01 or a maximum of 1000 epochs.

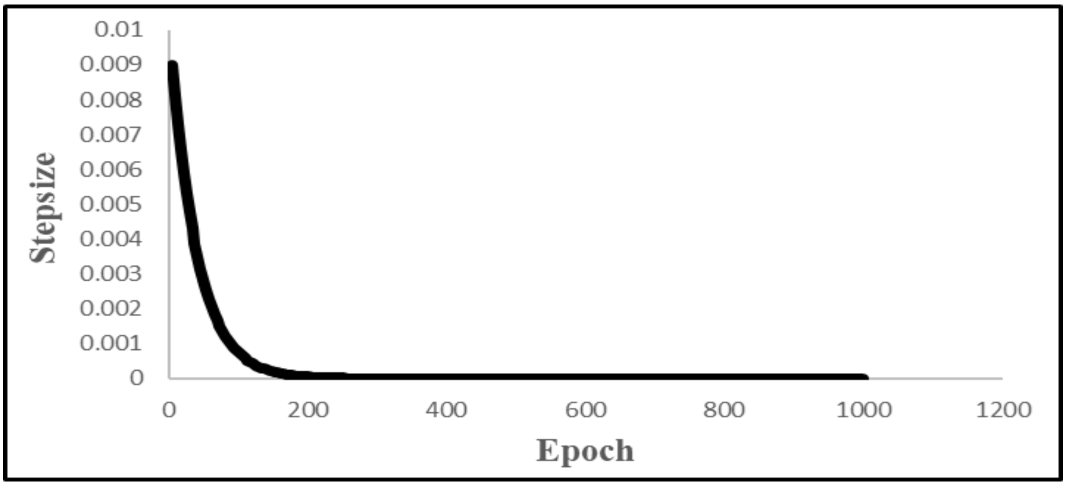

Figure 3. Adaptation of parameter steps of adaptive neuro-fuzzy inference system

4. Results

This dataset includes 3,772 samples, 1,144 males and 2,485 females. There were 3481(92.3□) thyroid patients, and the mean age of patients was 51.63 ± 18.98 years. The characteristics of the studied samples are presented in Table 3.

Table 3. Descriptive statistics of related variables to the occurrence of thyroid event

Variable	Minimum	Maximum	Mean±SD
Age (year)	1	94	**51.63 ± 18.98**
TT4	2	430	**108.32 ± 35.60**
FTI	2	395	110.47 ± 33.09
TSH	0	530	5.09 ± 24.52

According to the result of the multiple logistic regression model in Table 4, the effect of variables TSH ($P<0.001$), and FTI ($P<0.001$) on thyroid events was significant. Therefore, for a one-unit increase in the TSH variable when another variable is constant in the model, the odds of a person having thyroid will decrease by 0.796 times (95% confidence interval, 0.771-0.821). In addition, for one unit increase in the FTI variable when another variable is constant in the model, the odds of a person having thyroid will increase by 1.023 times (95% confidence interval, 1.011-1.035).

Table 4. Logistic regression analyses of factors associated with thyroid event

Variable	Beta	Exp(Beta)	Odds Ratio (95% CI*)	P-value
Age (year)	0.006	0.994	0.994 - 1.001	0.118
TSH	0.228	0.796	0.771 - 0.821	<0.001
TT4	0.007	1.007	0.997 - 1.017	0.155
FTI	0.023	1.023	1.011 - 1.035	<0.001

Table 5. Predictive performance of adaptive neuro-fuzzy inference system, artificial neural network, and logistic regression on the test and train sets

Classification method	Train				Test			
	Sensitivity	Specificity	Accuracy	AUC*	Sensitivity	Specificity	Accuracy	AUC
Adaptive neuro-fuzzy inference system	0.99	0.91	0.99	0.95	1	0.89	0.99	0.95
Artificial neural network	0.94	0.93	0.94	0.94	0.97	0.83	0.96	0.90
Logistic Regression	0.99	0.41	0.93	0.73	0.97	0.43	0.94	0.73

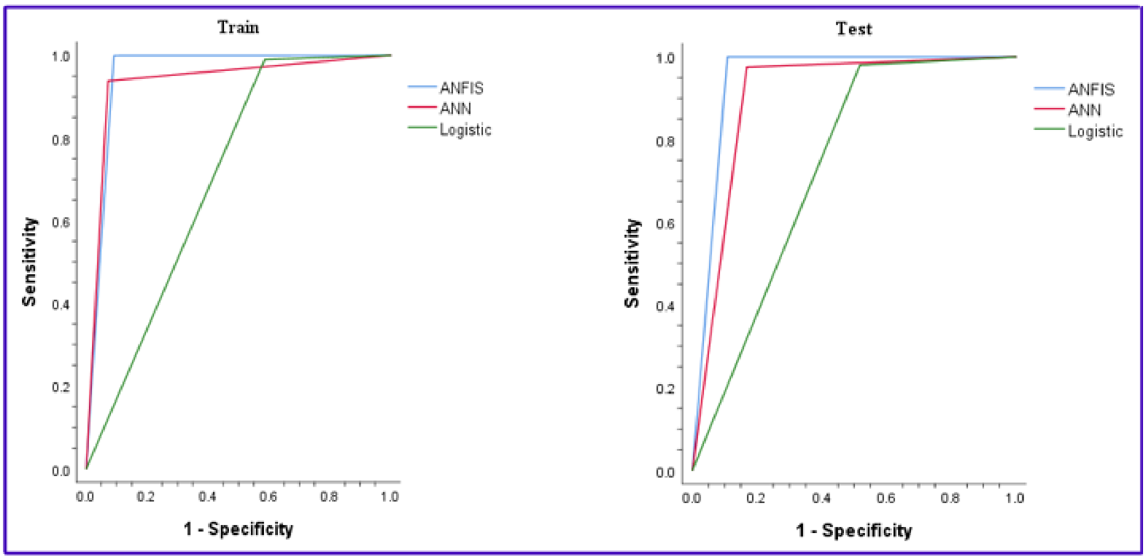

Figure 4. The area under the roc curve for the adaptive neuro-fuzzy inference system, artificial neural network, and logistic regression on the train and test sets

As illustrated in Table 5, based on the area under the curve and accuracy index, ANFIS and ANN and the logistic regression models work well in the prediction of thyroid disease. Nonetheless, the logistic regression model had a weaker performance than the other two. The ANFIS and ANN models, with an accuracy of 0.99 and 0.94, respectively, compared to the logistic regression model, with an accuracy of 0.93, had a better prediction for thyroid disease. Furthermore, it can be concluded that the ANFIS model performs better than the ANN model.

5. Discussion

In this research, a dataset of thyroid from the UCI database, including 3,772 samples with more than 20 features, was used. Among the variables in this study, only age, TSH, TT4, and FTI were considered thyroid disease due to their importance and also for better performance of the predicted model. In this dataset, 3,481 (92.3⍰) cases suffered from thyroid disease. In general, ANN can be considered an extension of the logistic regression model. The most important advantage of ANN over logistic regression models is in hidden layers. In fact, ANN is useful when there are complex relationships in the data, while logistic regression models are a better choice when statistical inference is needed (16).

A dearth of studies have been conducted using the logistic regression model to identify predictors and diagnose thyroid diseases. In our study, the effect of variables, such as TSH and FTI, was significant based on the multiple logistic regression model. In addition, ANFIS and ANN models were used to predict thyroid disease. Finally, these three models were compared using the accuracy and AUC index. The results of this study pointed out that the ANFIS method performed better than the ANN and logistic regression model. In general, there are various kinds of research with different approaches for thyroid classification, which are based on different data mining techniques (16). For example: in the study by Ahmed et al, the ANFIS model was used based on the three features of FTI, TSK, and TT4 to predict thyroid disease. The results indicated that the FIS and ANN perform better compared to the non-hybrid system (14). In the study by Daniel, the ANN was compared with another statistical method. The results suggested that the ANN model improved accuracy compared to any other statistical technique (8). Zabah et al. initially examined the effectiveness of ANN for diagnosing thyroid disease. Subsequently, they introduced an algorithm named "Combination of neural networks using a hierarchical method." The findings indicated that both models exhibited satisfactory performance in diagnosing thyroid disease. Nevertheless, the hierarchical method of combining ANN achieved higher accuracy (100%) as compared to the standalone ANN method (96.6%) (26). Azar et al. explored the application of both Fuzzy and hard clustering analyses in the context of thyroid disease. Their study yielded promising results, demonstrating the effectiveness of the system in the prediction of thyroid disease. The system categorized thyroid conditions into three groups: normal (1), hyperthyroidism (2), and hypothyroidism (3) (27). Hameed conducted a study where an ANN system was employed to detect thyroid conditions. The error backpropagation algorithm was utilized to train the network. The study incorporated such variables as TSH, T4, and T3 as inputs to the model. With a hidden layer consisting of 10 neurons, the ANN achieved an average classification rate of 96.26%. The findings of the study indicated that the ANN approach exhibits a high classification rate, around 92.2%, highlighting its efficacy in accurately categorizing different types of thyroid cases (28).

Borzouei et al. used ANN and logistic regression methods to diagnose thyroid disease and then compared these two methods using the accuracy index. In the stated study, the variables of gender, age, body mass index (BMI), History of the disease, TSH, TT4, Hyper Score, and Hypo Score were considered to enter the model. In addition, if a person had the desired symptoms, the value was 1, and if there were no symptoms, the value was 0. The results of this study pinpointed that the ANN model performs better than the logistic regression (16).

Rastogi et al. focused on utilizing feedforward ANNs and employing the backpropagation algorithm for thyroid disease classification in their study. The mentioned study incorporated variables such as T3, T4, and TSH as inputs for the model while considering different types of thyroid diseases, including normal, Hypo, and Hyper. The findings of the study demonstrated that the feedforward ANN approach can be effectively utilized for the diagnosis of thyroid diseases(29).

Temurtas conducted a comparative study on thyroid disease diagnosis, employing an ANN as the methodology. The study aimed to compare the effectiveness of different types of ANN models, including multilayer, probabilistic, and learning vector quantization ANN, with the Levenberg-Marquardt experimental algorithm in diagnosing thyroid diseases. The outcomes of this research demonstrated an impressive accuracy rate exceeding 90%. These results indicate that the ANN exhibited strong performance in accurately classifying thyroid disease. (30).

The results show the better performance of hybrid networks than logistic regression; however, the evaluation of optimized models is needed to achieve accurate rate measurement.

6. Conclusion

Among the three models analyzed, namely ANN, logistic regression, and ANFIS, all demonstrate high accuracy in predicting thyroid disorders. Notably, ANFIS outperforms the other two models in terms of performance. More precise forecasts can be achieved in medical research by employing predictive models, particularly hybrid approaches like the ANFIS model. The model proposed in this study has potential application in screening programs to identify individuals at risk. Furthermore, we suggest that data mining techniques can be effectively utilized for predicting the occurrence of specific diseases.

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Footnotes

Conflicts of Interest: Not applicable.
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Ethical Statements: Not applicable.

References

1. Biyouki SA, Turksen I, Zarandi MF, editors. Fuzzy rule-based expert system for diagnosis of thyroid disease. 2015 *IEEE* Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB). 2015. doi: 10.1109/CIBCB.2015.7300333.
2. Vietti-Cook AL, Dicus C. COMMISSION VOTING RECORD DECISION ITEM: SECY-01-0069 TITLE: STATUS OF POTASSIUM IODIDE ACTIVITIES. 2001.
3. Prasad MNV. Iodine Essentiality for Human Health: Sources, Toxicity, Biogeochemistry, and Strategies for Alleviation of Iodine Deficiency Disorders. *Medical Geology: En route to One Health*. 2023:155-74. doi: 10.1002/9781119867371.ch10.
4. Can AS, Nagalli S. Substernal Goiter. *StatPearls Publishing*. 2023.
5. Dogantekin E, Dogantekin A, Avci D. An expert system based on generalized discriminant analysis and wavelet support vector machine for diagnosis of thyroid diseases. *Expert Systems with Applications*. 2011;**38**(1):146-50. doi: 10.1016/j.eswa.2010.06.029.
6. Maniakas A, Davies L, Zafereo ME. Thyroid Disease Around the World. *Otolaryngol Clin North Am*. 2018;**51**(3):631-42. doi: 10.1016/j.otc.2018.01.014. [PubMed: 29548512].
7. Zou LB, Chen H, Cao TS, Wu HS, Ma KQ. PHQ-9 scores for depression associated with high prevalence of thyroid disease in US adults: a cross-sectional study. 2023. doi: 10.21203/rs.3.rs-2604468/v1.
8. Sargent DJ. Comparison of artificial neural networks with other statistical approaches: results from medical data sets. *Cancer*. 2001;**91**(S8):1636-42. doi: 10.1002/1097-0142(20010415)91:8+<1636::aid-cncr1176>3.0.co;2-d. [PubMed: 11309761].
9. Maroco J, Silva D, Rodrigues A, Guerreiro M, Santana I, de Mendonça A. Data mining methods in the prediction of Dementia: A real-data comparison of the accuracy, sensitivity and specificity of linear discriminant analysis, logistic regression, neural networks, support vector machines, classification trees and random forests. *BMC research notes*. 2011;**4**(1):1-14. doi: 10.1186/1756-0500-4-299. [PubMed: 21849043].
10. Tyagi A, Mehra R, Saxena A, editors. Interactive thyroid disease prediction system using machine learning technique. 2018 Fifth international conference on parallel, distributed and grid

computing (PDGC); 2018. doi: 10.1109/PDGC.2018.8745910.
11. Godara S, Kumar S. Prediction of thyroid disease using machine learning techniques. *International Journal of Electronics Engineering*. 2018;**10**(2):787-93.
12. Islam SS, Haque MS, Miah MSU, Sarwar TB, Nugraha R. Application of machine learning algorithms to predict the thyroid disease risk: an experimental comparative study. *PeerJ Computer Science*. 2022;**8**:e898. doi: 10.7717/peerj-cs.898. [PubMed: 35494828].
13. Duggal P, Shukla S, editors. Prediction of thyroid disorders using advanced machine learning techniques. 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence). *IEEE*. 2020. doi: 10.1109/Confluence47617.2020.9058102.
14. Ahmad W, Huang L, Ahmad A, Shah F, Iqbal A, Saeed A. Thyroid diseases forecasting using a hybrid decision support system based on ANFIS, k-NN and information gain method. *J Appl Environ Biol Sci*. 2017;**7**(10):78-85.
15. Dua D, Graff C. UCI Machine Learning Repository. University of California, School of Information and Computer Science, Irvine, CA (2019). http://archive.ics.uci.edu/ml/datasets/Thyroid+Disease.
16. Borzouei S, Mahjub H, Sajadi NA, Farhadian M. Diagnosing thyroid disorders: Comparison of logistic regression and neural network models. *Journal of family medicine and primary care*. 2020;**9**(3):1470. doi: 10.4103/jfmpc.jfmpc_910_19. [Pub Med: 32509635].
17. Hastie T, Tibshirani R, Friedman JH, Friedman JH. The elements of statistical learning. *Springer*. 2009.
18. Biglarian A, Bakhshi E, Rahgozar M, Karimloo M. Comparison of artificial neural network and logistic regression in predicting of binary response for medical data The stage of disease in gastric cancer. *North Khorasan University of Medical Sciences*. 2012;**3**(5):15-21. doi: 10.29252/jnkums.3.5.S5.15.
19. Senol C, Yildirim T. Thyroid and breast cancer disease diagnosis using fuzzy-neural networks. International Conference on Electrical and Electronics Engineering-ELECO. *IEEE*. 2009.
20. Das R, Turkoglu I, Sengur A. Effective diagnosis of heart disease through neural networks ensembles. *Expert systems with applications.* 2009;**36**(4):7675-80.
21. Nouei MT, Kamyad AV, Sarzaeem M, Ghazalbash S. Fuzzy risk assessment of mortality after coronary surgery using a combination of adaptive neuro-fuzzy inference system and K-means clustering. *Expert Systems*. 2013;**33**(3):230-38. doi: 10.1111/exsy.12145.
22. Polat K, Şahan S, Güneş S. Automatic detection of heart disease using an artificial immune recognition system (AIRS) with fuzzy resource allocation mechanism and k-nn (nearest neighbour) based weighting preprocessing. *Expert Systems with Applications*. 2007;**32**(2):625-31. doi: 10.1016/j.eswa.2006.01.027.
23. Dehdar Karsidani S, Farhadian M, Mahjub H, Mozayanimonfared A. Intelligent prediction of major adverse cardiovascular events (MACCE) following percutaneous coronary intervention using ANFIS-PSO model. *BMC Cardiovasc Disord*. 2022;**22**(1):389. doi: 10.1186/s12872-022-02825-0. [PubMed: 36042392].
24. Jang J-SR, Sun CT, Mizutani E. Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]. *IEEE Transactions on automatic control.* 1997;**42**(10):1482-84. doi: 10.1109/TAC.1997.633847.
25. Muthuvijayalaksh M. CLASSIFICATION OF TB DISEA. 2014.
26. Zabbah I, Yasrebi Naeini SE, Ramazanpoor Z, Sahragard K. The diagnosis of thyroid diseases using combinati on of neural networks through hierarchical method. *Journal of Health and Biomedical Informatics*. 2017;**4**(1):21-31.
27. Azar AT, El-Said SA, Hassanien AE. Fuzzy and hard clustering analysis for thyroid disease. *Comput Methods Programs Biomed*. 2013;**111**(1):1-16. doi: 10.1016/j.cmpb.2013.01.002. [PubMed: 23357404].
28. Hameed MA. Artificial neural network system for thyroid diagnosis. *Journal of Babylon University*. 2017;**25**(2):518-28.
29. Rastogi AB, Monika A. Study of neural network in diagnosis of thyroid. *International Journal of Computer Technology and Electronics Engineering*. 2014.
30. Temurtas F. A comparative study on thyroid disease diagnosis using neural networks. *Expert Systems with Applications*. 2009;**36**(1):944-9. doi: 10.1016/j.eswa.2007.10.010.