Thyroid Disease Prediction with Machine Learning Algorithms

Article · April 2023

CITATIONS
0

READS
16

3 authors, including:

Qabeela Q. Thabit
Ministry of Education, Iraq
15 PUBLICATIONS **27** CITATIONS
SEE PROFILE

Alyaa Ibrahim
Southern Technical University -Iraq
12 PUBLICATIONS **6** CITATIONS
SEE PROFILE

Thyroid Disease Prediction with Machine Learning Algorithms

Alyaa I. Dawood
Engineering Technical College Southern Technical University
Basrah, Iraq
alyaa.dawood@stu.edu.iq

Qabeela Q. Thabit
Basrah Education Directorate
Ministry of education
Basrah, Iraq
qabeelaqassim@basrahaoe.iq
qabelh2010@gmail.com

Taqwa O. Fahad
Biomedical Engineering Department
University of Tecnology- Iraq
Baghdad, Iraq
taqwa.o.fahad@uotechnology.edu.iq

ABSTRACT

In recent years, machine learning techniques have been used to predict disease occurrences, limit disease spread, and find appropriate treatment methods in their early stages. Thyroid diseases are common diseases in this era, and women had the largest share in them, as the thyroid gland secretes hormones in the blood and affects the food metabolism in the body as well as the building and growth of the body in children. This study deals with detection of the hormonal activity of the thyroid gland, with its two types: hyperthyroidism (excess secretion of the hormone) and hypothyroidism (decreased secretion of the hormone) using various of machine learning algorithms as a classifier, such as Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Naive Bays (NB) classifiers. All algorithms are simulated by a Python in Anaconda environment specific uses Spyder platform, comparing and choosing the most accurate. The DT and RF algorithm showed the best results through five experiments reach to 0.9933 and 0.9973, respectively.

Keywords: Machine learning, Thyroid disease detection, Classifier Decision Tree, Accuracy, Confusion matrix

I. INTRODUCTION

The body's "thyroid gland" is one of the most noticeable endocrine glands. Its form resembles that of a butterfly. It is found in the front of the neck and comprises of two lobes. Cystic cells, which are present in its lining and are in charge of the secretion of gland hormones. Men and women both have the gland. Defects in its functions, which play a crucial and important role in the body's numerous activities, including growth, mobility, reproduction processes, and metabolic processes, can lead to a variety of health issues. The thyroid gland is located in the neck and secretes three types of hormones: TSH (thyroid stimulating hormone), T3 (triiodothyronine) and T4 (thyroid hormone), which affect the functions of different parts of the body, such as heart rate, temperature, and others.

Early detection, diagnosis and treatment of the disease is important to reduce the risk of its spread or death. Since thyroid diseases are now widely spread among humans, machine learning theories have been harnessed to deal with the huge data of patients with hyperthyroidism or underactive thyroid, which is the most common disease that affects the thyroid gland. Machine learning theories have been widely used in the medical field such as detection About diabetes[1] heart disease [2],Alzheimer's disease [3] and more.

Researchers used different types of decision tree theories and appeared a good ability to classify the type of thyroid disease [4,5]. It may be used to purify data from unwanted data and append it to another class, such as the Naïve Bayes algorithm, to reach high-accuracy results [6]. It was also developed in [7] as an Extra decision tree for more accurate results. When compared to other classifiers, the random forest algorithm's accuracy was the greatest, achieving 98.93 [8]. The addition of the reverse triiodothyronine test (RT3), using the C4.5 classification algorithm, led to a more accurate result of 99.25% [9]. For more accuracy, sometimes the data is large and it need to reduce its dimensions using one of the reduction algorithms such as Principal component analysis before it is fed into a classifier such as the K-Nearest Neighbors (KNN) and another type is Neural Network (NN) classifiers. A success rate of 99.57 percent was attained after the neural network underwent systematic training and testing [10] or use one of the data mining techniques for the same purpose [11], also combining both the neural network and logistic regression models to reach a high level of predictive power for disease diagnosis [12,13].

We presented this research to complement existing work in this area that makes use of machine learning techniques, given the significance of disease detection research and the need to suggest effective approaches for diagnosis.

The research focused on the algorithms within a data set, and we were able to obtain the findings by changing the research's settings as well as methodically altering the training and test cases' data sizes.

This paper presents machine learning through a binary classification method using Python and based on a dataset of thyroid patients. Using a variety of machine learning classification algorithms, including the Logistic Regression Classifier (LR), Supporting Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), K-Nearest Neighbors (KNN), and Naive Bays (NB), the goal of this research is to determine whether a patient has thyroid disease (hyperthyroidism or hypothyroidism). To get the best outcomes when tested on the data set, these algorithms employ various data preparation procedures (cleaning, feature selection, scaling, and data splitting).

II. ARCHITECTURE OF THE PREDICTION SYSTEM

A. *Prediction Flow Diagram*

The work is to apply machine learning algorithms by adjusting the division of data distributed between training and testing with different distributions (15-85, 20-80, 30-70, 40-60) and we also changed the random state values and the selection of features,the procedure simplified in the following steps :

1) Database obtaining, here use the Pima Indian dataset.

2) Data preparation, consisting of data cleansing, feature selection, scaling, and splitting.

3) Classification methods :

- LR algorithm.
- DT algorithm.
- RF algorithm.
- KNN algorithm
- SVC algorithm.
- NB algorithm.

4) Performance metrics evaluation: They comprise the computation of the F1 score, ROCAUC score, sensitivity, specificity, and accuracy.

5) Thyroid Prediction.

B. Data set

C. The 3772 patient samples included in this study range in age from 15 to 85 years, with 2480 of them being female. The data includes patient information for 27 features [15] as input and one output represented in two values; 0 denotes no thyroid case and 1 represents thyroid case presented in data.

D. Data preparation

Sometimes the medical data contains some missing information for some reason, or it is not important to be used in the research topic, or it may have no effect on the results. Therefore, the data must be refined and the missing information filled with others calculated according to the approved theories before entering it into the system and conducting experiments on it. The data initialization process includes the following steps:

- Data cleaning: It is represented by processing and filling the empty cells with a calculated data by a set of instructions. Then. The total data was analyzed using the count and the average or mean for each characteristic or parameter, which reflect all statistical measurements.
- Selection of features: There are a number of techniques used to select the factors influencing the measurements that help produce better findings. Finding the key characteristics is necessary.
- Data scaling: To acquire exact, accurate, and quick measurements when the data spacing results in a delay in obtaining the desired findings, the data is roughly scaled to a close digital scale.
- Splitting the data into two sets: the training set, which typically comprises 6–8% of the total data, and the test set, which typically comprises 2–4% of the total data. methods for classifying

One of the disciplines of artificial intelligence that has recently seen an increase in applications to provide consumers new services is machine learning. It is described as the science that enables programs to forecast events and take suitable, timely judgments "automatically" utilizing algorithms that enable them to do so without the need for any prior knowledge or experience. There are three branches to it: Learning that is both supervised and unsupervised Using reinforcement learning for supervision. In this paper, supervised learning algorithms were used to classify the algorithms as follows [16]:

E. Logisitic Regression

LR is a type of supervised machine learning that is used to solve regression problems. It employs the sigmoid function to estimate the relationship between at least one individual variable, at least two sets of dependent variables, and to evaluate probabilities. The principle of this algorithm is to model a binary dependent variable (0/1, or -1/1, or represent in true/false) in terms of one or more independent variables (binary variable, ordinal, interval, or ratio) and prediction to find the probability of an event related to that variable. The main advantage of this algorithm is the ease of implementation and efficiency in training. The sigmoid function or logistical function gives in Equation (1) [17]:

$$LR(X) = \frac{1}{1+e^{-x}} \qquad (1)$$

F. Support Vector Machine

It is a supervised learning algorithm that is used for classification more than regression. This algorithm uses hyperplane to split data into separate classes [5]. It uses less memory for training as it trains a subset of data and this can be considered an advantage in the algorithm [17].

G. Decision Tree

Another illustration of supervised learning techniques that resemble trees is decision trees. Due to the fact that they mimic human expectations, DTs are simple to understand, thinking and decision-making. The tree structure is represented in the form of 3 nodes. The root node is the highest node in the tree, and from which the internal nodes (decision nodes) branch, which in turn branch to the terminal nodes. The outcome is achieved by monitoring the path leading to the terminating node. The decision tree, as seen in Fig. 1, functions well because it makes decisions by subdividing each node into sub-nodes beginning with the first node, and this procedure is repeated numerous times during the training stage until only homogenous nodes are disregarded. Decision trees are widely used in healthcare research and particular in thyroid disease diagnosis [7-12].

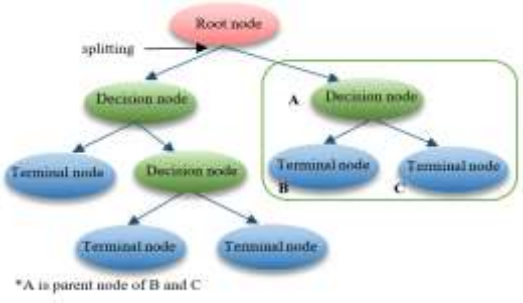

Fig. 1 Decision tree.

H. Random Forest

A random-forest classifier is formed from the set of decision trees groups, and it is trained through the set of decision trees to determine the best solution based on the votes of the different decision trees[18].

I. K-Nearest Neighbor

For determining the class of a particular data point, the KNN approach chooses the number of nearest neighbors to take into account based on the value of k [5,17]. It is an easy algorithm that sorts the available classes and classifies the new data based on the similarity scale. When given a training set, KNN simply stores it and waits until it is given a test set. It then stores training sets or "instances". 'closeness' is specified as a measure of distance e.g. 'Euclidean distance' and the separation between each sample point and each training point is measured; The closest neighbor is the location from which the greatest distance separates them.

J. Naïve Bays

Increase the likelihood of classification in variable and conditional factors using the probability and statistics approach by employing a classification method derived from the Bayes' theorem for subsequent probability maximization [19,20]. The well-known Bayes theorem predicts the future based on probabilities based on previous experiences, and its most important advantages are that it requires a small set of training set of data to limited the range of parameters used in each classification process, as the variable is taken only in the required category without the need for the entire covariance matrix to determine the classification [21]. it is also very fast and accurate when using large data for small errors.

III. Result OF Experimental and DESCUSSION

A. Measures of Performance Evaluation

Confusion matrix is displayed in Table I. There are four possible values for the matrix findings to assess how well the suggested method is performing: False Negative (FN), True Positive (TP), True Negative (TN), and False Positive (FN). In order to measure the accuracy of calculating the performance evaluation factors of the classification methodology, the calculation of the accuracy rate is shown in equation (2), depending on the results of the confusion matrix [22].

TABLE I. CONFUSION MATRIX PARAMETERS.

		Prediction Case	
		1	***0***
Acual Case	***1***	TruePositive (TP)	False Positive (FP)
	0	FalseNegative (FN)	TrueNegative (TN)

$$Accuracy\ Rate = \frac{TP+TN}{TP+FP+TN+FN} \qquad (2)$$

Experiment 1:

In this experiment, 42% (random state) were selected without traits being selected. This rate was chosen after several trials and attempts to get the best results, since using all the data at once and training it makes the algorithms less efficient and their performance very slow. Different divisions of the ratio (test data to training data) were chosen as follows (15:85, 20:80, 30:70, 40:60) and a confusion matrix and accuracy rate were found for each case and for the above six algorithms as shown in TABLE II.

TABLE II. ACCURACY RATE FOR EXPERMENT 1.

Algorithm	**Test Data-Train Data**			
	15-85	***20-80***	***30-70***	***40-80***
LR	0.9695	0.9695	0.9695	0.9695
DT	0.9876	0.9933	0.9867	0.8913
RF	0.9876	0.9973	0.9911	0.9025
KNN	0.9434	0.9456	0.9514	0.9403
SVC	0.9487	0.9496	0.9549	0.9483
NB	0.9240	0.9231	0.9284	0.9257

DT and RF algorithms both showed the highest accuracy for case (15:85) as showed in TABLE II, while the RF algorithm showed the highest accuracy for cases (20:80) and (30:70). There

was a high level of LR in this case (40:60). According to the experiment in general, RF algorithm (20:80) had an accuracy rate of 0.973 for the case.

Experiment 2:

The random state was chosen with a value of 44% for this experiment and the condition without feature selection. For the same data division ratios (test data for training data) (15:85, 20:80, 30:70, 40:60) the confusion matrix results and accuracy rate for each condition were calculated as shown in TABLE III. The DT and RF algorithms showed the highest accuracy in the case (15:85), and for the case (20:80) DT was the most prominent among them and for the case (30:70) both DT and RF had the highest accuracy and for (40:60) was the RF algorithm. In general, the DT algorithm is the highest at (20:80) among all cases with an accuracy rate of 0.9894.

TABLE III. ACCURACY RATE FOR EXPERMENT 2.

Algorithm	Test Data-Train Data			
	15-85	***20-80***	***30-70***	***40-80***
LR	0.9681	0.9721	0.9655	0.9648
DT	0.9858	0.9894	0.9840	0.9887
RF	0.9858	0.9880	0.9840	0.9893
KNN	0.9540	0.9549	0.9425	0.9436
SVC	0.9575	0.9629	0.9522	0.9529
NB	0.9275	0.9364	0.9266	0.9290

Experiment 3:

In this experiment, the first experiment was repeated with the addition of the feature selection condition, the random case with a value of 42%. With the same data split ratios (test data for training data) (15:85, 20:80, 30:70, 40:60) the results of the confusion matrix and the accuracy rate for each condition were calculated as shown in the TABLE IV. RF algorithm showed the best accuracy in all cases, with a 0.9761 accuracy rate at (20:80) among all cases.

TABLE IV. ACCURACY RATE FOR EXPERMENT 3.

Algorithm	Test Data-Train Data			
	15-85	***20-80***	***30-70***	***40-80***
LR	0.9593	0.9629	0.9584	0.9569
DT	0.9611	0.9682	0.9673	0.9734
RF	0.9752	0.9761	0.9726	0.9748
KNN	0.9646	0.9695	0.9628	0.9622
SVC	0.9611	0.9708	0.9549	0.9562
NB	0.9611	0.9615	0.9584	0.9569

Experiment 4:

Here with the addition of the feature selection condition, the random rate has a value of 44%. With the same data split ratios (test data for training data) (15:85, 20:80, 30:70, 40:60), the confusion matrix and accuracy rate for each condition were as shown in TABLE V. The DT and RF algorithm showed the best accuracy for the case (15:85), DT was best among the algorithms for (20:80), while RF was best for (30:70) and (40:60). The highest accuracy in this experiment was for the DT algorithm at the state (20:80) with a value of 0.9907.

TABLE V. ACCURACY RATE FOR EXPERMENT 4.

Algorithm	Test Data-Train Data			
	15-85	***20-80***	***30-70***	***40-80***
LR	0.9646	0.9721	0.9611	0.9609
DT	0.9858	0.9907	0.9814	0.9834
RF	0.9858	0.9880	0.9840	0.9874
KNN	0.9611	0.9549	0.9611	0.9615
SVC	0.9628	0.9629	0.9593	0.9595
NB	0.9275	0.9364	0.9266	0.9290

Experiment 5:

A new data division was used for this experiment (22,78) and all previous algorithms were tested and the confusion matrix and accuracy rate were calculated as shown in TABLE VI. It is worth noting that all algorithms showed a high accuracy that exceeded all previous experiments, and DT was the most prominent among them, with an accuracy of 0.9927.

TABLE VI. ACCURACY RATE FOR EXPERMENT 5.

Algrithm	Test Data-Train Data(22-78)
LR	0.9710
DT	0.9927
RF	0.9915
KNN	0.9518
SVC	0.9638
NB	0.9373

IV. COMPARISON OF PERFORMANCE MEASURES

This study employed six classifiers to forecast the prevalence of thyroid illness. In comparison to the same algorithms used in earlier studies, our results are better. They are as follows: LR, DT, RF, KNN, SVC, and NB, 97.21, 99.33, 99.73, 96.95, and 97.08, respectively.

Table VII lists the results of the comparison with earlier investigations.

TABLE VII . COMPARISION THE ACCURACY RATE WITH PREVIOUS WORKS

Ref. No.	Authors	Algorithm	Accuracy (%)
[23]	Dharmarajan, K., et al	NB DT SVM KNN	91.60 97.35 95.30 94.20
[24]	Jayamini , et al	RF	98.40
[25]	Shivastuti, et al	SVM RF	93.00 92.00
[26]	Razia, et al	SVM NB DT	96.00 6.31 99.20
[27]	Raisinghani, et al	SVM RL DT RF	96.25 97.50 99.46 99.30
[28]	Alyas ,et al	RF	94.80
[29]	Rao et al	DT	95.00
[30]	Chandan et al	KNN SVM DT LR	93.84 95.38 92.30 96.92

V. Conclusion

In recent decades, artificial intelligence, and specifically machine learning, has contributed greatly to medicine by saving time and effort and accelerating the timely detection and treatment of diseases before they deteriorate. This paper deals with the implementation of six machine learning algorithms (LR, DT, RF, KNN, SVC, NB). For the purpose of predicting thyroid disease, data from 3772 patients were trained, with 27 features of different ages. In training and examination, we relied on changing the data ratio adjusting to different cases and monitoring the results with the change of a number of parameters. The accuracy ratio was evaluated for each case, and the DT and RF algorithm showed the best results, reaching 0.9933 and 0.9973 through five experiments with two types of randomized percentage (42% and 44%). All accuracy rates for all experiments are shown in the Figures. 4,5,6, and 7 the division ratios (15:85, 20:80, 30:70, 40:60) are named (case 1, case 2, case 3, case 4) respectively.

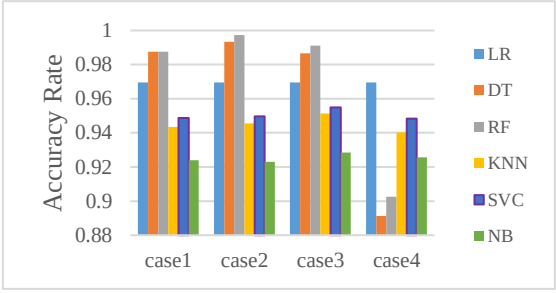

Fig. 4 Experiment 1

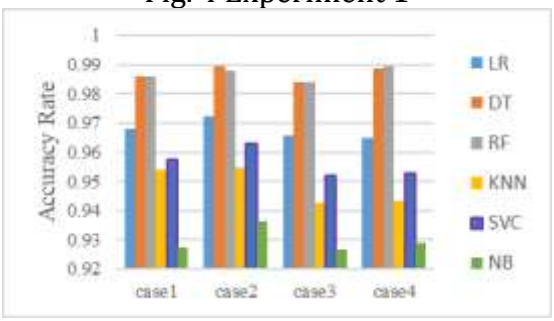

Fig. 5 Experiment 2.

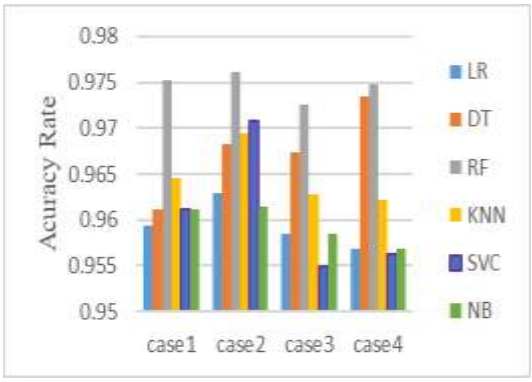

Fig. 6 Experiment 3.

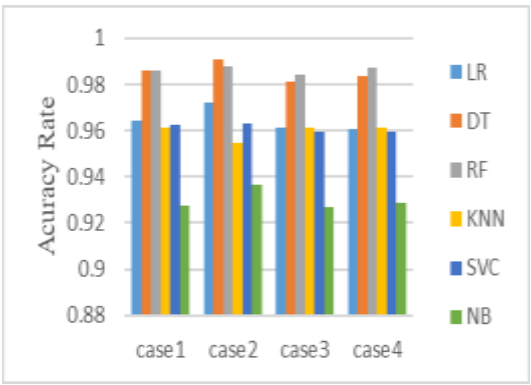

Fig. 7 Experiment 4.

REFERENCES

[1] C. C. Olisah, L. Smith, and M. Smith, "Diabetes mellitus prediction and diagnosis from a data preprocessing and machine learning perspective," Computer Methods and Programs in Biomedicine, vol. 220, pp. 1-12, 2022. https://doi.org/10.1016/j.cmpb.2022.106773

[2] P. Rani, R. Kumar, NM. Ahmed, and A. A. Jain, "decision support system for heart disease prediction based upon machine learning", Journal of Reliable Intelligent Environments, Sep;vol 7, No 3, pp. 263-75 ,2021. https://doi.org/10.1007/s40860-021-00133-6

[3] M. B. Antor, A. H. M. Jamil, M. Mamtaz, M. M. Khan, S. Aljahdali, M. Kaur, P. Singh, and Mehedi Masud. "A comparative analysis of machine learning algorithms to predict alzheimer's disease." Journal of Healthcare Engineering 2021 (2021). https://doi.org/10.1155/2021/9917919

[4] A. Pak, A. Ziyaden, K. Tukeshev, A. Jaxylykova, and D. Abdullina, "Comparative analysis of deep learning methods of detection of diabetic retinopathy," Cogent Engineering, vol. 7, pp.1-9, 2020. https://doi.org/10.1109/IRI54793.2022.00046

[5] E. Turanoglu-Bekar, G. Ulutagay, and G. Ulutagay "Classification of Thyroid Disease by Using Data Mining Models: A Comparison of Decision Tree Algorithms", Oxford Journal of Intelligent Decision and Data Science , vol. 2016, No. 2, pp. 13-28, 2016. https://doi.org/10.5899/2016/ojids-00002

[6] T. Ankita, R. Mehra, and A. Saxena. "Interactive thyroid disease prediction system using machine learning technique." 2018 Fifth international conference on parallel, distributed and grid computing (PDGC). IEEE, 2018. https://doi.org/10.1109/PDGC.2018.8745910

[7] R. Amulya, and B. S. Renuka. "A machine learning approach to predict thyroid disease at early stages of diagnosis." 2020 IEEE International Conference for Innovation in Technology (INOCON). IEEE, pp. 1-4, 2020. https://doi.org/10.1109/INOCON50539.2020.9298252

[8] L. Aversano, M.L. Bernardi, M. Cimitile, M. Iammarino, P.E. Macchia, I.C. Nettore, and C.Verdone, "Thyroid disease treatment prediction with machine learning approaches", Procedia Computer Science, 192, pp.1031-1040, 2021. https://doi.org/10.1016/j.procs.2021.08.106

[9] D. C. Yadav, S. Pal, "Thyroid prediction using ensemble data mining techniques", *International journal of information technology,* vol. 14, pp. 1273–1283, 2022. https://doi.org/10.1007/s41870-019-00395-7

[10] Qabeela Q. Thabit, Alyaa Ibrahim Dawood and Bayadir A. Issa, "Implementation three-step algorithm based on signed digit number system by using neural network", Indonesian Journal of Electrical Engineering and Computer Science, 24(3), pp. 1832-1839, 2021. http://doi.org/10.11591/ijeecs.v24.i3.pp1832-1839

[11] J. Ritesh, V. Bhattacharjee, and A. Mustafi. "Increasing the Prediction Accuracy for Thyroid Disease: A Step Towards Better Health for Society", Wireless Personal Communications, pp. 1921-1938, 2022. https://doi.org/10.1007/s11277-021-08974-3

[12] A. Begum and A. Parkavi, "Prediction of thyroid Disease Using Data Mining Techniques," 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), pp. 342-345, 2019. https://doi.org/10.1109/ICACCS.2019.8728320

[13] S. Borzouei, H. Mahjub, N.A. Sajadi, and M. Farhadian, "Diagnosing thyroid disorders: Comparison of logistic regression and neural network models" *Journal of Family Medicine and Primary Care*, vol 9, No 3, pp.1470, 06 2020. https://doi.org/10.4103%2Fjfmpc.jfmpc_910_19

[14] Dreiseitl, Stephan, and Lucila Ohno-Machado. "Logistic regression and artificial neural network classification models: a methodology review." Journal of biomedical informatics 35.5-6 (2002): 352-359. https://doi.org/10.1016/S1532-0464(03)00034-0

[15] https://www.kaggle.com/datasets/yasserhessein/thyroid-disease-data-set.

[16] N. P. Tiggaa, and S. Garga," Prediction of Type 2 Diabetes using Machine Learning Classification Methods", Procedia Computer Science, vol. 167, pp.706–716, 2020. https://doi.org/10.1016/j.procs.2020.03.336

[17] S. Uddin, A. Khan, , M. E. Hossain, and M. A. Moni, " Comparing different supervised machine learning algorithms for disease prediction", BMC medical informatics and decision making, vol 19, No 1, pp. 1-16, 2019 . https://doi.org/10.1186/s12911-019-1004-8

[18] G. Manuel, I. Zoppis, G. De Sio, C. Chinello, F. Pagni, F. Magni, and G. Mauri, "A support vector machine classification of thyroid bioptic specimens using MALDI-MSI data", Advances in bioinformatics 2016 (2016). https://doi.org/10.1155/2016/3791214

[19] Paulo C. Marques F., "Confidence intervals for the random forest generalization error," Pattern Recognition Letters, vol. 158, pp. 171-175, 2022. https://doi.org/10.1016/j.patrec.2022.04.031

[20] A. Yudhana, D. Sulistyo,and I. Mufandi, "GIS-based and Naïve Bayes for nitrogen soil mapping in Lendah, Indonesia," Sensing and Bio-Sensing Research, vol. 33, pp.1-11, 2021. https://doi.org/10.1016/j.sbsr.2021.100435

[21] N. Jalal, A. Mehmood, G.S. Choi, I. Ashraf, "A novel improved random forest for text classification using feature ranking and optimal number of trees," Journal of King Saud University , vol. 34, issue 6, pp. 2733-2742, 2022. https://doi.org/10.1016/j.jksuci.2022.03.012

[22] Qabeela Q Thabit, Taqwa O Fahad, Alyaa I Dawood, Detecting Diabetes Using Machine Learning Algorithms, 2022 Iraqi International Conference on Communication and Information Technologies, IEEE, 131-136. 10.1109/IICCIT55816.2022.10010408

[23] K. Dharmarajan, K. Balasree, A. S. Arunachalam, . and K. Abirmai, "Thyroid disease classification using decision tree and SVM", . executive editor, vol 11,No. 03, 2020. https://doi.org/10.37506/ijphrd.v11i3.822

[24] W. K. D. Jayamini, and H. D. Weerasinghe. "Decision Support for Diagnosing Thyroid Diseases Using Machine Learning", 3rd International Conference on Advances in Computing and Technology (ICACT–2018), Faculty of Computing and Technology, University of Kelaniya, Sri Lanka., 2018. http://dx.doi.org/10.29322/IJSRP.11.06.2021.p11402

[25] S. H. Kour, J. Manhas, and V. Sharma, "Performance Evaluation of SVM and Random Forest for the Diagnosis of Thyroid Disorder", Int. J. Res. Appl. Sci. Eng. Technol 9 ,pp. 945-947, 2021. https://doi.org/10.22214/ijraset.2021.34381

[26] S. Razia, , P.S. Prathyusha, N.V. Krishna, and , N.S. Sumana, "A Comparative study of machine learning algorithms on thyroid disease prediction", Int. J. Eng. Technol , vol. 7 , pp. 315-319, 2018. http://dx.doi.org/10.14419/ijet.v7i2.8.10432

[27] S. Raisinghani, R. Shamdasani, M. Motwani, A. Bahreja, and P. Lalitha, , " Thyroid prediction using machine learning techniques", International Conference on Advances in Computing and Data Sciences, Springer, Singapore ,pp. 140-150, 2019. https://doi.org/10.1007/978-981-13-9939-8_13

[28] T. Alyas, M. Hamid, K. Alissa, T. Faiz, N. Tabassum, and A. Ahmad, " Empirical Method for Thyroid Disease Classification Using a Machine Learning Approach", BioMed Research International, vol. 2022, 2022. https://doi.org/10.1155/2022/9809932

[29] A. R. Rao, and B. S. Renuka, "A machine learning approach to predict thyroid disease at early stages of diagnosis", International Conference for Innovation in Technology

(INOCON), pp. 1-4 , IEEE. 2020, November, 2020. https://doi.org/10.1109/INOCON50539.2020.9298252

[30] R. Chandan, M.S. Chethan, C. Vasan, and H. S. Devikarani, "Thyroid Detection Using Machine Learning" , International Journal of Engineering Applied Sciences and Technology", Vol. 5, PP. 173-177, 2021. http://dx.doi.org/10.33564/IJEAST.2021.v05i09.028