Measurement: Sensors 24 (2022) 100482

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

Early prediction of hypothyroidism and multiclass classification using predictive machine learning and deep learning

Kalpna Guleria [a], Shagun Sharma [a,*], Sushil Kumar [b], Sunita Tiwari [b]

[a] Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India
[b] Department of CSE, G B Pant DSEU Okhla I Campus, Delhi, India

A R T I C L E I N F O

Keywords:
Machine learning (ML)
Deep learning (DL)
ANN
Decision tree
Random forest
Multi-class classification
Hypothyroidism
Thyroid disorder
Hyperthyroidism

A B S T R A C T

Thyroid disease is considered one of the most common health disorders, which may lead to various health problems. Recent studies reveal that approximately 42 million people in India face thyroid dysfunction or disorder problems. The thyroid hormone is responsible for thyroid disorder which may lead to hypothyroidism or hyperthyroidism problems. TSH (Thyroid Stimulating Hormone), T3 (Triiodothyronine, T3-RIA), FT4 (FT4, Free Thyroxine), T4 (Thyroxine), FTI (Free Thyroxine Index, FTI, T7) are the significant components of thyroid test which is performed to diagnose the behavior of thyroid hormone. However, manual analysis of these parameters on large databases to diagnose and predict hypothyroidism or hyperthyroidism is tedious. In this article, various machine learning-based techniques have been applied to build predictive models, which includes decision tree, random forest, naive Bayes and multiclass classifier and a deep learning (DL) based model Artificial Neural Network (ANN), which is best known for dealing with text data has been applied to predict the class of hypothyroidism. The performance evaluation indicates that the decision tree and random forest provide better results with the highest accuracy of 99.5758% and 99.3107% and very few error rates of 0.0424 and 0.0689, respectively. Furthermore, a comparison among the presented classifiers has been made, and also the proposed model has been compared with previous works, and it has been found that it shows better accuracy as compared to other related works. The DL-based ANN model also offers a competitive accuracy which is 93.8226%. Furthermore, this study can be useful for researchers to identify a suitable model for hypothyroidism detection and classification.

1. Introduction

Thyroid disorder is considered one of the common endocrine dysfunction problems worldwide [1]. As per a study, approximately 4.6% of persons over the age of 12 suffer from the issue of hypothyroidism, and in the USA alone, 1.2% or each person among 100 people have hyperthyroidism whereas almost 1 in every 10 persons in India is affected from this disease which is becoming a severe problem day by day [1,2]. The thyroid gland is responsible for producing various essential hormones in human beings. It maintains our metabolism. Thyroid disorder is one of the major causes of infertility, obesity, heart disease, and joint pain. However, these diseases develop at later stages, but some of the symptoms may also appear at an early stage. There are two significant types of thyroid, namely: hypothyroidism and hyperthyroidism [3]. In hyperthyroidism, there is a huge amount of release of thyroid hormones which causes the extra increase in levels of thyroid hormones.

In contrast, hypothyroidism is a disease caused by the reduction in the release of thyroid hormones and an increase in the release of thyroxine. It accelerates metabolism but causes weight loss and heat problems which may cause rapid or irregular cardiac function. It also results in low heartbeat rate, fatigue, puffy face, weight gain, dry skin, and neck swelling [1,3]. Women above 60 years of age are more prone to hypothyroidism. Approximately 11% of people in India are affected by this disease which is a very large number in comparison to 2% in the United Kingdom and 4.6% in the USA. This is due to the fact that there has been a long-standing iodine deficiency among the underprivileged people in the country. However, the government of India is trying hard to improve the deficiency, but it has been partly corrected. There are other factors that may lead to hypothyroidism which is an endocrine

* Corresponding author.
E-mail addresses: guleria.kalpna@gmail.com (K. Guleria), shagunsharma7098@gmail.com (S. Sharma), sushilyadav.thapar@gmail.com (S. Kumar), sutiwari@gmail.com (S. Tiwari).

https://doi.org/10.1016/j.measen.2022.100482
Received 21 August 2022; Received in revised form 20 September 2022; Accepted 22 September 2022
Available online 23 September 2022

disorder, contaminated drinking water, and unregulated usage of pesticides.

The diagnosis of hypothyroidism is required to reduce the problems of joint pain, heart issues, and obesity. If it is not detected on time, it may lead to various severe health problems, including mental and breathing challenges. Also, if it occurs in women noticeably, it can result in infertility which can cause a life-threatening issue called myxedema. This study allows for early diagnosis of hypothyroidism, saving lives and reducing the mortality rate. Further, it motivates and provides extra support to clinicians and doctors in case of early identifying hypothyroidism health issues based on the available dataset.

Fig. 1 shows the yearly occurrence of hypothyroidism in various countries. In 1976–1990, the cases of hypothyroidism in USA have been reported as 4.2% while in Germany(2005–2012), Germany(2000), Iran (2003–2006), Iran(2012–2014), Wales(2006–2007), Spain (2007–2011), and Wales(1997–2005) have reported 4.2%, 2.6%, 6%, 7.6%, 18.5%, 6.4%, 33.5%, and 20.8%, respectively [4–11]. The data science analytics drawn from machine learning (ML) has been playing a major role in the field of bioinformatics and provides solutions to various medical problems, including thyroid prediction, pneumonia identification, and covid-19 prediction [3,12]. Further, it provided stimulus to deep learning (DL) and supervised ML-based methods to detect thyroid hormone dysfunction.

The rest of the paper is as follows: Section 2 introduces various related works in this domain, and section 3 presents the material and methodology used for the identification of hypothyroidism. Section 4 describes the results of various proposed ML and DL models using various performance evaluation metrics and a comparison with the related works. Lastly, section 5 concludes the article with the highlights of the results of the proposed work.

2. Previous works

In the recent past, various researchers have explored varied datasets in the medical domain and analyzed the performance of these proposed models. In Ref. [2], the authors have used various ML algorithms, namely random forest, ANN, decision tree, and KNN, for the identification of hyperthyroidism, which resulted in the random forest model as the best performing model with the highest prediction accuracy as 94.8%. Various ML models have been used in Ref. [3] i.e., logistic regression, random forest, and many more, for the prediction of three types of thyroidism: hypothyroidism, hyperthyroidism, and normal. The study has resulted in multilayer perceptron as the best performing model with the highest accuracy of 96.4%, whereas other ML models, decision tree, random forest, SVM, naive Bayes, logistic regression, KNN, and linear discriminant analysis have resulted in the accuracy of 90.13%, 92.53%, 90.67%, 91.73%, 91.47%, and 83.2%, respectively.

A study has been conducted in Ref. [13] to distinguish the patients

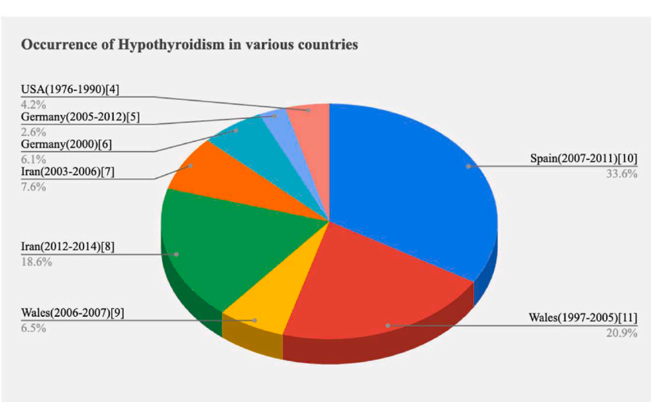

Fig. 1. Occurrence of hypothyroidism in various countries.

with hyperthyroidism and hypothyroidism by using ML models. This study has resulted in the outcome in the form of accuracy, where the accuracy of prediction of hyperthyroidism and hypothyroidism has been identified as 93.8% and 90.9%, respectively. In Ref. [14], an XGBoost model has been used for the prediction of thyroid in a UC Irvin knowledge discovery dataset. The accuracy of the proposed model was compared with the prediction performance of KNN, logistic regression, and decision tree, which resulted in XGBoost as the best-performing model with the highest accuracy.

In [15], the authors have presented an epidemiological model for the prediction of COVID-19 cases in India based on the pattern of China. In Ref. [16], the authors have presented a modified fuzzy-based model for thyroid detection, which utilizes various classification and clustering techniques. In Ref. [17], authors have explored thyroid disease detection using an expert system to build up a foresight about the thyroid disease depending upon its various symptoms. In Ref. [18], authors have proposed simplified swarm optimization (SSO) to perform an analysis of the functioning of the thyroid gland. The authors have performed SSO on the dataset taken from UCI [19]. In Ref. [20], authors have applied the Artificial Neural Networks (ANN) approach for thyroid disease detection. The results have been shown through the back-propagation algorithm, radial basis function, and learning vector quantization. In Ref. [21], the authors applied similarity measures for the detection of various patterns related to thyroid, cancer, and diabetes. In Ref. [22], the authors have presented a review of support vector machines (SVM), neural networks, and artificial neural networks (ANN), which have been used for the detection of thyroid disease. In Ref. [23], authors have applied the SVM approach using feature selection for the classification of the thyroid.

In this article, various ML-based classifiers have been used for hypothyroidism detection and classification, which include: random forest, multiclass model, naive Bayes, decision tree, and a DL-based model ANN, which performs well on text data, has been applied. These thyroid prediction models show thyroid prediction and classification in four classes: negative class, compensated hypothyroidism class, primary hypothyroidism, and secondary hypothyroidism. The results exhibit better accuracy, precision, and recall than existing techniques. It has been revealed that performance in the decision tree and random forest provides the best performance results for the prediction and diagnosis of thyroid disorders.

3. Materials and methods

In this paper, supervised learning is employed for predictive model building and a DL-based model in order to diagnose thyroid disorders. The dataset of hypothyroidism is available in the WEKA simulator's data repository [24]. The dataset has 30 attributes and 3772 instances related to hypothyroidism. WEKA 3.8.4 simulator has been used in this work to perform experiments [24,25]. This subsection presents various ML and DL methods: naive Bayes, decision tree, ANN, random forest, and multiclass classification, which have been used for the identification of the presence of hypothyroidism in the dataset.

3.1. Predictive model construction for hypothyroidism classification

ML allows machines or computers to learn and improve their experience without applying explicit programming. The ML model-building process utilizes various classification approaches to draw analytics from the data [26]. ML has varied applications in various sectors, including robotics and healthcare diagnostics, which avoid repetitive tests and improve diagnosis [26–30]. Fig. 2 depicts the predictive model building process, which includes various steps such as data collection, preprocessing, feature selection, training, and testing.

Data preprocessing is the initial step of any ML or DL technique. In this, the raw data is transformed in such a form that the data will become useful and efficient. It performs data cleaning or data integration

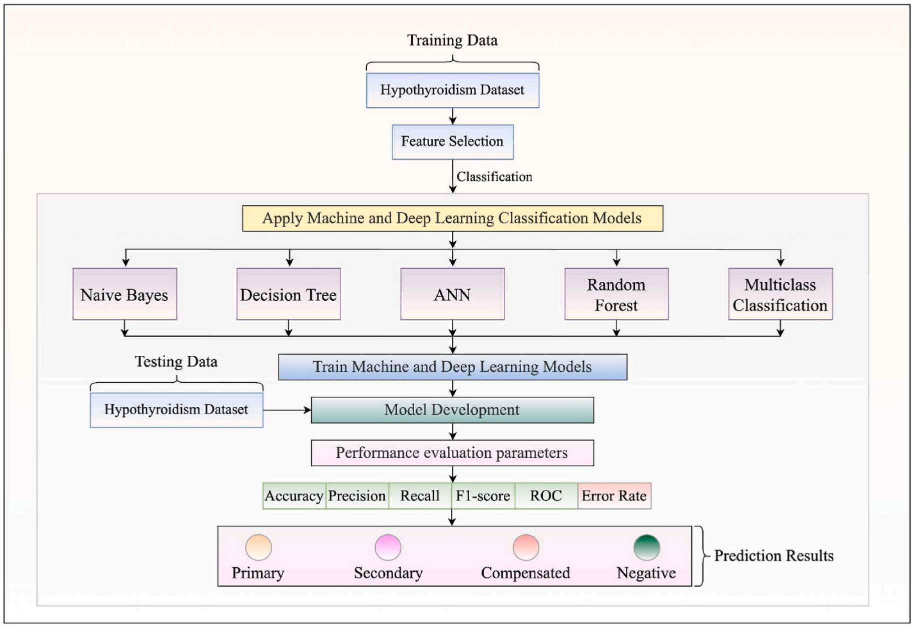

Fig. 2. The process of predictive model construction for hypothyroidism classification.

operation such as the missing data being filled manually or filled with the mean of the attributes. Sometimes the raw dataset includes noisy data, which may create disturbance in the prediction model, so for removing such data from the whole dataset, the binning methods are used. The range of the columns may vary differently, which requires all the datasets to be in the same range; hence various data normalization techniques can be used and lead to better prediction models.

Further, the feature selection method is performed to identify the most important features which are relevant for the prediction of the output. This step is performed in the present study to remove redundant data for improving and enhancing the accuracy and other performance results, such as precision and recall, by reducing the computation time. Feature selection can be made by utilizing various available methods: embedded method, filter method, and wrapper method. After the feature selection step, various ML and DL methods have been applied to the selected featured dataset to train the model and test it further to provide predictive results [31]. ML and DL techniques have been used to build the predictive model for hypothyroidism classification. Lastly, the classification results have been identified using accuracy, precision, recall, F1-score, ROC, and loss function.

This section provides a brief introduction to various ML and DL-based ANN models which have been used for the prediction and diagnosis of thyroid disorder. ML and DL approaches that have been applied to build the predictive model are as follows: Naive Bayes, Decision tree, Random forest, Multiclass classification, and ANN.

Bayesian classifiers utilize Bayes' theorem to perform classification [32]. Prediction about the membership probability of a class is performed to know the class of a given tuple to which it belongs. A naive Bayes classifier has the ability to deal with large dataset problems with higher accuracy and less computational time. This classifier learns the conditional probability of each attribute from the training dataset and thereafter applies the Bayes rule. Higher posterior probability values are used to determine the prediction of a particular class.

Decision trees perform classification by utilizing classification trees [33,34]. In a decision tree, internal nodes correspond to an attribute, and branches represent attribute values. Leaf nodes perform classification. Mutually exclusive regions of a dataset are formed by decision trees. The decisions are made in a hierarchical fashion which represents a tree. The tree consists of internal as well as external nodes. Decisions are formed on the basis of internal nodes; however, external nodes characterize a label. During the process of decision tree construction, information gain is calculated as mentioned below:

Information gain = entropy (parent)-[weight average]*entropy (children)

This algorithm finds the highest information gain among all attributes. The attribute with the highest gain will be the root and used for split first to form a decision tree. J48 (C4.5) is a decision tree algorithm that is an extended version of the ID3 algorithm [35,36]. It performs classification by dealing with missing values and calculating gain. A decision tree is a very versatile method for performing numeric prediction [25]. It consists of an ordered set of IF-then rules which provides a more easily understandable solution in comparison to decision trees. It exists under rule base classifiers in WEKA. It is simpler and less complex in comparison to a decision tree.

Random forest is an ML model which comes under supervised ML. It is used for regression as well as classification tasks [37]. It is the combination of decision trees and takes the maximum of the same types of results to classify the test data. When the variables are categorical and continuous, it performs classification and regression, respectively. Multiclass classification is an ML model which is used for classifying the data into more than two classes [38]. It shows better classification results if the data has more than two outputs. It is a well-suited algorithm for classification tasks in healthcare etc. It works on the basis of conditional probabilities and uses the Bayes theorem to predict the class of unlabeled data.

DL is a branch of artificial intelligence that gives the power to the machine to learn like a human being [39,40]. It has many algorithms; specifically, ANN is a DL model which requires a huge amount of data for training, due to which it is capable of accurately classifying the test data [41]. It is a computational model consisting of various layers, namely the input layer, hidden layer, and output layer, as depicted in Fig. 3, which act the same as a human nervous system. It has numerous neurons which forward the information to the next layer from the previous layers. It is a well-known DL algorithm that works effectively on comma-separated files and requires a high volume of data for the correct prediction.

4. Results and discussion

WEKA employs JAVA language for the implementation of various

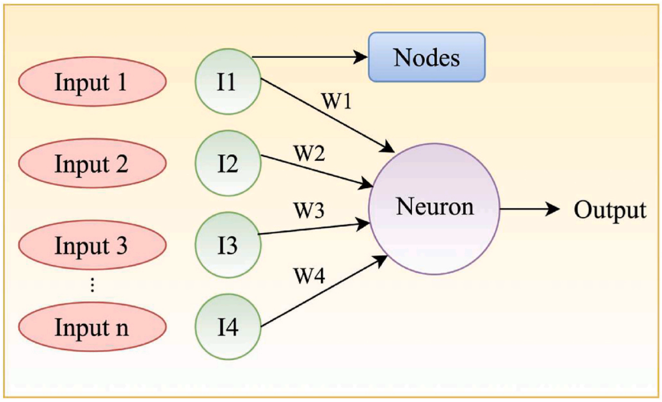

Fig. 3. Systematic framework of ANN model.

supervised or unsupervised ML algorithms. It has a visualization environment, and it also supports the implementation of new ML algorithms. 10-fold cross-validation is applied during the prediction model construction. The performance evaluation is based on the following measures: accuracy, precision, recall, F1-score, and ROC measure [38,42].

4.1. Comparative analysis of prediction results of proposed model

This section provides the results of the proposed hypothyroidism detection model. Fig. 4, Fig. 5, Fig. 6, Fig. 7, and Fig. 8 show the performance results of naive Bayes, decision tree, random forest, multiclass classifier, and ANN respectively in the form of precision, accuracy, recall, F1-score, and ROC for each class, i.e., negative, compensated, primary and secondary in the dataset. The results show that in the case of negative, compensated, and primary classification, the random forest model, shows the highest precision as 0.998, 0.97, and 0.957, which is quite high as compared to other models. Similarly, in the case of a recall, F1-score and ROC, again, the random forest outperforms as compared to other models taken for the study.

The requirement of any model is to show a good amount of accuracy in a very short span of time. In this work, time has also been taken as a major metric for identifying the results of the proposed model. It is an important parameter through which the best suitable model can be identified for any problem. Hence, the results have also been analyzed in the form of time taken for running the complete model, as shown in Fig. 9, in which the comparison has resulted that the naive Bayes classifier has taken the lesser time for the experiment and the ANN model has been found as the highest time-consuming model. The decision tree is also found as a less time-consuming model than the naive Bayes. The order of the highest to lowest time-consuming models for the prediction

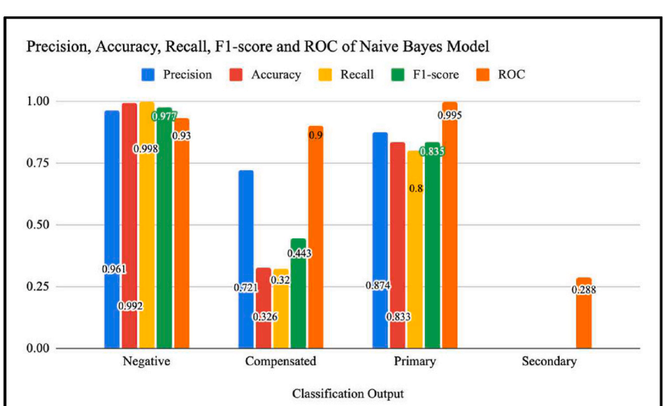

Fig. 4. Simulation results of Naive Bayes.

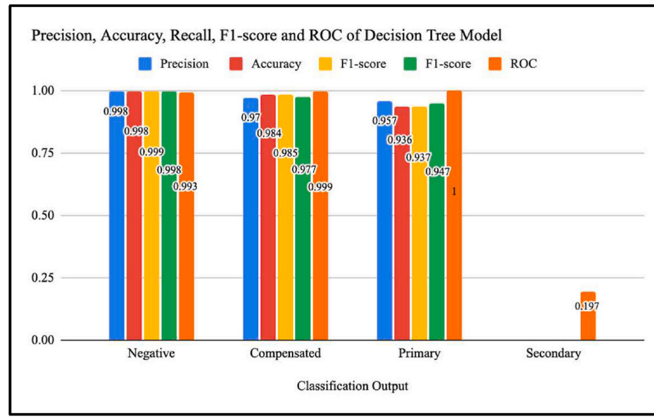

Fig. 5. Simulation results of Decision Tree.

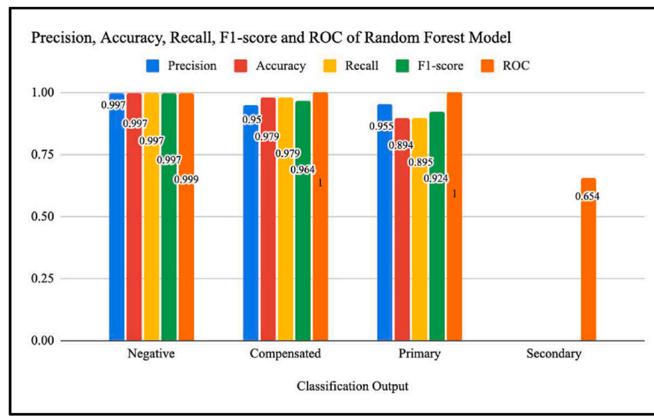

Fig. 6. Simulation results of Random Forest.

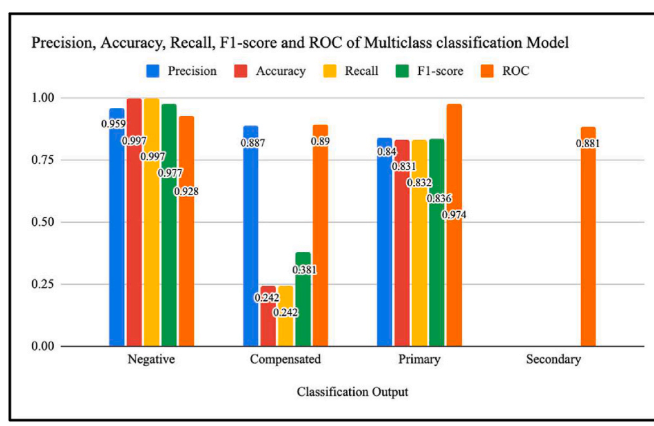

Fig. 7. Simulation results of Multiclass classifier.

of hypothyroidism has been found as ANN, multiclass classifier, random forest, decision tree, and naive Bayes.

Table 1 depicts the performance of various prediction models. The model classifies hyperthyroidism into four categories: negative class, compensated hypothyroidism class, primary hypothyroidism class, and secondary hypothyroidism class. The naive Bayes classifier provides a good accuracy result of 95.281% with an overall error rate of 0.417. The decision tree shows a very less error rate of 0.0424 with a better accuracy value of 99.5758%, which is higher than the naive Bayes classifier. The complete error rate of the random forest model is identified as 0.0689, with an accuracy value of 99.3107%. This model exhibits good

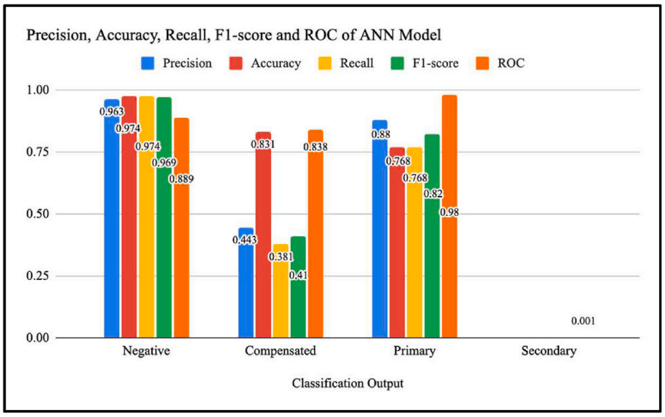

Fig. 8. Simulation results of ANN.

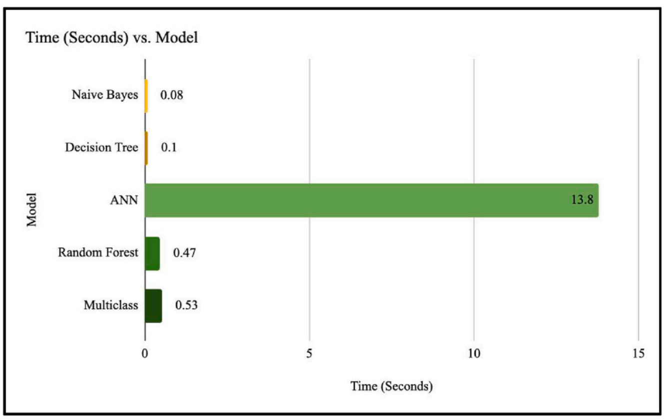

Fig. 9. Computational time comparison of various ML and DL models.

Table 1
Comparison of performance results of naive Bayes, decision tree, ANN, random forest and multiclass classifier.

Classifier	Naive Bayes	Decision Tree	ANN	Random Forest	Multiclass Classifier
Accuracy	95.281%	99.5758%	93.8226%	99.3107%	95.3606%
Error rate	0.417	0.0424	0.6177	0.0689	0.463
Precision	0.946	NA	NA	NA	0.951
Recall	0.953	0.996	0.938	0.993	0.954
F1-score	0.945	NA	NA	NA	0.943
ROC	0.929	0.993	0.889	0.999	0.928

accuracy in comparison to the naive Bayes and ANN models after the decision tree model.

The error rate in the multiclass model is identified as 0.463, while the accuracy value is 95.3606%. This model performs better than the ANN model but is not the best model due to its less accuracy as compared to naive Bayes, random forest, and decision tree models. Lastly, the DL-based ANN classifier shows the error rate as 0.6177 with an accuracy value of 93.8226%, which is a competitively good score. As a result, two models, namely decision tree and random forest, have been identified as the best performing models with the highest accuracy values as 99.5758% and 99.3107%, respectively, as shown in Fig. 10. The ANN model also exhibits good accuracy of 93.8226% for this dataset because; it is a DL model and requires a huge amount of data for training, to get more improved results. It has resulted in the accuracy value of 93.8226%, which is quite good and a competitive score; however, for the presented dataset, ML models decision tree, and random forest has achieved better accuracy.

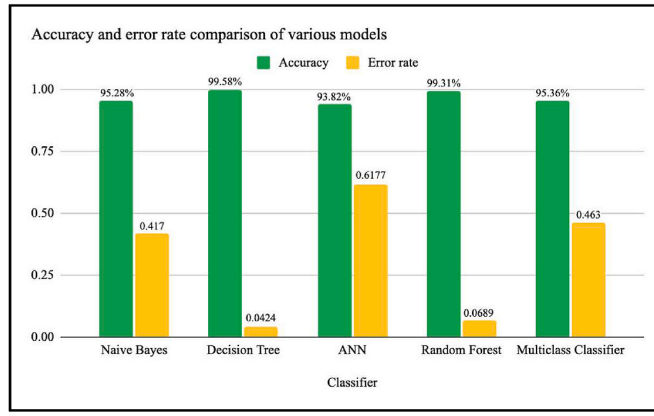

Fig. 10. Accuracy and error rate comparison of various ML and DL models.

In an overall prediction comparison, by taking precision, recall, F1-score, and ROC, the decision tree has been identified as the best model in the case of a recall. In precision, the multiclass model has been identified as the best model with a higher value of precision as compared to naive Bayes. While naive Bayes performs better than the multiclass model in a comparison of F1-score, as shown in Fig. 11.

4.2. Results and discussion of multiclass classification of hypothyroidism by ML and DL techniques

Fig. 12 identifies the percentage of correct identification of each output class in the dataset. The secondary class in each algorithm has been incorrectly classified. The naive Bayes classifier correctly classifies 99.28% of negative, 32.65% of compensated, and 83.35% of primary instances in the dataset. The decision tree shows the highest accuracy of the identification of negative class, compensated class, and primary class as 99.86%, 98.45%, and 93.68%, respectively. The random forest classifier has shown a good correct prediction accuracy for negative, compensated, and primary hypothyroidism as 99.71%, 97.93%, and 89.47%, respectively.

Lastly, the multiclass and ANN model has shown the accuracy of (99.71%, 24.22%, 83.15%) and (97.44%, 38.14%, and 76.84%) for identifying negative, compensated, and primary hypothyroidism, respectively. However, the multiclass classifier has shown less accuracy of correct identification of compensated class but shows good accuracy for negative class and medium accuracy for primary hypothyroidism. ANN model has achieved a good accuracy of classifying negative classes, while for compensated class; it has shown less accuracy but greater than the accuracy of naive Bayes model.

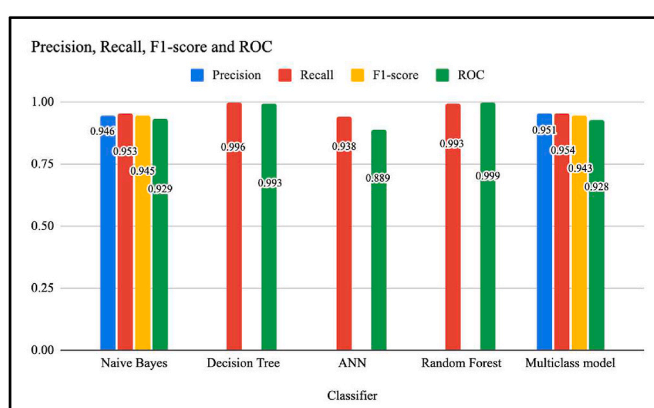

Fig. 11. Overall results comparison of ML and DL models.

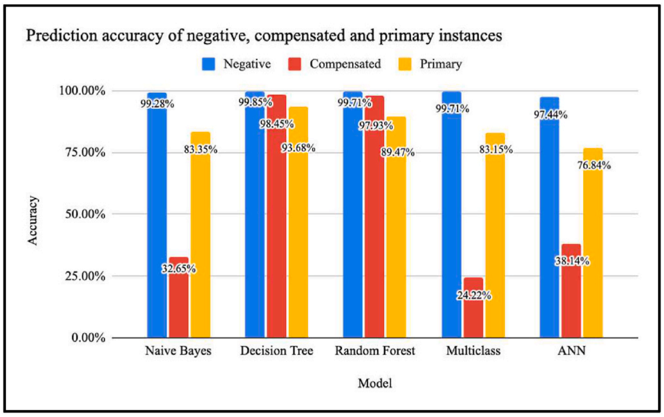

Fig. 12. Comparison results of the percentage of correctly predicted instances.

Fig. 13 shows the error rate of the prediction of negative, compensated, and primary instances in the dataset. The multiclass model has shown the highest error rate for predicting the compensated instance, while for negative, compensated, and primary hypothyroidism, the decision tree has the 2nd lowest, and random forest has the lowest error rate.

4.3. Comparative analysis with previous works

There are various ML and DL models which have been used by various authors for the prediction of hypothyroidism class. The results have been found good in previous works, but the proposed model has better results. This subsection compares the results of the proposed model with the previous works.

Fig. 14 shows the performance comparison with previous works, in which the proposed decision tree model has been identified as the best performing model with the highest accuracy of 99.5758%. While other existing models also perform well but have less accuracy than the proposed model. Hence, this comparison depicts the proposed model as the outperforming model.

Fig. 15 shows the comparative analysis of the error rate of the proposed model with previous works. It shows that the proposed decision tree and random forest model perform better with the least error rate of 0.04242 and 0.06893, respectively. While other state-of-the-art models have a higher error rate as compared to the proposed work, specifically, the KNN model has the highest error rate of 4.1.

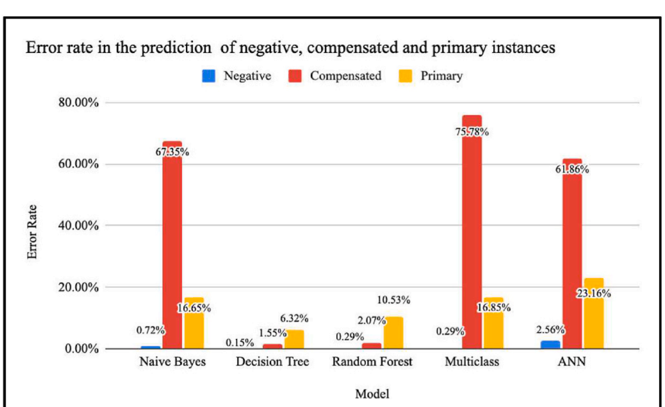

Fig. 13. Comparison results of the percentage of incorrectly predicted instances.

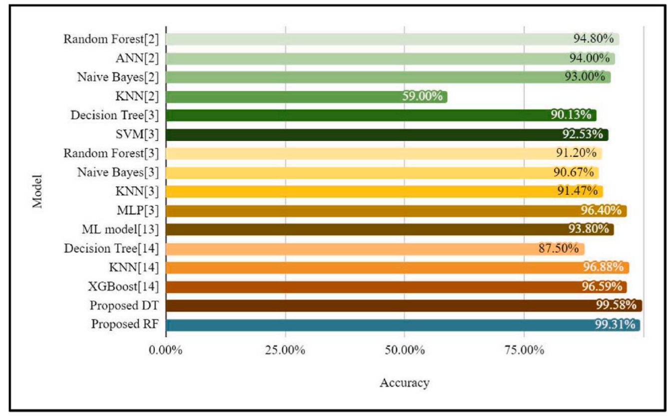

Fig. 14. Accuracy comparison of the proposed model with state-of-the-art models.

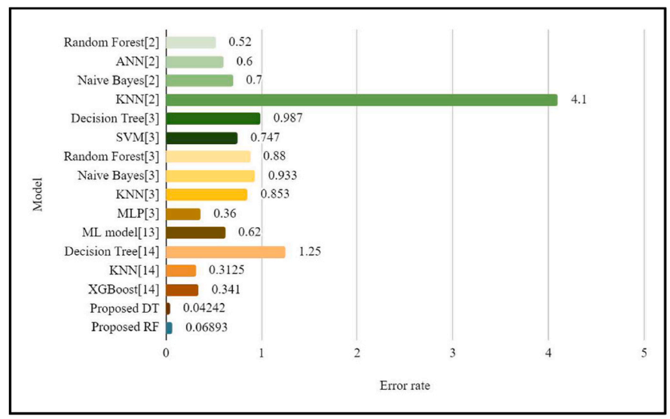

Fig. 15. Error rate comparison of the proposed model with state-of-the-art models.

5. Conclusion

The article performs the prediction of hypothyroid and its multiclass classification by applying ML and DL models. ML techniques utilized for model building are naïve Bayes, random forest, multiclass classification, and decision tree, along with the DL-based ANN model. The performance of predictive models has been compared using precision, recall, F1-score, ROC, and accuracy. It is observed that prediction models built up using a decision tree and random forest provide the highest accuracy, which is 99.5758% and 99.3107%, respectively. Where the error rate is also very less in both the models which concludes them as the best performing models in case of correct prediction of hypothyroidism type. Furthermore, the DL-based ANN model has also shown an accuracy of 93.82%, which is quite good and a competitive score, however, for the presented dataset, ML models decision tree, and random forest has achieved better accuracy. ANN is a good DL-based model which provides good results for text data. As it comes under DL models, hence it requires a large amount of information for training to correctly classify the data. Lastly, this work can be used for further research on the early detection of hypothyroid and its classification so that the timely treatment of the disease can be done and may lead to slowing down the enhancement in mortality rate.

In the future, the work can be used in hospitals to provide support to doctors and clinicians during the diagnosis of hypothyroidism. Further, the dataset can be increased, and academic researchers in the medical area can also use this work to identify more ML or DL based prediction models to detect hypothyroidism.

CRediT authorship contribution statement

Kalpna Guleria: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, preparation, Writing – review & editing, Visualization, Supervision. **Shagun Sharma:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, preparation, Writing – review & editing, Visualization. **Sushil Kumar:** Methodology, Formal analysis, Resources, Data curation, Writing – review & editing, Visualization. **Sunita Tiwari:** Methodology, Validation, Investigation, Resources, Writing – review & editing, Visualization, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset link is mentioned in the manuscript.

References

[1] R. Siegel, C. Desantis, A. Jemal, Colorectal cancer statistics, 2014: colorectal cancer statistics, 2014, CA Cancer J. Clin. 64 (2) (2014) 104–117.
[2] T. Alyas, M. Hamid, K. Alissa, T. Faiz, N. Tabassum, A. Ahmad, Empirical method for thyroid disease classification using a machine learning approach, BioMed Res. Int. 2022 (2022), 9809932.
[3] K. Salman, E. Sonuç, Thyroid disease classification using machine learning algorithms, J. Phys. Conf. Ser. 1963 (1) (2021), 012140.
[4] G.B. Bartley, et al., Clinical features of Graves' ophthalmopathy in an incidence cohort, Am. J. Ophthalmol. 121 (3) (1996) 284–290.
[5] K.A. Ponto, et al., Prevalence, phenotype, and psychosocial well-being in euthyroid/hypothyroid thyroid-associated orbitopathy, Thyroid 25 (8) (2015) 942–948.
[6] A.K. Eckstein, et al., Euthyroid and primarily hypothyroid patients develop milder and significantly more asymmetrical Graves ophthalmopathy, Br. J. Ophthalmol. 93 (8) (2009) 1052–1056.
[7] M.B. Kashkouli, F. Pakdel, V. Kiavash, I. Heidari, A. Heirati, S. Jam, Hyperthyroid vs hypothyroid eye disease: the same severity and activity, Early Years Educat. 25 (11) (2011) 1442–1446.
[8] A. Medghalchi, M. Akbari, Y. Alizadeh, R.S. Moghadam, The epidemiological characteristics of patients with thyroid eye disease in a referral center in northern Iran, J. Curr. Ophthalmol. 30 (4) (2018) 353–358.
[9] D. McKeag, et al., Clinical features of dysthyroid optic neuropathy: a European Group on Graves' Orbitopathy (EUGOGO) survey, Br. J. Ophthalmol. 91 (4) (2007) 455–458.
[10] M. Expósito, M. Moreno, P.M. Moreno, I.P. Sánchez, C.M. Jiménez, P.B. López, Evaluación de la efectividad del tratamiento con glucocorticoides intravenosos en la oftalmopatía de Graves, vol. 60, Endocrinología y Nutrición Elsevier, 2013, pp. 10–14.
[11] I. Cozma, L. Cozma, R. Boyce, M.E. Ludgate, J.H. Lazarus, C. Lane, Variation in thyroid status in patients with Graves 'orbitopathy, Acta Endocrinol. 5 (2009) 191–198.
[12] S. Sharma, K. Guleria, Deep learning models for image classification: comparison and applications, in: 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE, 2022.
[13] M. Hu, et al., Development and preliminary validation of a machine learning system for thyroid dysfunction diagnosis based on routine laboratory tests, Commun. Med. 2 (1) (2022) 9.
[14] S. Sankar, A. Potti, G.N. Chandrika, S. Ramasubbareddy, Thyroid disease prediction using XGBoost algorithms, J. mob. multimed. 18 (3) (2022) 1–8.
[15] S. Tiwari, S. Kumar, K. Guleria, Outbreak trends of coronavirus disease-2019 in India: a prediction, Disaster Med. Public Health Prep. (2020) 1–6.
[16] S.N. Kulkarni, A.R. Karwankar, Thyroid disease detection using modified fuzzy hyperline segment clustering neural network, Int. J. Comput. Technol. 3 (3b) (2012) 466–469.
[17] A. Keleş, A. Keleş, ESTDD: expert system for thyroid diseases diagnosis, Expert Syst. Appl. 34 (1) (2008) 242–246.
[18] W.-C. Yeh, Novel swarm optimization for mining classification rules on thyroid gland data, Inf. Sci. 197 (2012) 65–76.
[19] S.D. Bay, D. Kibler, M.J. Pazzani, P. Smyth, The UCI KDD archive of large data sets for data mining research and experimentation, SIGKDD Explor. 2 (2) (2000) 81–85.
[20] A. Shukla, R. Tiwari, P. Kaur, R.R. Janghel, Diagnosis of thyroid disorders using artificial neural networks, in: 2009 IEEE International Advance Computing Conference, 2009.
[21] K. Saastamoinen, J. Ketola, Medical data classification using logical similarity based measures, in: 2006 IEEE Conference on Cybernetics and Intelligent Systems, 2006.
[22] S. Shariati, M.M. Haghighi, Comparison of anfis Neural Network with several other ANNs and Support Vector Machine for diagnosing hepatitis and thyroid diseases, in: 2010 International Conference on Computer Information Systems and Industrial Management Applications, CISIM, 2010.
[23] K. Shankar, S.K. Lakshmanaprabu, D. Gupta, A. Maseleno, V.H.C. de Albuquerque, Optimal feature-based multi-kernel SVM approach for thyroid disease classification, J. Supercomput. 76 (2) (2020) 1128–1143.
[24] Weka 3 - data mining with open source machine learning software in java, Waikato.ac.nz [Online]. Available: https://www.cs.waikato.ac.nz/ml/weka/ [Accessed: 15-July-2022].
[25] E. Frank, et al., Weka-A machine learning workbench for data mining, in: Data Mining and Knowledge Discovery Handbook, Springer US, Boston, MA, 2009, pp. 1269–1277.
[26] A.L. Beam, I.S. Kohane, Big data and machine learning in health care, JAMA 319 (13) (2018) 1317–1318.
[27] S. Subburaj, S. Murugavalli, Survey on sign language recognition in context of vision-based and deep learning, Measurement: Sensors 23 (100385) (2022), 100385.
[28] S. Kumar, K. Guleria, S. Tiwari, An Analytical Study of Covid-19 Pandemic: Fatality Rate and Influential Factors," Design Engineering, 2021, pp. 12213–12225.
[29] S.S. Vidhya, A. Karthi, Soft Sensor Data Based Autonomous Detection of Aneurysm Impacted Coronary Illness Using Machine Learning Algorithms, Measurement: Sensors, 2022.
[30] S. Sharma, K. Guleria, A deep learning model for early prediction of pneumonia using VGG19 and neural networks, in: 3rd International Conference on Mobile Radio Communications & 5G Networks, (MRCN-2022), Springer, 2022, pp. 1–12. In press.
[31] F. Babič, L. Majnarić, A. Lukáčová, J. Paralič, A. Holzinger, On patient's characteristics extraction for metabolic syndrome diagnosis: predictive modelling based on machine learning, in: Information Technology in Bio- and Medical Informatics, Springer International Publishing, Cham, 2014, pp. 118–132.
[32] J. Han, M. Kamber, Data Mining: Concepts and Techniques, the Morgan Kaufinann Series in Data Management Systems. Jim Gray, Morgan Kaufmann Publishers, 2000.
[33] Y. Wu, K. Ianakiev, V. Govindaraju, Improved k-nearest neighbor classification, Pattern Recogn. 35 (10) (2002) 2311–2318.
[34] P. Cunningham and S. J. Delany, "K-nearest neighbour classifiers-a tutorial," ACM Comput. Surv., vol. 54, no. 6, pp. 1–25.
[35] H. Zhang, L. Jiang, L. Yu, Class-specific attribute value weighting for Naive Bayes, Inf. Sci. 508 (2020) 260–274.
[36] M. Loor, G. De Tré, Contextualizing naive Bayes predictions, in: Information Processing and Management of Uncertainty in Knowledge-Based Systems, Springer International Publishing, Cham, 2020, pp. 814–827.
[37] A. Sarica, A. Cerasa, A. Quattrone, Random Forest algorithm for the classification of neuroimaging data in Alzheimer's disease: a systematic review, Front. Aging Neurosci. 9 (2017) 329.
[38] J. Nabi, "Machine learning — multiclass classification with imbalanced dataset," towards Data Science. https://towardsdatascience.com/machine-learning-multiclass-classification-with-imbalanced-data-set-29f6a177c1a, 22-Dec-2018. (Accessed 17 July 2022).
[39] K. Saini, N. Marriwala, Deep learning-based face mask detecting system: an initiative against COVID-19, in: Emergent Converging Technologies and Biomedical Systems, Springer, Singapore, 2022, pp. 729–742.
[40] S. Jindal, A. Sharma, A. Joshi, M. Gupta, Artificial intelligence fuelling the health care, in: Mobile Radio Communications and 5G Networks, Springer Singapore, Singapore, 2021, pp. 501–507.
[41] D. McKeag, et al., Clinical features of dysthyroid optic neuropathy: a European Group on Graves' Orbitopathy (EUGOGO) survey, Br. J. Ophthalmol. 91 (4) (2007) 455–458.
[42] G. Stiglic, S. Kocbek, I. Pernek, P. Kokol, Comprehensive decision tree models in bioinformatics, PLoS One 7 (3) (2012), e33812.