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Thyroid Diseases Detection Using Evolutionary Machine Learning and Deep Learning : A survey

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This paper presents a survey of studies and research on machine learning techniques, deep learning, as well as research using optimization algorithms, and evolutionary algorithms, in relation to discoveries of diagnosing thyroid disorders. The paper includes an analysis of recent studies. The techniques of researchers in this field of diseases (thyroid diseases) are shown. As well as the results of the aforementioned studies on accuracy factors, Precision, Recall, F1-scor and. Advantages and disadvantages of advanced algorithms. By analyzing the current methods that were surveyed, it was proven that transfer learning techniques, as well as techniques that use optimization algorithms, are the most efficient. In some research, preprocessing plays a major role in obtaining better results in the model training stage.

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1. INTRODUCTION

The thyroid is an adult's biggest endocrine gland, Butterfly-like in form and found in the lower neck. It regulates the balance of calcium in the body and releases hormones to control cell metabolism. A healthy thyroid gland produces enough hormones to support optimal metabolism[1]. Early identification of thyroid illnesses is crucial for reducing the number of new cases[2]. TD is divided into four categories: thyroiditis, hypothyroidism, hyperthyroidism, and Hashimoto, thyroiditis,[3],[4].

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Doctors emphasize the need of early illness identification, diagnosis, and care in reducing disease progression and mortality. Early detection and differential diagnosis improves treatment outcomes for several types of abnormalities. Clinical diagnosis remains challenging, despite repeated trials[5]. Thyroid diseases are diagnosed with laboratory blood tests, especially for thyroiditis and hyperthyroidism[6] . Ultrasonography is essential for assessing the presence of nodules, thyroid disease, and other pathological conditions. This imaging modality has become increasingly important in recent decades[7].

Traditional clinical and laboratory investigations are frequently insufficient for accurately diagnosing thyroid disorders. In this context, thyroid problems are detected using machine learning and deep learning to improve diagnostic accuracy while saving time and effort. Machine learning and deep learning can help discriminate between people with and without thyroid illness. . Therefore, the diagnosis of thyroid diseases is an important classification problem. As a result, specialized models are built by specialists in the field of computer science to diagnose thyroid diseases[8],[9],[10],[11]. Recently, evolutionary optimization methods have been utilized to enhance disease diagnostic findings while also making models more effective and save time.

2. thyroid disease detection

The literature review can be divided into several main sections based on the type of techniques used to thyroid diseases detection.

2.1. Thyroid Diseases detection using Machine / Deep Learning ‘

Recent advances in machine learning and Deep learning have changed the accuracy of computer aided diagnosis (ACD) and data analysis tools that address the problem of thyroid disease diagnosis. In this survey, we illustrate the goals of machine learning, and deep learning for thyroid disease diagnosis and conduct a literature review that has diagnosed TD. Table (1) provides Collection of relevant studies to the question asked.

Vadhiraj, V et al. in [12] have presented Thyroid nodule categorization from ultrasound images using machine learning methods. For the identification of thyroid carcinoma, This work focused on the categorization of benign from malignant tumors by developing a computer-aided diagnostic system that was combined with multiple-instance learning (MIL). Image pre-processing and segmentation in this investigation were accomplished using the median filter and image binarization. extracted seven characteristics from the ultrasounds picture thru, the grey, level co-occurrence matrix (GLCM). From the Universidad Nacional de Colombia, data were used. It was 96% accurate achieved.

A joint convolutional neural network ((IF-JCNN)) based on information fusion has been presented by Liu, Z. et al. in [13] for the purpose of differentiating between benign and malignant thyroid nodules. For deep feature extraction, the IF-JCNN has two branching CNNs: one for US pictures and another for RF signals. At the backend of IF-JCNN, the extracted features are fused for TN classification. dataset made up of pertinent raw RF signals and US photos of TNs. It was 95% accurate. The shortcoming of merely employing US pictures in CNNs to characterize TNs was addressed by the suggested IF-JCNN paradigm

Wang, L. et al. in [14] have presented a novel a DNN, architectures is suggested for the automated detection of thyroid nodules and the diagnosis of thyroid cancer. Three networks make up the suggested method: a classification network, attention-based features, aggregation networks, and a feature extraction network. The thyroid ultrasonography pictures from a central city hospital are assembled into the dataset utilized in this work. The suggested method's accuracy was 87.32. Compared to earlier research, a larger database was employed in this work.

Nguyen, D. et al. in [15] have proposed a diagnosis based on, ultrasound image, for the malignant thyroid nodules, methods using AI based on the analysis in each spatial, and frequency domains. The ultrasonic thyroid image was analyzed using two alternative CNN designs, each with its own depth and network structure. Combining the classification outcomes of two CNN networks, they improved the overall performance.. the dataset used Thyroid, Digital Image Database (TDID). The accuracy for Proposed Method was 92.05%.

In [16], Srivastava et al. examined four pre-trained DCNN models (ShuffleNetV2, AlexNet, ResNet-34, and MobileNetV3,) for the multiple medical picture categorization of thyroid disease kinds. After undergoing fivefold cross-validation, the top-performing model was evaluated once again, and its diagnosis accuracy was contrasted with that of junior Senior nuclear, medicine, and physicians. In terms of identifying thyroid, scintillation pictures, the DCNN-based model fared well. SPECT thyroid imaging was the dataset that was utilized. With an accuracy of 0.944, the modified ResNet-34 model behaved the best

In [17], Chandana, K. et al. presented a diagnosis model for thyroid illness based on a cutting-edge deep CNN architecture. Use two types of datasets: computed tomography (CT) scans and ultrasonography pictures. The model performs well in both types of medical imaging, with accuracy scores of 0.972 for computed tomography (CT) scans and 0.942 for ultrasound images.

Yadav, D et al. in [18] have presented a decision tree to predict thyroid illness by extracting hidden patterns from the stored information. Using, random forests, decision trees, and classification, and regression trees (CART), examined the thyroid disease dataset. Once had the output from these classifiers improved the findings by applying the bagging ensemble approach. created an improved accuracy bagging ensemble approach by merging the three fundamental tree classifiers and applying it once more to the same dataset. The thyroid disease dataset is taken from the UCI, ML repository for analysis. This model's accuracy reached 100 percent

Pal, M et al. in [19] have presented three, ML models such as (KNN), decision tree (DT), and multi-layer perceptron (MLP), for thyroid disease predictions, and measured the performance, of these models in form of accuracy, and area, under the curve . When it comes to diagnosing thyroid illness, the MLP performs better. The dataset that was obtained through the UCI repository. 95.73 was the accuracy value

Vasile, C. et al.[20]. They created an ensemble technique that combines two DL models: one based on, convolutional neural networks, and the other on, transfer learning. For diagnosing thyroid ultrasound imaging. The first model, known as 5-CNN, was built as an efficient end-to-end trained model with five convolutional layers, whereas the second model was repurposed optimized, and trained using the pre-trained VGG-19 architecture. The model named CNN-VGG . dataset thyroidal US images . The accuracy for this model was 97.35%

In [21], Zhang et al. developed a unique multi-channel convolutional neural network (CNN) for multi-classifying thyroid disorders. The multi-channel CNN uses computed tomography to generate a comprehensive diagnostic judgment for the entire thyroid gland, highlighting the illness co-existence scenario. Use alternate tactics to improve CNN models' diagnostic accuracy by concatenating feature maps of different sizes. This model uses datasets obtainable on GitHub .The model's accuracy was 90.9%.

Sultana, A. et al. [22] presented RF coupled with LASSO as a robust and effective, ML-based strategy for predicting, TD. To train the model, six various machine learning classifiers were used: Support, Vector Machine, (SVM), AdaBoost (AB), Gradient Boosting (GB), Decision Tree (DT), (KNN), and Random Forest. The (UCI) repository is where the dataset originated. An RF classifier's accuracy was 99%. A limited sample size, an imbalanced dataset, and a high proportion of categorical variables relative to continuous characteristics are the main constraints of this research.

Tabrej Khan in [23] have presented predictive model to predicted the onset, of thyroid disease . Filter-based, feature selection approaches, especially mutual information, in combination with a two-class, (NN) classifier, were utilized to build a model using Azure Machine Learning resources. The two-class (NN) model created utilizing specified features in conjunction with SMOTE outperformed other recent ML, models. The database is obtainable in UCI's ML, repository. The model's accuracy is 98.1%.

Soma Prathibha et al. in [24] Have proposed CNN-based DL technology, is used to detecting thyroid diseases . CNN-based modified, Res-Net architecture, is applied, to detect thyroid diseases .In the proposed study, the training process is upgraded employing an extra optimizer for more precise accuracy and outcomes. It was found that using Adam and Stochastic Gradient Descent optimizers during the training phase of the proposed model improved the operational efficiency of the modified Res-Net model. Used the datasets, UCI repository in this model . The accuracy get from this model was 97%

Srivastava et al. [25] proposed a bilinear convolutional architecture that combines the output of two CNN models utilizing outer products to classify thyroid nodules. Eleven CNN, and bilinear BCNN, algorithms are used, include VGG-19, ResNet-50, VGG-16, BCNN(Inception V3)2, Inception-V3, Inception-V3,, BCNN(VGG-19)2, BCN

Inception-V3, N(ResNet-50)2, BCNN(VGG-16,ResNet-50), BCNN(VGG-19,ResNet-50), and BCNN(VGG-19,VGG-16),. Use the public dataset, which includes 447 ultrasound images. The results reveal that BCNN, algorithms beat CNN architecture in thyroid nodules classification .

Srivastava et al.[26] introduced a deep learning technique, Convolutional Neural Network, to classify thyroid lesions from ultrasound images. This suggested technique makes use of the Residual Network (ResNet), a deep Convolutional Neural Network, as a cutting-edge picture categorization model. Datasets from the TDID are used. The ResNet, model was compared to the VGG-16, model, whichwas had accuracy 74.69%, while the suggested technique reached 83%.

TABLE 1: An Overview of Existing Machine/Deep Learning Studies for Detecting Thyroid Disease.

Ref	Year	Dataset	Dataset type	ML/DL	Methods	Performance (Accuracy)
[12]	2021	UCL	US image	SVM	developing a computer-aided diagnostic system that was combined with multiple-instance learning (MIL)	96%
[13]	2021	US for TNs ,RF signals	US image ,RF signals	CNN	A joint, convolutional neural network (IF_JCNN) based on information fusion has been differentiating between benign and malignant thyroid nodules	95%
[14]	2020	From hospital, in the central city, is constructed	US image	DNN	Three networks make up the suggested method: a classification network an attention-based features aggregation network, and a feature extraction network	87.32%
[15]	2020	TDID	US image	CNN	Different, CNN architectures, which were different in depth, and networks structure to analyzes an ultrasound thyroid images	92.02%
[16]	2023	SPECT	image	DL	examined four pre-trained DCNN models (Alex-Net, ShuffleNetV2, MobileNetV3, and ResNet-34) for the multiple medical picture categorization of thyroid disease kinds	94.4%
[17]	2023	CT scan, US image dataset	CT scan, US image	DL	diagnosis model for thyroid illness based on a cutting-edge deep convolutional neural network architecture	97.2 for CT & 94.2 for US
[18]	2020	UCI	Real, integer	ML	decision tree to predict thyroid illness by extracting hidden patterns from the stored information	100%
[19]	2022	UCI	numeric and categorical	ML	three ML models such, as KNN, decision tree, and multi-layer perceptron, (MLP) for prediction, of thyroid disease	95.73%
[20]	2021	TDID	US image	DL	Created an ensemble technique that combines two DL models: one based on, convolutional neural networks and the other on, transfer learning	97.35%

[21]	2022	CT scan	CT	CNNs	developed a unique multi-channel, CNN for multi-classifying, thyroid disorders	90.9%
[22]	2023	UCI	categorical	ML	presented RF coupled with LASSO as a robust, and effective, ML-based strategy to predicting TD	99%
[23]	2021	UCI	numeric and categorical	ML	Filter-based features selection, approaches, especially mutual information, in combination with a two-class, Neural Network (NN) classifier, were utilized to build a model using Azure Machine Learning resources	98.1%
[24]	2023	UCI	image	DL	CNN-based modified, Res-Net architecture, is applied, to detect thyroid diseases	97%
[25]	2023	TDID	US image	CNNs	bilinear convolutional architecture that combines the outputs, of two CNN models utilizing outers product to classify thyroid nodules	87.72%
[26]	2022	TDID	US image	DL	suggested technique makes use of the Residual Network (ResNet), a deep Convolutional Neural Network, as a cutting-edge picture categorization model.	83%

2.2. Thyroid Disease diagnosis using Evolutionary Deep Learning.

To improve thyroid illness identification, researchers applied optimization methods to create ML, and DL, models. Evolutionary algorithms might detect basic features in DL networks and modify hyper-parameter to improve their design. Evolutionary methods optimize weights and biases, resulting in quicker convergence[27]. Deep neural network-based evolutionary techniques attempt to enhance detection accuracy. (Table 2) provides various instances of systematic reviews that address this issue.

Jopate et al.[28] introduced a unique deep learning approach that was utilized to predicting the diagnosis and categorization, of thyroid disease. To overcome these restrictions, use the Adaptive Elephant, Herd Optimisation Algorithm (AEHOA) model, to identify optimum features. To begin, smooth the data using an artificial minority oversampling technique known as SMOTE. Finally, the AEHOA parameters are fed into the CNN to improve data categorization and prediction accuracy. The dataset utilized in this study was obtained from the UCI, ML repository. The accuracy of this model was 88.2%.

Namdeo, R. et al. in[29] have developed a new two-phase thyroid diagnosis model that combines feature extraction and classification. Deep feature extraction is the method by which Convolutional Neural Networks (CNN) are utilized for picture classification. A neural network, is used to classify diseases, by using data characteristics, and image as inputs . Ultimately the combination, of both the classed results NN and CNN, improves the diagnosis accuracy rate. In this work proposes a new modified algorithm, Worst Fitness-based, Cuckoo Search (WF-CS), which is a modified version of the Cuckoo Search Algorithm (CS), for these optimizations. The performance of the proposed CS-WF is compared with other conventional methods and the superiority is proven accurately 0.99%.

Srivastava et al. in [30] have created Deep Neural Networks (DNN) are the most important and effective technology for predicting thyroid disorders. Within the realm of medical research, the diagnosis and prognosis of thyroid disease pose significant challenges due to its unpredictable start. A unique Long Short-Term Memory, based CNN (LSTM-CNN), with occurrence area Vgg19 is used to identify sickness. The approach, of bias field correction is combined with the hybrid, optimization strategy, namely Black Widow, Optimization and Mayfly Optimization, Approach ((HBWO-MOA)) for feature selection. Additionally, the LSTM and Vgg-19 ,of Deep Learning are introduced for disease detection. The thyroid illness, prediction and categorization using the ultrasound image in DDTI database is effective. the accuracy of the system was 98.8%.

Alsudani, S et al. in [31] have propose a unique approach, to enhancement the diagnostic, accuracy of thyroid diseases, by the union of the Emperor penguin Optimization, Algorithm (EPO). By employing EPO, optimize the selection of apposite diagnostic features, and tune the parameters of ML models. For this study, use the Thyroid Disease, Dataset . the accuracy for the system was 99.7% .

Kumar, S. et al.[32] Proposed optimization-based picking of features for thyroid prediction using differential evolution, and the Butterfly optimization method (DE-BOA). The fuzzy C-means strategy (FCM) acts as the classifier. Thyroid disease data from UCI was used. The model's accuracy was 94.3%..

Gupta, P et al. in[33] The suggested technique employs a differential evolution-based optimization approach to modify the parameters of ML models for early diagnosis of thyroid illness. This model incorporates RF, LR, SVM, AdaBoost, CNN, RNN, GBM, and LSTM. The AdaBoost with DE optimization outperforms current state-of-art models. Thyroid Disease Dataset from the Kaggle repository were utilized.The greatest result attained was 99.8% accuracy using AdaBoost with the DE optimization model.

Sha et al.[34] have proposed a system that integrates quantum, computing with machine learning to improve computational power and accuracy for thyroid illness prediction. For feature selection, the system uses a modified QPSO (Quantum Particle Swarm Optimization) algorithm. The QSVM (Quantum Support Vector Machine) is able to detect complicated patterns in data because to the high dimensional features space used by quantum a kernel functions. The thyroid disease dataset UCI is being used. The accuracy of the suggested model was 98.77%.

In [35], Pavithra et al. introduced the PIO-DBN model, which amass Pigeon Inspired Optimization with Deep Belief Network, for thyroid illness detection and categorization. To increase data nature, the PIO-DBN model, preprocesses the medical data. The PIO method is used to optimize the parameters of the DBN model, which was inspired by pigeon foraging behavior. Two datasets (new-thyriod and ann-thyriod) are employed. The accuracy was 98.91%.

Ma, L et al. in [36] have developed CNN with optimization-based, computer-aided diagnosis, of thyroid illnesses harnessing SPECT images . A modified DenseNet, conception of CNN is employing, and the training strategy is improved. conception is modifying by add the practice weights parameter to each miss out connection, in DenseNet. And the practice method is improved, by optimization the learning rate, with flower pollination algorithm, since network, training . dataset gatting from Heilongjiang Provincial Hospital. The accuracy for this model was 99.08%

Vanitha, R. et al. in [37] introduced a unique approach, C4.5 add to Firefly Optimization Algorithm(CFOA), for detecting thyroid malignant tumor in its early stages. The datasets were collected from the UCI Machine Learning repository. The performance of this suggested technique was compared to state-of-the-art current methods such as the Naive Bayes algorithm, the KNN algorithm, and Adaboost. When compared to current methods, the suggested approach achieved the highest precision (0.9935), recall (0.9971), F1-score (0.9951), and accuracy (0.9981). The C4.5 add to Firefly Optimization method was designed to speed up, and improve the performance of the ML method.

Gjecka, A. et al In [38], a mixed intelligent diagnosis model, It is suggested to combine gray wolf optimization (GWO), with artificial neural networks, the critical yet under Determine it problem of improved thyroid disease diagnosis to enable timely diagnosis, and interventions . use the modified meta-heuristic (M.H) methods of GWO with the ANN, classification method, so that the predict of thyroid illness becomes easier, and faster, If a decision support system help a doctors diagnoses disease in real time, this method reports the GWO model with ANN has greatly improved accuracy of 98% on real patients data, outperforming traditional ANN..

Sharma, R. et al. in[39] have proposed a binary versions of FOX-optimization methods for feature selection. For feature extraction, the vision transformer-based pre-trained models (DeiT and Swin Transformer) are employed. Local linear embedding is used to convert the retrieved features, and binary FOX optimization methods are used for features selection together with the Naïve Bayes, classifier. use the Tarun Tompson Histopathology Dataset and the Tyroid Digital Image Database (TDID). For the ultrasound dataset, the accuracy was 94.75%, while for the histopathology dataset, it was 89.71%.

Göreke, V. in [40] have developed A unique architecture for the categorization of thyroid nodule using ultrasound pictures, based on DL. A unique multi-layer computer-aided diagnostic approach for the identification of thyroid cancer was proposed in this work. A unique approach to feature extraction based on the class similarity of pictures was created in the first layer of the system. A unique pre-weighting layer was suggested for the second layer by adjusting the genetic algorithm. This model made use of the Images of B-mode Thyroid Ultrasonography dataset. 99.95% accuracy was achieved.

Srivastava et al. in [41] have presented a Novel Architecture for Identifying Thyroid Disorders with the Use of Hybrid, AGTEO Features Selection, and GRU Classification Model. First, preparing datasets using an outlier detection way, via Isolated Forest, and data normalization technique, to remove noise, creating a solid foundation for further research, is the first stage. Next, an enhanced Alex-Net architecture is used for feature extraction, which is then enhanced by more complex Chameleon Swarm, Algorithm (CSA) method to identify finer patterns in the data and improve the feature extraction process discrriminative power. Subsequently, a hybrid optimization feature selection strategy is implemented, combining the advantages of the Equilibrium Optimizer and the Artificial, gorilla Troops Optimizer , into a hybrid model called HAGTEO . The goal of this strategy is to find the most educative features, thereby lowering dimensionality and improving classifier performance. Finally, the retrieved and chosen characteristics are used to train the Gated Recurrent Unit, classifier for thyroid illness classification. The two datasets utilized to detect thyroid problems are the Thyroid Disease Dataset, and the Mikeizbikiv Dataset, with accuracy rates of 98.07% and 98.00% for datasets respectively.

For the purpose of classifying thyroid ultrasound image Srivastava et al. in [42] have proposed the Improved Gazelle Optimization Algorithm with Extreme Gradient Boosting (IGOA –XG-Boost). Since the CNN can recognize ultrasound pictures with ease, it is utilized to extract pertinent characteristics. The XG-Boost classifier receives the CNN output and uses it to categorize the input picture into classes that are either benign or malignant. Traditional GOA initializes logistic mapping in order to maximize XG-Boost's hyper-parameters, improve global search, and achieve fast convergence, all of which contribute to the greatest potential performance. The dataset utilized in this paper is the DDTI dataset. There was 99.62% accuracy.

TABLE 2: A Comprehensive Review of Existing Work on Detecting Thyroid Disease Using Evolutionary ML and DL

Ref	Year	Dataset	Dataset types	ML/DL	Evolutionary Machine	Methods	performance (Accuracy
[28]	2024	UCI ML repository	Numerical, categorical	CNN	AEHOA	Adaptive Elephant, Herd Optimization Algorithm model to identify optimum features	88.2%
[29]	2022	UCI	images	CNN	WF-CS	Ultimately, the combine of both the classed results (NN and CNN) improved the diagnosis accuracy, (WF-CS) used to these optimizations	99%
[30]	2023	DDTI	US image	LSTM-CNN	HBWO-MOA	The approach of bias field correction is combined with the hybrid optimization strategy, namely (HBWO-MOA), for feature selection	98.8%
[31]	2023	UCI	categorical, numerical	ML+DL	EPO	By employing EPO, optimize the selection of relevant diagnostic features and fine-tune the parameters of machine learning models	99.7%
[32]	2023	UCI	Nominal, Numerical	ML	C-means+ DE-BOA	optimization-based picking of features for thyroid prediction using differential evolution, and the Butterfly optimization	94.3%

[33]	2024	UCI	Categorical	ML	AdaBoost+ DE	differential evolution-based optimization approach to modify the parameters	99.8%
[34]	2024	UCI	Categorical	QSVM	QPSO	proposed a system that integrates quantum computing with machine learning to improve computational power and precision for thyroid illness	98.77%
[35]	2020	TDID	US image	DBN	PIO	introduced the PIO-DBN model, which mixed Pigeon Inspired Optimization (PIO) with Deep Belief Network (DL) for thyroid illness detection and categorization	98.91%
[36]	2019	SPECT	image	ML	FPA	developed CNN with optimization based computer aided diagnosis of thyroid diseases used SPECT images	99.08%
[37]	2022	UCI	image	C4.5	CFOA	unique approach, C4.5 add to Firefly Optimization, Algorithm (CFOA), for detecting thyroid cancer, in its early stages	99.81%
[38]	2023	thyroid dataset	numerical	ANN	GWO	intelligent diagnosis model is proposed mixed gray wolf optimization (GWO), and artificial neural networks (ANN)	98%
[39]	2023	TDID	US image	ML	FOX	Local linear embedding is used to convert the retrieved features, and binary FOX optimization methods are used for features selection together with the Naïve Bayes, classifier	94.75%
[40]	2023	TDTI	US image	RNN	GA	A unique multi-layer computer-aided diagnostic approach for the identification of thyroid cancer was proposed in this work	99.95%
[41]	2024	TDID, Mikeizbikiv	image	CNN	AGTEO	Novel Architecture for Identifying Thyroid Disorders with the Use of Hybrid AGTEO Features Selection, and GRU Classification, Model	98.07% and 98.0% respectively
[42]	2024	DDTI	US image	CNN	IGOA	the Improved Gazelle Optimization Algorithm with Extreme Gradient Boosting (IGOA -XGBoost) classifying thyroid ultrasound image	99.62%

3. Discussion

In this research, we reviewed Previous research in detecting thyroid diseases using machine learning and deep learning, in addition to improving the models using optimization algorithms. Researchers diagnosed the disease based on data available in data containers such as (UCI, TDID and DDTI) and some models were applied in real life. In both cases, the models achieved high results in diagnosis according to known performance metrics, without resorting to taking laboratory biopsies, which are painful and expensive. Researchers should Consider the advantages and disadvantages of each approach, considering its accuracy, reliability, speed, and ease of use. This comprehensive research found that although deep learning methods such as CNN produced highly accurate results, they took a long time to train. In some models, pre-trained models were used using a technique called transfer learning to reduce the diagnosis time. The CNN is often used as a common deep learning approach to identify thyroid diseases. Many optimization algorithms and evolutionary optimization algorithms were applied to neural networks to make them More efficient. The structures and parameters of deep learning models are improved with the help of evolutionary algorithms.

4. Conclusion

This paper reviews the traditional and recent works based on ACD to detect thyroid diseases ML and DL which are improved via EA . CNN are the most common deep learning methods for detecting thyroid diseases. The optimization algorithms discussed in this paper are the most widely used in disease diagnosis, and are used to optimize CNNs and other DL models to, the purpose to detecting thyroid diseases. Plus to other OA, EA are used to improve the structures and hyper-parameters in ML and DL models. Most common datasets to training machine learning and deep learning models for thyroid disease detection are UCI, TDID and DDTI datasets. As a result, thyroid disease detection using EV-enhanced ML/DL is a viable strategy to improve disease detection and diagnosis.

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