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Grey Wolf Optimization-Based Hyper Parameter Tuning For Deep Neural Networks in Thyroid Disease Diagnosis

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ABSTRACT
Thyroid disorders affect millions of people worldwide, however quick treatment is vulnerable by high rates of misdiagnosis. The lack of current clinical decision support systems inspires the development of novel approaches. In mandate to increase thyroid disease prediction, this study finds a gap in the use of machine learning, optimization and deep learning algorithms. The age and gender for thyroid data is predicted by using the proposed Deep Learning method based optimization technique called Grey Wolf Optimization-based hyper parameter tuning with Deep Neural Network. Initially, data cleaning is applied to the thyroid data to replace missing values and for raw data conversion. Next, the data are featured using the Recursive Feature Elimination, to identifying its most important features and eliminating others from thyroid dataset. Finally, a GWO based DNN framework is processed to enhance the classification of thyroid disease diagnosis. Using python software the proposed framework an improved accuracy of 92% is accomplished when compared to other techniques.

Keywords: Thyroid Disease Diagnosis (TDD), Data cleaning, Data transformation, Recursive Feature Elimination (RFE), Grey Wolf Optimization (GWO), Hyper parameter Tuning, Deep Neural Network.

1 Introduction

Incidences of thyroid disease have increased recently in worldwide [1]. Since it is the only organ in the body that produces hormones, which are essential for controlling the metabolism of all cells, the thyroid gland is a crucial endocrine organ. There are two types of thyroid diseases: neoplastic and functional. Whereas a neoplastic disorder is divided into benign and malignant categories in figure 1, a functional disease is either hyperthyroidism or hypothyroidism [2]. This affects the newborn too so the newborn has to be protected from sudden infant death syndrome in a cunning manner. This method is a different idea that will assist parents and caregivers to know their newborn better [3]. For these diseases, a critical care plan is essential, especially if the patient is disabled. It is achieved by integration of focal health care business models with Information and Communication Technologies (ICT) [4].

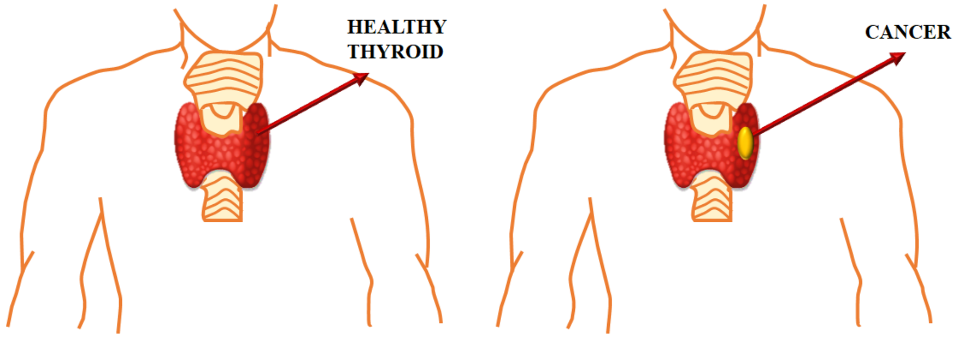

Figure 1: *Overview of healthy and cancer thyroid disease*

To save human lives and medical costs, a proactive thyroid disease prediction is necessary to treat the patient appropriately at the correct time [5]. In Hypothyroid: when the thyroid gland is unable to produce enough thyroid hormones Thyroid Simulating Hormones (TSH) levels rise and T3 and T4 levels fall. It exhibits as fatigue, brain fog, weight loss, etc [6]. Hyperthyroidism: when the thyroid gland producing other thyroid hormone than the body truly needs low TSH levels and extremely high T3 and T4 levels. Its symptoms include restlessness, sweating, hair loss, and more [7].

To identify thyroid diseases K-Nearest Neighbor (KNN) and its several distance functions are used. Using a chi-squared based feature selection method, the Euclidean and Cosine distance functions had the higher accuracy. It is slow to calculate new data points intensely [8]. Conversely, the performance of the Random Forest (RF) classification technique is used to test the hypothyroidism problem. Here decision rules and random forest have good performance when predicting thyroid disorders. The process of the testing is slow, when dealing with large datasets [9]. Moreover, using Support Vector Machine (SVM) classifiers the thyroid disease is predicted and classified successfully. It is difficult to handle unbalanced data and inadequate performance when dealing with noisy data [10].

For thyroid disease diagnosis several deep learning is used as following. To enhance the classification performance the bagging method rules were combined with the outputs of multiple CNN models. Based on artificial intelligence and a diagnosis of a cancerous thyroid nodule from an ultrasound scan the image is classified. Training takes lot of time when bagging rule follows [11]. However, to increase the accuracy of thyroid disease detection an Artificial Neural Networks (ANN) is used. In order to enhance simplicity and avoid over-fitting of ANNs, a set of Multiple Multilayer Perceptron (MMLP) neural networks with the capacity to propagate errors backward have been trained. Long training period when using huge datasets are handled [12]. Moreover, to improve the accuracy CNN is utilized which is good at automatically learning high-level and different level reflections from visual information when using CNN technique. To utility well, CNNs need a lot of labeled training data [13].

Using an ultrasound images a Joint-Training Convolutional Neural Network (CNN) locate the thyroid node. Here using Faster Region based CNN (Faster R-CNN) the normal objects are detected successfully. Faster R-CNN produces less accurate localizations because it requires a fixed-size input [14]. Moreover, using multi-task model Mask R-CNN the thyroid disease is detected with high performances. Nodule detection issue is happened with ultrasound scans [15]. To overcome the limitations, the developed work introduces GWO-DNN.

2 Related work

Namdeo *et al* (2022) [16] have proposed a Worst Fitness-based Cuckoo Search (WF-CS) to extract both the image and data features for diagnosing. To increase the accuracy rate modified system of Cuckoo Search Algorithm (CS) is used for automatic diagnosis of thyroid disease. Premature convergence risk and there is a chance of becoming trapped in local optima.

Gjecka *et al* (2024) [17] have suggested a Practical Swarm Optimization algorithm (PSO) with an Artificial Neural Network (ANN) for the automatic identification of the disease. Here thyroid disease is identified by using PSO-ANN for improving the detection performances. It have a poor rate of convergence in the iterative process and is prone to local optimum in high-dimensional space.

Sinha *et al* (2023) [18] have proposed a Light Gradient Boosting Machine (Light GBM) with Sequential Backward Selection (SBS) based Whale Optimization (WO) is a metaheuristic technique used to detect thyroid disease with high performance. Low accuracy in complex issues, especially when working with high-dimensional search spaces.

El-Hassani *et al* (2024) [19] have proposed a back-propagation (BP) and genetic algorithms (GA) to identify and classify thyroid illnesses effectually and competently. The MLP-GA/BP model is reliable enough to accurately and efficiently identify and classify thyroid conditions. Slow convergence and local minima susceptibility are two drawbacks of conventional back-propagation neural networks.

Gupta *et al* (2020) [20] have proposed a Modified Ant Lion Optimization system (MALO) designed for refining the diagnostic accuracy of thyroid illness. The MALO is used as a feature selection approach to find the maximum important set of aspects after a big pool of accessible aspects, improving classification accuracy and decrease the computing time. Modified Ant Lion Optimization algorithms have limitation that is stuck in local optima

The contributions of the work are as follows:

- Data cleaning is utilized to effectively replace missing values from input data and data transformation is used to convert raw data to its structure from the input thyroid data by enhancing data quality for diagnosis.
- Recursive Feature Estimation is used to identifying its most important features and eliminating others for thyroid disease diagnosis.
- The proposed work utilizes Grey wolf optimized DNN classifier for effective classification of thyroid disease diagnosis.

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3 Proposed method

The proposed block diagram in figure 2 for thyroid disease diagnosis using machine learning technique is applied to thyroid datasets. The data are collected as a raw data which includes male and female data. At first the input data is processed using the data pre-processing stage that includes replacing missing values and raw data is converted to structure for analysis using data cleaning and data transformation technique. Then the processed data is given as the input to recursive feature elimination here it identifies the important feature and eliminate the others to extract the thyroid disease.

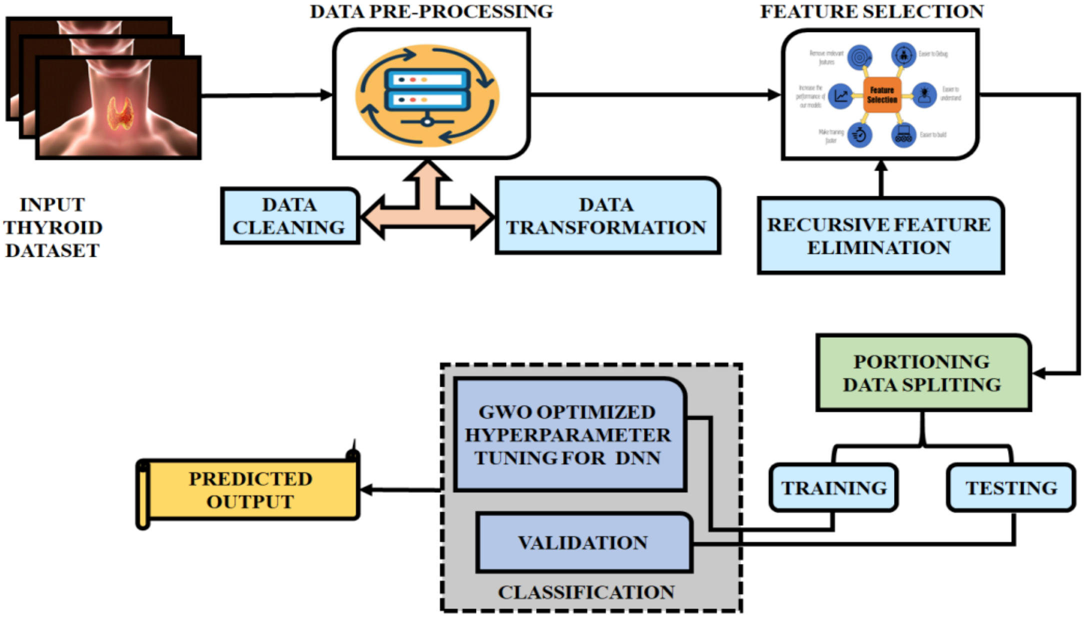

Figure 2: *Block diagram for proposed method*

At last model training is optimized using the featured data. To evaluate the model's accuracy and generalizability the dataset is partition split into training and testing data. In classification stage, a GWO-DNN is utilized to increase the accuracy and efficiency. To improve model accuracy, faster convergence, and reliable predictions of thyroid disease the optimization technique is used.

3.1 Data pre-processing for TDD

In the thyroid disease diagnosis the data pre-processing have two technique data cleaning and data transformation.

3.1.1 Data Cleaning for TDD

Data cleaning methods include removing unnecessary columns, replacing missing values, and converting categorical variables to numeric. Cleaning up the dataset is the primary objective in order to standardize data analysis and make it easier to locate the right data for a query.

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Duplicate data observation occurs during dataset collection. Because of the inconsistent data, the dataset is skewed, making it difficult for the machine learning algorithms to produce reliable predictions.

3.1.2 Data Transformation for TDD

The process of transforming raw data into structure for analysis in order to enhance its quality is known as data transformation. Data transformations have the impact of outliers using a variety of data transformation techniques, such as log transformation, here the impact of a very large outlier value and a square root transformation, which works well with positively skewed data and is somewhat slighter than log transformation. Following to this the pre-processed data is given to the feature selection.

3.2 Feature Selection for TDD

For thyroid disease diagnosis the feature is extracted using Recursive Feature Elimination technique.

3.2.1 Recursive Feature Elimination (RFE)

The RFE methodology is a common way to choose relevant attributes. It is a method for making a model simpler by identifying its most important features and eliminating others that aren't as important. The original set of features is used to train the estimating model, and then an arbitrary attribute is used to determine the significance of each outcome in figure 3. The least significant characteristics are then removed from the current set of attributes. Subsequently, the process is carried out recursively on the reduced crew until the target number of features is reached. Algorithm for recursive feature elimination in table 1.

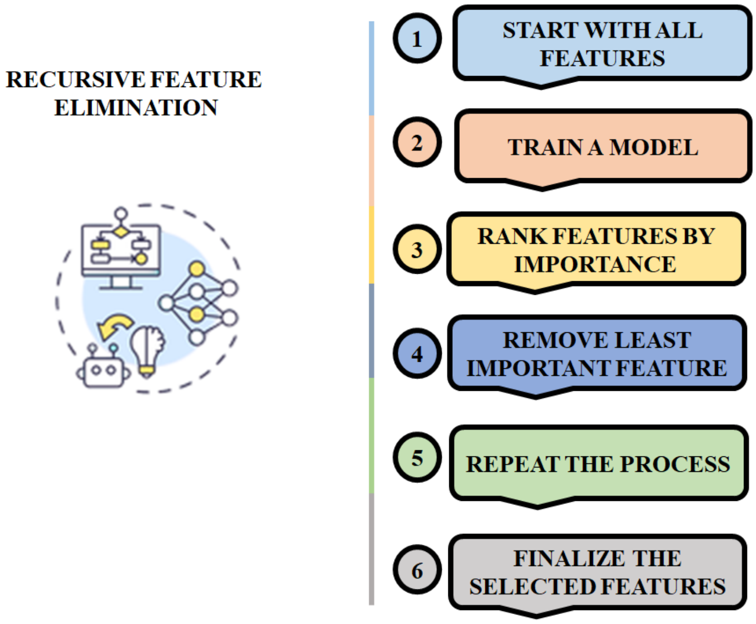

Figure 3: *Steps in recursive feature elimination*

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Table 1: *Algorithm for Recursive Feature Elimination*

Algorithm for Recursive Feature Elimination
Apply the predictors to the training set to train the model
Determine the simulation's performance.
Determine the rankings or relevance of the variables
for every subset size S_i, where, i=1,…..S do
Keep the S_i most important variables
Train the model on the training set using S_i predictors
Calculate model performance
Recalculate the ranking of each predictor
end
Calculate the performance profile over the S_i
Determine the appropriate number of predictors
Use the model corresponding to the optimal S_i

3.3 Data splitting for TDD

Data splitting involves dividing the thyroid disease dataset into training and testing sets. The ML algorithm is trained on the training set, and the model's performance is assessed on the testing set. However, the thyroid disease data is splitted as 80 trained and 20 testing samples. Next by data splitting the thyroid disease data is given to the proposed GWO optimized DNN technique.

3.4 Classification by GWO based DNN for TDD

In this proposed work Deep Learning method called GWO optimization based hyper parameter tuning with DNN is utilized for effective diagnosis for thyroid disease. A deep neural network is trained and grey wolf optimization is a swarm intelligence system data is utilized as hunting behavior of grey wolves.

3.4.1 Deep Neural network

The deep neural networks consist of a convolutional layer (Conv) which is made up of each of the four residual blocks have two convolutional in figure 4. Each convolutional layer's output is input into a Rectified Linear activation Unit (ReLU) afterward being rescaled using Batch Normalization (BN). Following the nonlinearity, Dropout50 is applied. DNN initial by 4096 models besides 64 filters for the residual block and first layer, the convolutional layers have filter lengths of 16. The amount of filters increases through 64 for all second in residual block, and each residual block is subsampled by a factor of 4.

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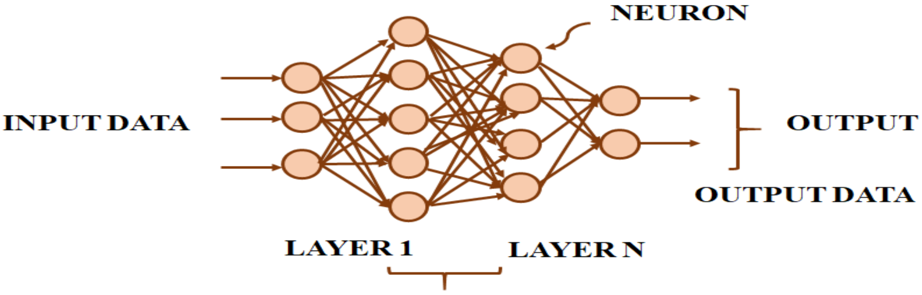

Figure 4: *Deep Neural Network*

3.4.2 Hyper parameter tuning

Tuning the amount of neurons in every hidden layer is the main priority even though exploring neural network hyper parameter optimization. Although alteration is available, in all layers currently it share the same amount of neurons. Each layer have a parameter called an activation function. To achieve the minimal loss function, the optimizer must adjust the neural network's learning rate and neuron weights. However to get the best accuracy or the least amount of loss, an optimizer is important.

3.4.3 Grey wolf optimization

The GWO based hyper parameter tuning with DNN is optimized to get better classification. One type of swarm intelligence is Grey Wolf Optimization (GWO) system that chooses pertinent features from data by utilizing the social hierarchy and hunting behavior of grey wolves. Because they alive in packages and are at the top of the food chain, grey wolves are regarded as the largest predators. Five to twelve wolves make up the group. These are separated into four groups. Alpha is the first group, which is made up of a male and female couple who make all of the decisions. The fact that they take for the benefit of the herd rather than for individuals is a plus. Wolves at the beta level are subservient to alpha and assist in making decisions on other pack activities. In the event that one of the alpha pairs lives, these are the most suitable options for the alpha wind pipe.
Although it commands the other levels, this one respects the alpha. The final category, known as omega, falls under each of the abovementioned groups. They appear in the least significant group, but in addition to meeting the group's needs, they also uphold the hierarchy of dominance from the other groups, frequently acting as the group's children's guardians. A category above omega is delta, which is the other group. It serves a number of purposes, including keeping an eye on the territory's boundaries, ensuring the group's safety, and advising the hunter and alpha. Hunting is the initial action, and it is modeled as follows:

$$X(t+1) = X(t) - A.D \tag{1}$$

Where A is a coefficient, X(t+1) is the wolves' location, X(t) is their current position, and is a vector that is determined by the press's position X(p) and is computed as follows:

$$D = \left|C.X_p(t) - X(t)\right| ku\ C = 2.r_2 \tag{2}$$

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Where the random vector r_2 falls between 0 and 1 and the wolves must adjust their positions in the following ways in order to obtain the local optimum:

$$X(t+1) = \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \tag{3}$$

Where X1, X2, and X3 are determined in this way:

$$X_1 = X_\alpha(t) - A_1.D_\alpha \tag{4}$$

$$X_2 = X_\beta(t) - A_2.D_\beta \tag{5}$$

$$X_3 = X_\gamma(t) - A_3.D_\gamma \tag{6}$$

The Pseudo code of grey wolf optimization algorithm is in table 2 to calculate the calculation technique.

Table 2: *Pseudo code of grey wolf optimization algorithm*

Pseudo code of grey wolf optimization algorithm
Input: Size of the population and the problem
Output: Pg _ best
Start
Grey wolf population Xi initialization (i=1, 2… n)
Setting up a, A, and C initially
Determining search agents fitness values and assigning them a grade
(In the search agent, $X\alpha$ the best solution, $X\beta$ the second best solution and $X\gamma$ the third best solution)
t=0
While (t < Maximum number of iterations)
For every search agent
Modernizing the current search agent's location using an calculation
End for
Informing of A, C and a
Determining and grading each search agent's fitness values
Updating the positions of $X\alpha, X\beta, and\ X\delta$
t=t+1
End while
End

4 Result and discussion

A medical technique called thyroid is used to look at the necks structures, namely the thyroid disease. Dataset is taken from kaggle.com for disease diagnosis. Deep learning models are then applied to train thyroid data.

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4.1 Dataset Collection

The proposed model is analysed on thyroid data consisting of age and gender distribution. The dataset is distributed as 80% for training and 20% for testing.

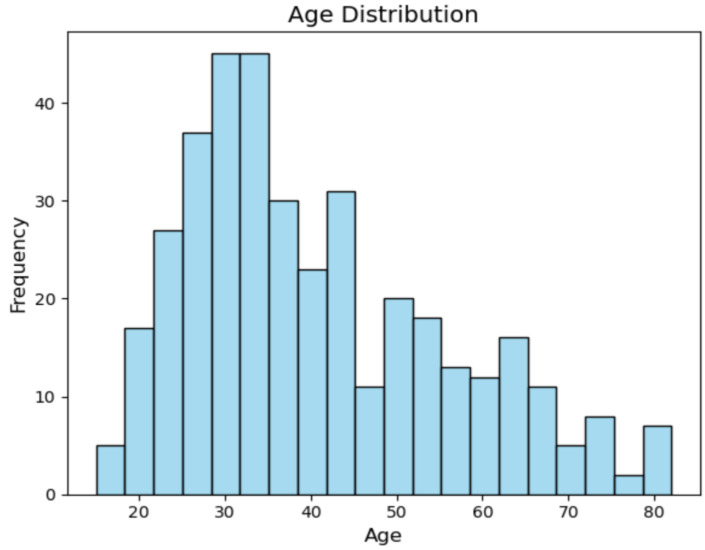

Figure 5: *Age distribution for TDD*

The figure 5 shows the age distribution of thyroid dataset. Here the age distribution is from newborn to 80 years. Thyroid is very high in the age of 30 with 45 Hz and then in the age of 45 also the frequency is high.

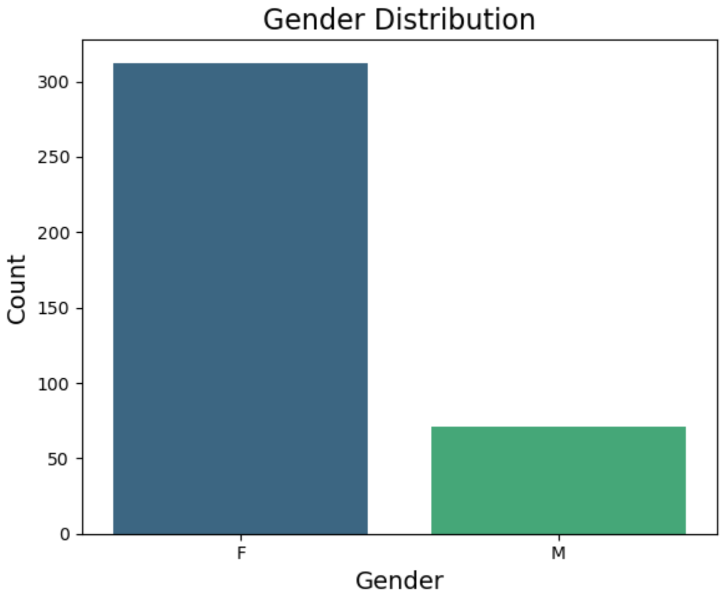

Figure 6: *Gender distribution of TDD*

In the figure 6 gender distribution of thyroid disease is plotted. Gender distribution is plotted for both male and female with counts, here the total number of counts is 0 to 400.

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Furthermore, 55 counts of male affected by thyroid and 320 counts of female affected by thyroid. Moreover female counts is higher than the male count were affected by thyroid.

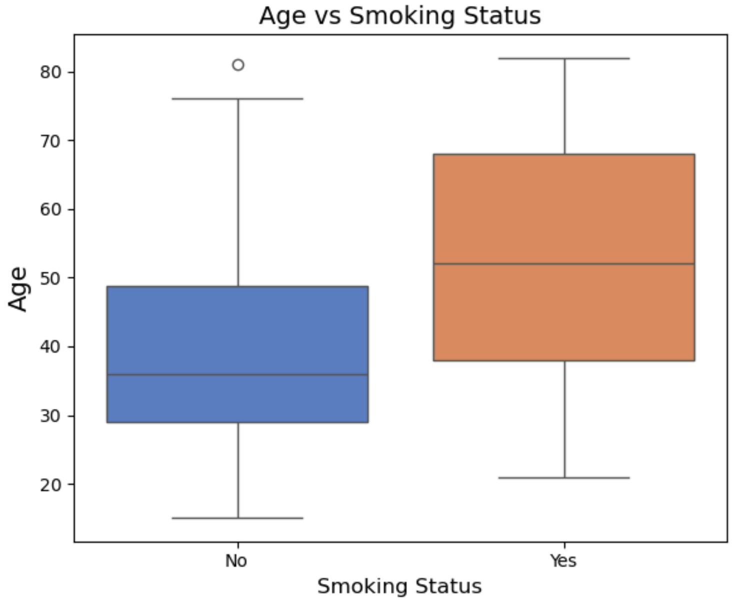

Figure 7: *Age vs Smoking status for thyroid disease*

Age vs smoking status for thyroid disease is plotted in figure 7. Here, the thyroid disease diagnosis for age between 20 to 80 and smoking status is yes and no is plotted. There is no smoking status in between age of 30 to 50 and there is a smoking status in the age 40 to 65 years for both male and females.

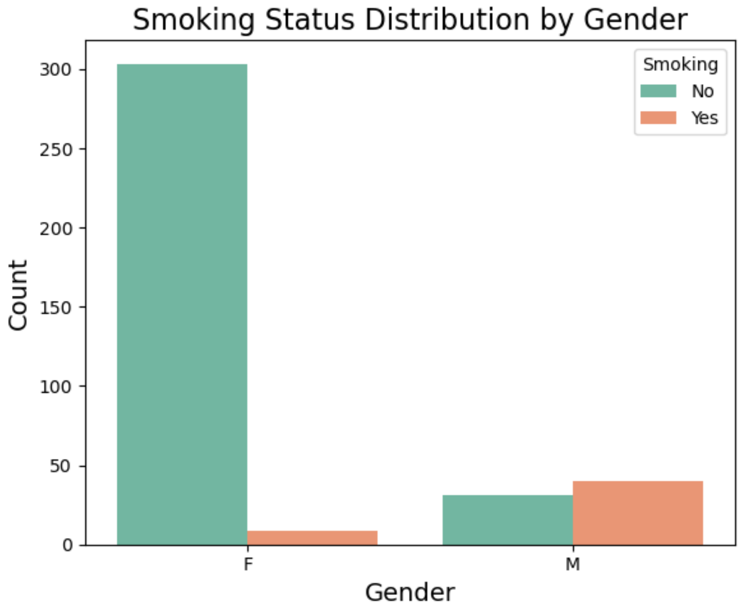

Figure 8: *Smoking status distribution by gender*

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In figure 8 smoking status distribution by gender for thyroid disease is plotted. The gender calculation for both male and female for smoking status with count is 1 to 300. For female there are no smoking counts and there is a smoking status with 10 counts. Moreover for male there is a smoking up to 50 counts and there is no smoking up to 40 counts.

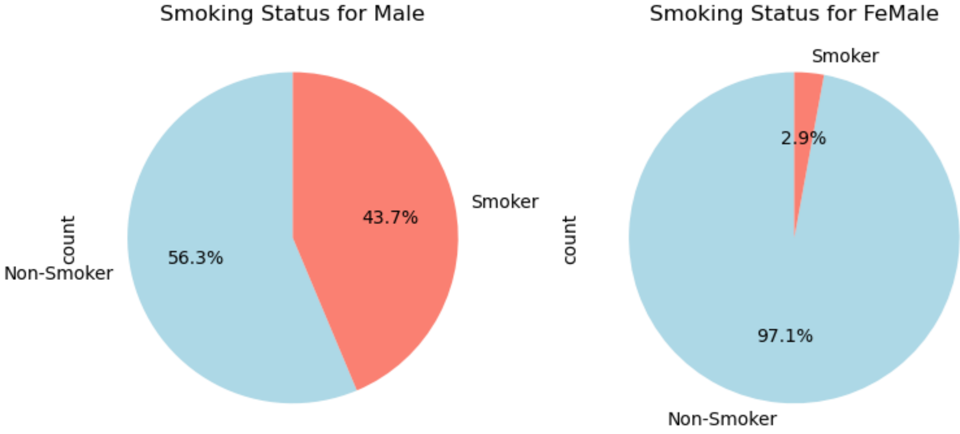

Figure 9: *Smoking status for male and female*

Thyroid disease smoking status for male and female is plotted in figure 9. Here there is a smoker and non-smoker in males and females for thyroid disease, the non-smoker count for male is 56.3% and smoker count is 43.7%. Whereas, thyroid disease for female the smoker count is 2.9% and non-smoker count is 97.1% respectively.

4.2 Performance metrics

Using various performance metrics the suggested method GWO based hyper tuning with DNN framework to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

4.2.1 Accuracy

$$\text{Accuracy} = \frac{(\text{TN+TP})}{\text{TS}} \tag{7}$$

4.2.2 Precision

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP+FP})} \tag{8}$$

4.2.3 Recall

$$\text{recall} = \frac{(\text{TP})}{(\text{TP+FN})} \tag{9}$$

4.2.4 F1 score

$$\text{F1} - \text{score} = \frac{(2*\text{Prec}*\text{Recal})}{(\text{Precision} + \text{Recal})} \tag{10}$$

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At last, the performance across classification thresholds is estimated using the AUC, which describes the correlation between the true positive and false positive rates for thyroid disease diagnosis.

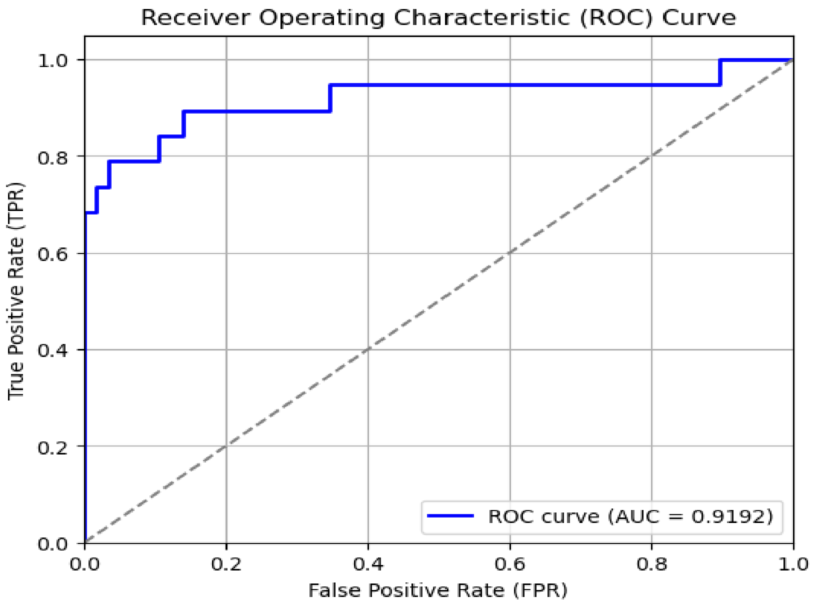

Figure 10: *ROC curve for thyroid disease*

According to the AUC results shown in Figure 10, the thyroid dataset for the proposed GWO-DNN, have the highest AUC value of 0.91, demonstrating the exceptional overview and flexibility of this approach.

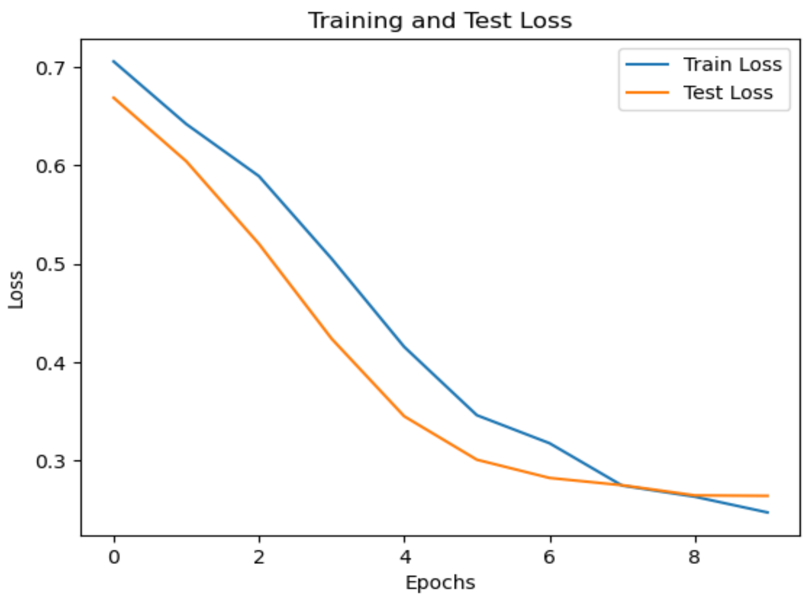

Figure 11: *Training and test loss*

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In figure 11 training and test loss for thyroid disease is calculated. Here the loss value is plotted from 0.1 to 0.72 and Epochs is up to 9. The training loss and test loss have distortion in epochs 7.

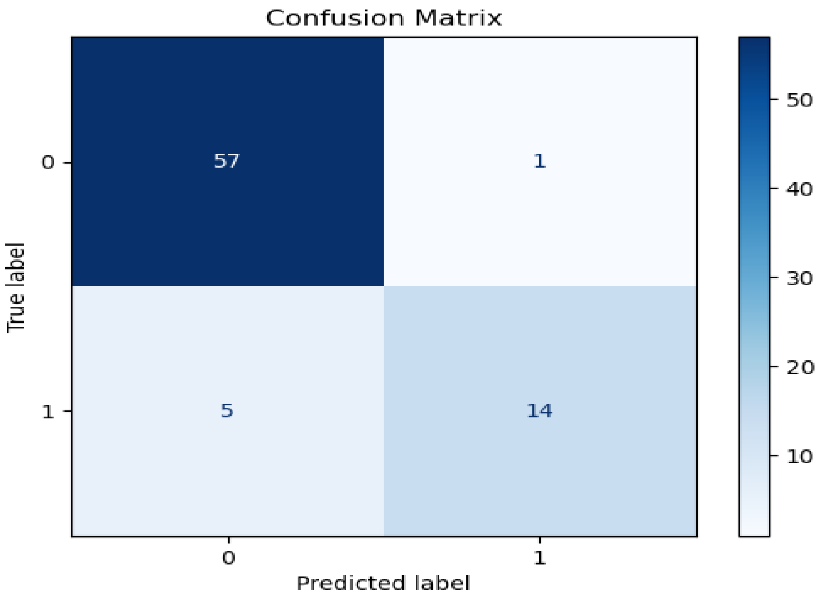

Figure 12: *Confusion matrix for proposed GWO-DNN*

Figure 12 illustrates the confusion matrix for GWO-DNN. This matrix shows the values for true and predicted labels. Confusion matrices are commonly used to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. Here the thyroid diseases by age, gender are matrixes.

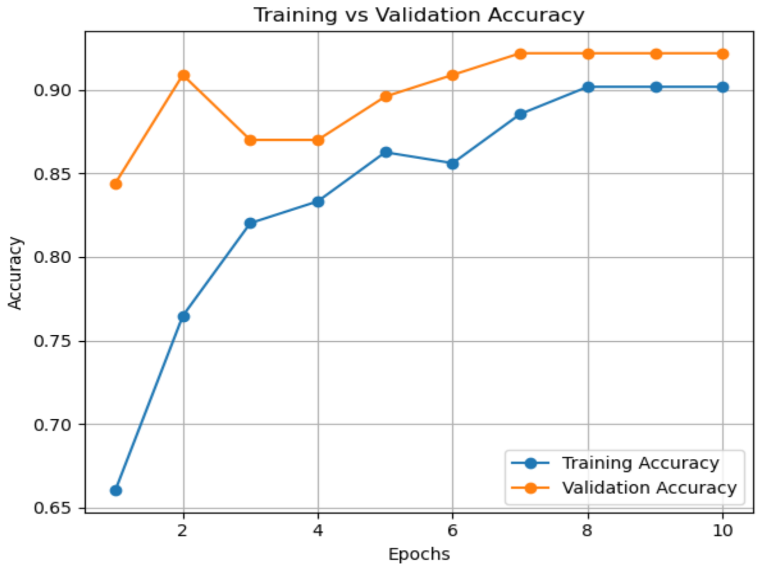

Figure 13: *Training vs validation accuracy for TDD*

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In figure 13 training vs validation accuracy for TDD is calculated. Model accuracy is the ratio of a model's accurate predictions to its total number of predictions. Here the accuracy is calculated using epoch's values. The accuracy for the proposed GWO-DNN method is 92%.

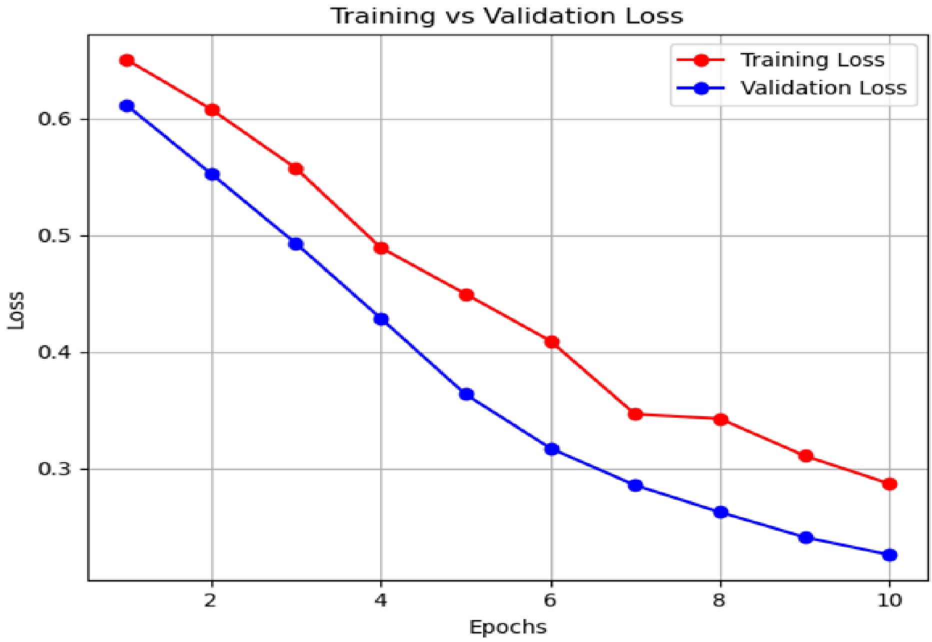

Figure 14: *Training vs validation loss for TDD*

Training vs validation loss for thyroid disease diagnosis is calculated in figure 14. Training loss is the error computed on the dataset from which the model is actively learning; here training loss is from 1 to 10 epochs. Whereas, validation loss is the lower than the training loss.

4.3 Comparison for the proposed method

Using the several other studies [15, 21] depend on baseline data, ignoring the training data's time series component. These studies did not sufficiently explain their findings and lacked training data for thyroid disease analysis.

Table 3: *Comparison for the proposed method*

Study	Method	Accuracy
Aversano *et al.*[21]	Extra -tree	82%
Abdolali *et al*. [15]	Mask R-CNN	84%
Proposed approach	GWO based hyper parameter tuning with DNN	92%

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4.4 Comparisons for precision and recall

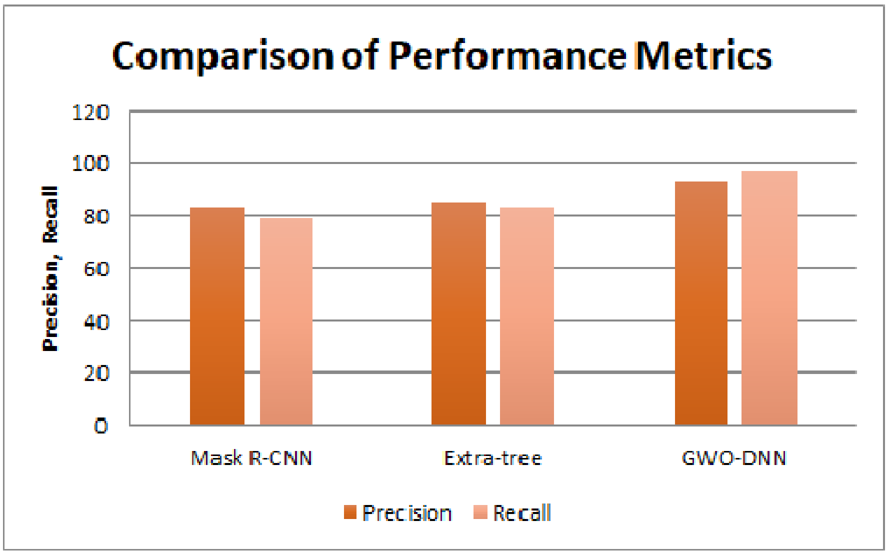

Figure 15: *Comparisons of performance metrics for thyroid disease*

For Precision and recall it gives better predicted value when compared to the Extra-tree [21] and Mask R-CNN [15]. Precision value of 93% and recall of 97% for the proposed GWO based hyper parameter tuning with DNN method predicted successfully in above figure 15.

5 Conclusion

Thyroid disease identification have become a significant medical issue with an alarming rise in recent years, necessitating effective prediction algorithms. A GWO-DNN model is proposed in this work for classification of thyroid, achieving a high accuracy of 92% using Python software. The data pre-processing stage effectively enhances image quality by replaced missing values and converted raw data to it's structured through data cleaning and data transformation. Furthermore, Recursive feature elimination based feature extraction recognised the important feature and eliminated the others for thyroid disease diagnosis. The proposed GWO-CNN classifier demonstrates performance with state-of-the-art methods demonstrates its superiority.

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