Deep Learning-Based Approach for Thyroid Dysfunction Prediction

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Abstract – *Globally, thyroid dysfunction is a major health concern caused due to irregular hormone production by the thyroid gland. Millions of populations are getting affected by this disease regularly. Accurate diagnosis of thyroid dysfunction is crucial for effective treatment and management of the disease, but this is challenging given the condition's complex and varied symptoms. In this paper, a deep learning-based neural network algorithm for generating predictions is constructed based on a dataset of approximately 3772 patient records with 28 features. The Artificial Neural Network (ANN) model was trained and evaluated using standard machine learning techniques and achieved high-level accuracy (98.8%) in identifying instances of thyroid dysfunction. The findings demonstrate that the proposed ANN model can be a reliable and effective tool for early diagnosis of thyroid dysfunction. The suggested model has several advantages, including its ability to handle a large number of input parameters and its ability to learn intricate relationships between input and output variables. However, further research is required to assess if the suggested approach can apply to more extensive and diverse patient populations. Overall, the results of this study lay out the potential of machine learning and ANN models in the diagnosis of thyroid dysfunction and may aid in creating more precise and effective diagnostic equipment for this prevalent endocrine illness.*

Key Words: **Thyroid Dysfunction, Deep Learning, Neural Network, Artificial Neural Network, Machine Learning, accuracy, endocrine illness.**

1.INTRODUCTION

The thyroid gland is a tiny, butterfly-shaped organ situated in the front of the neck, surrounding the windpipe. Our body contains glands, which produce and release compounds that help the body to perform a specific function. The thyroid gland produces hormones, namely levothyroxine(T4) and triiodothyronine(T3), which assist in regulating metabolism, heart rate, body temperature, and other essential processes. When the thyroid gland is overactive or inactive, it can lead to various health problems.

Thyroid dysfunction is a widespread endocrine disorder affecting millions worldwide, irrespective of age, gender, and ethnicity. It occurs when the thyroid gland either produces excess or insufficient hormones, which can result in several health issues. Hypothyroidism, characterized by low thyroid hormone levels, and hyperthyroidism, characterized by high thyroid hormone levels, are the most common thyroid disorders. It can affect bodily functions like energy production, weight management, and mood regulation.

Symptoms of thyroid dysfunction can vary widely and include fatigue, weight gain, depression, and anxiety. Early detection and treatment of thyroid disorders are essential for managing the condition and avoiding severe complications. Diagnosing thyroid dysfunction requires a combination of clinical evaluation, biochemical tests, and imaging techniques. However, traditional diagnostic methods are time-consuming, expensive, and require specialized tools and expertise. Therefore, there is a need for a methodical and accurate approach to the identification of thyroid disorder.

Deep Learning-based model architecture has emerged as a convincing technique for improving the efficiency of thyroid dysfunction prediction. This paper presents a Deep Learning Artificial Neural Network (ANN) model for making a prediction using clinical and biochemical parameters.

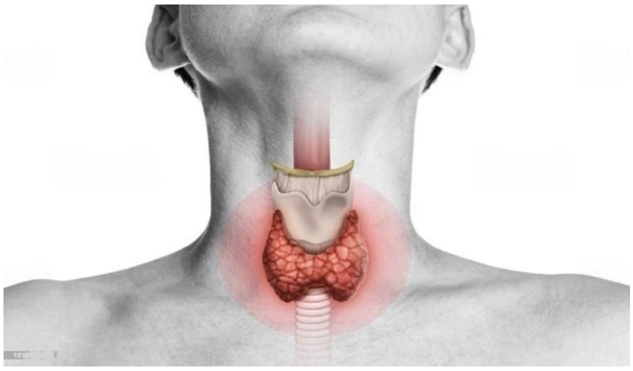

Fig -1: Thyroid gland

1.1 Deep Learning

Deep Learning lies within the strata of machine learning (ML) and artificial intelligence (AI). Its methodology is influenced by the human brain's structure and function. It involves training artificial neural networks, which are complex mathematical models that can learn to recognize patterns in data.

Deep Learning has risen in prominence in recent years, owing to the abundance of extensive amounts of data and powerful computing resources. It has enabled significant advances in several fields like natural language processing, computer vison, speech recognition, and medical science.

One of the critical strengths of deep learning is its ability to extract features from raw data automatically. This means that it can solve problems where traditional machine learning approaches require hand-crafted features or domain-specific knowledge.

Deep learning models generally feature layers of interconnected nodes, or neurons, that perform a simple mathematical operation on inputs. The output of one layer is fed into the next, and each layer learns to recognize more complex data features. Model training involves adjusting the weights of the connections between the neurons with an objective to minimize a cost function, which evaluates the difference between the predicted values and actual values. This is often achieved using an algorithm called stochastic gradient descent, which iteratively updates the weights based on the gradient of the cost function concerning the weights.

1.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are deep learning-based models designed to emulate the structure and function of biological neurons in the brain. ANNs are constructed up of layers of interconnected nodes, including an input layer, one or more hidden layers, and an output layer. They are utilized for analysing data patterns and making predictions based on information.

Each neuron in an ANN receives inputs from neurons in the preceding layer, which are merged and processed with the help of an activation function to generate an output. During training, the weights of the connections between neurons are altered to minimize the cost.

There are numerous types of ANNs, each having its own set of advantages and disadvantages. Feedforward neural networks are the simplest type, with layers that process unidirectional flow of information from the input to the output layer. Recurrent Neural Networks (RNN) are suitable for tasks involving data sequences due to their cyclic connections, allowing information to flow in cycles. Convolutional Neural Networks (CNN) are specialized for processing images and consist of layers that apply a series of convolutional filters to the input image, allowing the network to learn to recognize patterns at different scales.

Regardless of their success, ANNs have some limitations, like the requirement for substantial amounts of training data and the complexity of interpreting the inner workings of the models. However, they continue to be an active area of research and development and are likely to play a pivotal role in the future of artificial intelligence.

2. LITERATURE REVIEW

[1] This study utilizes a range of classification models to diagnose thyroid disorders based on parameters including TSH (Thyroid Stimulating Hormone), T4U, and goitre. Various classification techniques, including K-nearest neighbor (KNN), were employed to support the study's findings. Naïve Bayes and Support Vector Machine algorithms are also implemented. The test was carried out with the help of a Rapid Miner instrument. The results revealed that the KNN was more accurate than Naïve-Bayes in detecting thyroid disorder, with a 93.44% accuracy. The suggested KNN technique enhanced classification accuracy and contributed to better results. KNN exhibited superior performance compared to other methods, since the factors were independent of each other.

[2] In this research paper, the authors developed a machine learning algorithm to predict the most effective treatment for thyroid disease based on patient characteristics and medical history The data was collected from 282 patients with thyroid illness and performance was evaluated using multiple ML algorithms. The findings indicated that the Random Forest algorithm performed the best, getting an accuracy of 77.83% in predicting the most effective treatment. The authors noticed that the model could support clinical decision-making in treating thyroid disease, potentially improving patient outcomes.

[3] In this study, the authors proposed an ensemble method for classifying thyroid disease that involves optimization of features. They obtained data from patients diagnosed with thyroid disease and extracted a set of parameters related to the disease. They then used an ensemble classifier that combined several machine learning methods to predict the type of thyroid disease based on extracted features. The results showed that the proposed ensemble approach outperformed individual machine learning algorithms regarding accuracy. The study demonstrates the potential of an ensemble approach for enhancing the efficiency of thyroid disease classification.

[4] The authors of this research constructed a deep-learning model for predicting thyroid disorders by incorporating clinical data from over 20,000 Indian patients. The model was based on a CNN architecture and achieved an accuracy of 92.6% and a specificity of 96.3% in predicting hypothyroidism and an accuracy of 91.5%, and a specificity of 95% in predicting hyperthyroidism. The study highlights the potential of deep learning models for diagnosing and managing thyroid disease in India.

[5] This paper proposes an ANN model for the automated prediction of thyroid disease. The authors collected thyroid samples and trained an ANN model using an 80:20 ratio split of data for training and testing. The model achieved an average accuracy of 85% during training and 82% during testing. The study concludes that ANNs are a flexible and robust technique for thyroid disease diagnosis, with high reliability in different sampling situations.

3. METHODOLOGY

The proposed ANN-based approach consists of 4 stages: data collection, data preprocessing, model training, and model evaluation. This section lays out an overview of various steps involved in the prediction process. The figure below gives a representation of the workflow involved.

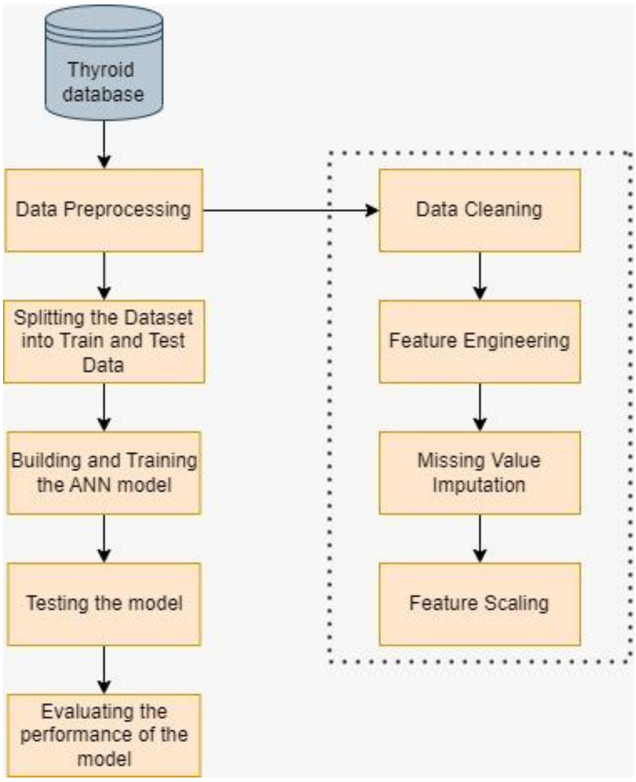

Fig -2: Workflow diagram

(I) *Data collection*

To conduct this research, a dataset comprising clinical and biochemical parameters of patients with and without thyroid disease was obtained from the UCI Machine Learning Repository. The dataset consists of 3772 instances, each containing 28 attributes, including age, sex, thyroxine and antithyroid medication details, thyroid surgery, pregnancy, sickness, hyperthyroid and hypothyroid queries, tumor and psych information, TSH, T3, and T4 levels, and various other chemical and biochemical parameters that are commonly used in diagnosing thyroid dysfunction. Table-1 and Table-2 show the numerical and categorical attributes respectively.

Table-1: Numerical Attributes

S.No.	Attribute Name	Data Type
1	age	object
2.	TSH	object
3.	T3	object
4.	TT4	object
5.	T4U	object
6.	FTI	object

Table-2: Categorical Attributes

.No.	Attribute Name	label
1	sex	F = female, M= male
2.	on thyroxine	f= false, t =true
3.	query on thyroxine	f= false, t =true
4.	On antithyroid medication	f= false, t =true
5.	sick	f= false, t =true
6.	pregnant	f= false, t =true
7.	thyroid surgery	f= false, t =true
8.	I131 treatment	f= false, t =true
9.	query hypothyroid	f= false, t =true
10.	query hyperthyroid	f= false, t =true
11.	lithium	f= false, t =true
12.	goitre	f= false, t =true
13.	tumor	f= false, t =true
14.	hypopituitary	f= false, t =true
15.	psych	f= false, t =true
16.	TSH measured	f= false, t =true
17.	T3 measured	f= false, t =true
18.	TT4 measured	f= false, t =true
19.	FTI measured	f= false, t =true
20.	TBG measured	f= false, t =true
21.	referral source	other, SVHC, SVI
22.	Binary Class	P = positive, N= negative

(II) *Data Preprocessing*

Data preprocessing is a crucial stage in any machine learning project. The following steps are performed in this stage:

- Data Cleaning: The 'binaryClass' column in the dataset is converted to numerical values, 't' and 'f' values are replaced with 1 and 0, respectively, and '?' values are replaced with NaN.

- Feature Engineering: The 'sex' column is converted to numerical values, and the 'referral source' column is dropped from the dataset.

- Handling missing values: The missing values are imputed with the mean value of the respective column.

- Splitting the dataset: The dataset is divided into training and testing sets with the 'train_test_split()' function from sklearn.

- Feature scaling: The training and testing sets are scaled using the 'StandardScaler()' function to ensure all the features are on the same scale.

(III) *Model Building*

The proposed research involves the creation of a deep learning model based on ANN architecture to predict thyroid disease. The model is implemented using the Tensorflow Keras API. The model's architecture comprises a sequence of four densely connected layers, where each neuron is linked to every neuron in the next layer. The input layer has 256 neurons, which is equal to the number of features in the input dataset and uses the Rectified Linear Unit (ReLU) activation function.

The dropout layer is then added after the first, second, and third hidden layers, respectively, with 0.4, 0.3, and 0.2 dropout rates. Dropout is, basically, a regularization technique used in deep learning models to prevent overfitting. It randomly drops out some of the neurons in the hidden layer during training, which reduces the co-dependence between neurons and improves generalization.

The second hidden layer has 128 neurons, and the third hidden layer has 63 neurons, both activated using the ReLU activation function. The final output layer has only one neuron, which produces the probability output of the binary classification problem (0 or 1) using the sigmoid activation function. Figure 2 visualizes the developed ANN model architecture.

Next, the model is compiled using binary cross-entropy loss and the Adam optimizer.

ReduceLROnPlateau, ModelCheckpoint, and EarlyStopping are the callback functions used to monitor the training process, adjust the learning rate, save the best model, and stop the training if the accuracy becomes stable for a given number of epochs.

The model is then fit using the 'fit()' method with the training data, for 80 epochs, a batch size of 48, and a validation split of 0.1.

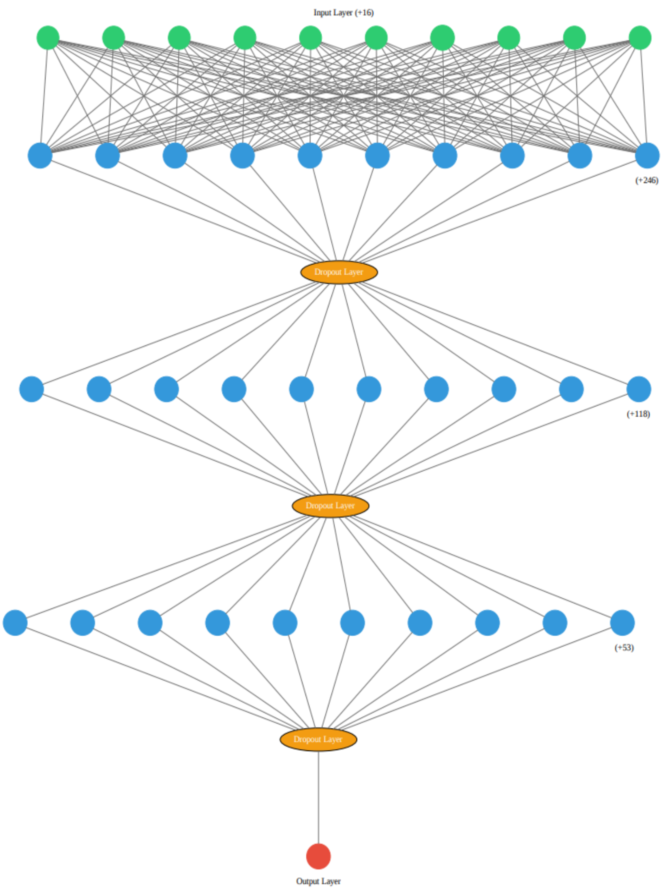

Fig -3: Proposed ANN model architecture

(IV) *Model Evaluation*

The trained model is evaluated using the test dataset that has not been used in the training process. The predictions are compared to the true labels using a confusion matrix, which is a valuable tool for evaluating the performance of a binary classification model. It is a table that shows the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) predictions of the model. From the confusion matrix, various performance metrics like accuracy, precision, recall, and F1 score are also calculated.

The accuracy metric measures the proportion of accurate predictions made by the model and it can be described as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Sometimes, accuracy can be misleading when the dataset is uneven, indicating that one class is substantially more prevalent than the other. In such instances, additional metrics such as precision, recall, and F1-score are more informative. The precision metric measures the percentage of true positives among the predicted positives and is a good indication of the model's ability to prevent false positives. The recall metric determines the proportion of true positives among the real positives and is a good measure of the model's capacity to detect all positive cases. The F1 score metric combines precision and recall to measure the accuracy of a binary classification model. It is the harmonic mean of precision and recall. The formulas for calculating precision, recall, and F1 score are defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Overall, evaluating a trained model using a test dataset and various performance metrics measures how well the model performs on unseen data and its ability to predict positive and negative cases correctly.

4. RESULTS & DISCUSSION

Based on the evaluation metrics, the trained ANN model effectively recognized thyroid dysfunction. The confusion matrix indicated that the model predicted 691 true positive (TP) cases and 55 true negative (TN) cases, with only 3 false positive (FP) and 6 false negative (FN) predictions. The overall accuracy score was 0.9888, the precision score was 0.992, the recall score was 0.992, and the F1 score was 0.970. The curve depicted in Figure 4 depicts how the model's accuracy on both the training and test datasets evolves throughout multiple epochs and rises over time as the model learns to match the data better. In summary, the proposed ANN model demonstrated high accuracy and balanced performance in identifying thyroid dysfunction. The strong performance on the test dataset implies that the model is not overfitting to the training set. These results suggest that the model can potentially assist in diagnosing thyroid dysfunction. Nevertheless, some limitations to this study should be considered, like the fact that the dataset was not diverse enough or that there were potential biases in the dataset that may have influenced the performance. Additionally, the model was trained and tested using medical record data, and its performance can be improved by incorporating other clinical information, such as patient history and imaging results.

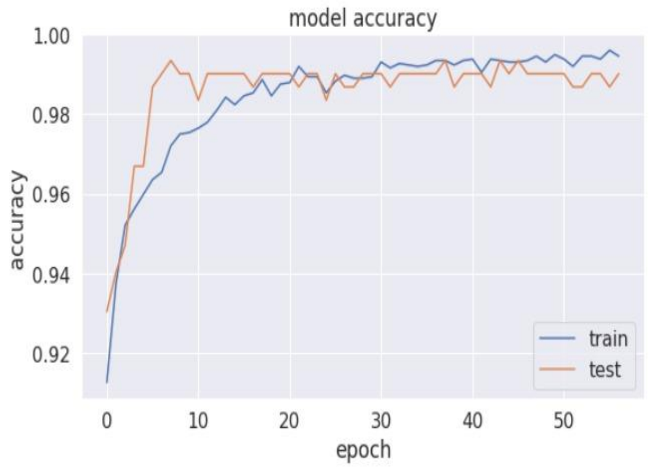

Fig -4: ANN model accuracy

5. CONCLUSION & FUTURE SCOPE

In conclusion, the developed deep learning model exhibited high accuracy and specificity, which indicates its potential usefulness in clinical practice. The model outperformed traditional machine learning algorithms, emphasizing the potential of deep Learning based neural network models in thyroid dysfunction prediction. Future studies should concentrate on expanding the dataset, incorporating additional relevant features, and further validating the model's performance on diverse populations. Moreover, the model can be integrated into clinical decision support systems to help physicians in accurate thyroid diagnosis and management.

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