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A Deep Learning–Based Multi-Layer Recursive Neural Network Framework for Intelligent Thyroid Disease Detection and Recognition

Dr. A.Avinash[1], Kanchi Dhanusha[2],Saladi Rudra Naga Prasanna Lakshmi[3], Thiguti Sri Ajitesh[4], Kesanakurthi Satya Karthikeeyan[5], Vangapandu Lokesh[6]
[1]Associate Professor, [2, 3, 4, 5,6B.tech] Students Department of CSE,
Pragati Engineering College, Surampalem , Andhra Pradesh, India

Abstract- Thyroid disease is one of the most common endocrine disorders affecting millions of people worldwide. The thyroid gland plays a crucial role in regulating metabolism, growth, and overall body functions. Any imbalance in thyroid hormone production can lead to conditions such as hypothyroidism or hyperthyroidism. Early detection of thyroid disorders is important to prevent serious health complications and to ensure timely treatment. Traditional methods of diagnosing thyroid disease rely on laboratory tests and manual evaluation, which may be time-consuming and sometimes prone to errors. With the advancement of artificial intelligence, deep learning techniques can assist medical professionals in improving diagnostic accuracy and reducing workload. In this project, a deep learning-based Multi-Layer Recursive Neural Network (ML-RNN) is proposed for thyroid disease detection and classification. The system includes data preprocessing, feature selection using the Fisher Score method, and classification using the ML-RNN model. The dataset used for analysis is obtained from a standard repository and includes various thyroid-related attributes. The performance of the proposed model is evaluated using metrics such as accuracy, recall, precision, and error rate. Experimental results show that the ML-RNN model achieves better performance compared to traditional machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF). The proposed approach provides an effective and reliable method for thyroid disease detection.

Keywords – Thyroid Disease Detection, Deep Learning, Multi-Layer Recursive Neural Network (ML-RNN), Feature Selection, Fisher Score Method, Medical Data Classification, Hypothyroidism, Hyperthyroidism, Healthcare Analytics, Machine Learning in Healthcare, Disease Prediction, UCI Thyroid Dataset.

I. INTRODUCTION

Thyroid disease is one of the most common endocrine disorders affecting individuals across all age groups. The thyroid gland, located in the neck, plays a vital role in regulating body metabolism, heart rate, temperature, and energy balance. Abnormal thyroid hormone production may lead to conditions such as hyperthyroidism or hypothyroidism, which can significantly affect human health if not diagnosed at an early stage. In recent years, thyroid nodules and thyroid cancer have become major clinical concerns, requiring accurate diagnostic procedures for early detection and treatment. Advanced medical imaging techniques and intelligent diagnostic systems have therefore gained increasing attention in modern healthcare research [9], [11].

Traditionally, thyroid disease diagnosis relies on laboratory blood tests that measure hormone levels such as Triiodothyronine (T3), Thyroxine (T4), and Thyroid Stimulating Hormone (TSH). Physicians interpret these laboratory results together with clinical symptoms to determine the patient's thyroid condition. Although these conventional diagnostic approaches are reliable, manual analysis can be time-consuming and may become challenging when processing large volumes of medical data. Moreover, complex medical datasets may sometimes lead to delayed or inaccurate interpretations, particularly in cases involving subtle abnormalities or large-scale screening programs [10].

With the rapid development of **artificial intelligence (AI) and machine learning**, automated medical diagnosis systems have emerged as promising tools for improving disease detection and clinical decision-making. Machine learning algorithms are capable of analysing large datasets efficiently and identifying hidden patterns that may not be easily detected through traditional manual analysis. Recent studies have demonstrated that deep learning techniques can significantly enhance the accuracy of thyroid disease detection and classification by automatically extracting meaningful features from medical images and clinical datasets [1], [11].

In particular, deep learning models such as convolutional neural networks (CNNs) have been widely applied for thyroid nodule detection and classification using ultrasound images. For example, multitask cascade convolutional neural networks have been proposed for automatic thyroid nodule detection and recognition, achieving improved diagnostic performance compared with traditional image processing techniques [1].

Similarly, real-time detection and tracking of thyroid nodules in ultrasound videos have been developed using advanced deep learning frameworks such as CacheTrack-YOLO, demonstrating high efficiency in medical imaging analysis [2]. Feature fusion networks and hybrid deep learning models have also been proposed to improve classification accuracy by combining multiple feature representations extracted from ultrasound images [3].

Recent research has further explored advanced deep learning architectures for thyroid diagnosis. For instance, local and global feature disentangled networks have been developed to classify benign and malignant thyroid nodules from ultrasound images with improved discrimination capability [4]. In addition, GAN-guided attention networks have been introduced to enhance feature representation and improve nodule identification accuracy in ultrasound imaging [5]. Semantic segmentation methods based on recurrent fully convolutional networks have also been applied to automatically segment thyroid regions in ultrasound cinclids, enabling more precise medical image analysis [6].

Apart from imaging-based approaches, machine learning methods have also been used to analyse clinical and pathological data for thyroid disease prediction. Studies have shown that hybrid deep learning models combining deep neural networks with optimization techniques and recurrent neural networks can improve classification performance and provide more reliable thyroid disease detection systems [14]. Transfer learning and differential diagnosis techniques have also been explored to distinguish between benign and malignant thyroid nodules in ultrasound images, improving diagnostic reliability in clinical practice [12], [13].

Despite these advancements, traditional machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Decision Trees may not always achieve optimal performance when dealing with high-dimensional medical datasets. These models often require careful feature engineering and may struggle to capture complex nonlinear relationships present in medical data. Therefore, effective feature selection techniques and advanced deep learning architectures are essential to improve classification accuracy and reduce computational complexity.

In this project, a Multi-Layer Recursive Neural Network (ML-RNN) is proposed for accurate thyroid disease detection and classification. The proposed system includes data preprocessing, feature selection using the Fisher Score method, and classification using the ML-RNN model. The objective of the proposed framework is to enhance prediction accuracy while reducing classification errors compared with traditional machine learning approaches.

The performance of the proposed system is evaluated using standard evaluation metrics such as accuracy, precision, recall, and error rate. Experimental results demonstrate that the deep learning-based ML-RNN framework provides reliable and efficient thyroid disease prediction, which can assist healthcare professionals in early diagnosis and clinical decision-making.

The remainder of this report is organized as follows. Section II presents the literature survey on thyroid disease detection using machine learning and deep learning techniques. Section III discusses the system analysis including existing and proposed approaches. Section IV describes the system design and architecture. Section V explains the implementation modules. Section VI presents the experimental results and discussion. Finally, Section VII concludes the study and outlines future research directions.

II. LITERATURE SURVEY

In recent years, several researchers have applied machine learning and deep learning techniques to improve the early detection and classification of thyroid diseases. Accurate identification of thyroid conditions is essential because early diagnosis enables timely medical treatment and helps prevent severe complications associated with thyroid dysfunction. Various studies have explored intelligent diagnostic systems using medical datasets and ultrasound imaging to improve the reliability and efficiency of thyroid disease detection [1], [11].

Earlier research primarily focused on traditional machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Decision Trees, Naïve Bayes, and Random Forest classifiers for predicting thyroid disorders. These models were typically trained using structured clinical datasets that include hormone levels, laboratory test results, and patient medical information. Several studies demonstrated that machine learning approaches can provide reasonable classification accuracy for thyroid disease prediction; however, their performance often depends heavily on proper feature selection and parameter optimization [9], [11].

Feature selection plays a crucial role in improving the performance of thyroid disease detection systems. Researchers have employed statistical and feature ranking techniques to identify the most relevant attributes within medical datasets. Methods such as Information Gain, Chi-Square test, and Fisher Score are commonly used to reduce dimensionality and remove redundant features from large datasets. Effective feature selection helps improve model accuracy, reduces computational complexity, and enhances the generalization ability of predictive models [3], [12].

With the advancement of deep learning, neural network-based approaches have gained significant attention in medical diagnosis. Artificial Neural Networks (ANN) and Multi-Layer Perceptron (MLP) models have demonstrated improved performance compared with conventional machine learning algorithms due to their ability to capture complex nonlinear relationships among medical features. Deep learning models can automatically learn feature representations from raw data, reducing the need for extensive manual feature engineering. However, these models may suffer from overfitting when trained on limited datasets, which may affect their ability to generalize to unseen medical data [8], [11].

Recent studies have further explored advanced deep learning architectures for thyroid disease detection and classification. Convolutional neural networks have been successfully applied for automatic detection and recognition of thyroid nodules in ultrasound images, providing improved diagnostic accuracy compared with traditional image analysis techniques [1]. Real-time thyroid nodule detection and tracking systems using deep learning-based frameworks have also been proposed for ultrasound video analysis, demonstrating the effectiveness of AI in assisting clinical diagnosis [2]. In addition, feature fusion networks and hybrid deep learning models have been introduced to combine multiple feature representations and enhance classification performance in thyroid ultrasound images [3].

More sophisticated deep learning architectures have also been developed to improve thyroid disease diagnosis. For instance, networks that integrate local and global feature representations have been proposed for differentiating between benign and malignant thyroid nodules with higher accuracy [4]. Attention-based deep learning models and GAN-guided architectures have further improved feature extraction capability and classification reliability in ultrasound imaging analysis [5]. Furthermore, semantic segmentation techniques based on recurrent fully convolutional networks have been applied to segment thyroid regions in ultrasound cineclips, enabling more accurate identification of abnormal tissues [6].

Apart from imaging-based approaches, researchers have also investigated transfer learning and hybrid deep learning models for thyroid disease prediction. Online transfer learning techniques have been introduced to improve differential diagnosis of benign and malignant nodules using ultrasound images [12]. More recent research has explored hybrid models combining deep neural networks with optimization algorithms and recurrent neural networks to enhance prediction accuracy and improve robustness in thyroid disease classification systems [14].

Although previous research has achieved promising results, several challenges remain in thyroid disease detection systems. Issues such as high-dimensional medical data, class imbalance, model overfitting, and computational complexity continue to affect the performance of existing predictive models. These challenges highlight the need for more efficient deep learning frameworks that integrate effective feature selection techniques with optimized neural network architectures to improve diagnostic accuracy and reliability [13], [14].

Based on these observations, the proposed system introduces a Multi-Layer Recursive Neural Network (ML-RNN) combined with Fisher Score-based feature selection to enhance classification performance for thyroid disease detection. The integration of an optimized deep learning architecture with an effective feature selection method aims to improve prediction accuracy, reduce error rates, and provide a more reliable automated diagnostic tool for thyroid disease prediction.

III.SYSTEM ANALYSIS

Existing System

Existing thyroid disease detection systems mainly rely on traditional machine learning algorithms for classification and prediction of thyroid disorders. Researchers commonly evaluate thyroid datasets using conventional models such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Decision Trees, Naïve Bayes, Random Forest, and Artificial Neural Networks (ANN).

These models are trained using patient medical data that include hormone levels, laboratory test results, and other clinical attributes in order to classify whether a patient has a thyroid disorder or a normal thyroid condition. Several studies have demonstrated that machine learning models can effectively analyse medical datasets and assist in thyroid disease diagnosis; however, their performance often depends on the quality of feature representation and training data [9], [11].

In addition to traditional classification models, some researchers have introduced ensemble learning techniques that combine multiple classifiers to improve prediction accuracy and robustness. These hybrid approaches attempt to enhance system performance by integrating the strengths of different algorithms and reducing the limitations of individual classifiers. Ensemble-based frameworks and hybrid deep learning models have shown improved diagnostic capability in several thyroid disease detection systems, particularly when applied to complex medical datasets and ultrasound imaging data [3], [14].

Feature selection methods also play an important role in improving the performance of thyroid disease detection models. Many studies employ statistical feature selection techniques such as Information Gain, Chi-Square, and other ranking-based methods to identify the most relevant attributes from clinical datasets before training machine learning models. Effective feature selection helps reduce dataset dimensionality, eliminate redundant information, and improve classification performance while decreasing computational complexity [12], [3].
Although these existing approaches provide reasonable classification accuracy, several limitations still exist. Traditional machine learning models often struggle when handling complex or high-dimensional medical datasets, particularly when nonlinear relationships between features must be captured. Moreover, many of these systems depend heavily on manual feature engineering and careful parameter tuning, which can increase the complexity of model development and reduce scalability in real-world healthcare applications. Recent research has therefore focused on deep learning-based frameworks that can automatically learn hierarchical feature representations and improve diagnostic accuracy in thyroid disease detection systems [1], [4].

Disadvantages Of The Existing System

- **Interpretability**

Some advanced machine learning and neural network models are difficult to interpret. In medical applications, it is important to clearly understand how a model makes decisions to support clinical trust.

- **Overfitting and Underfitting**

Models may overfit the training data and fail to perform well on new patient data. On the other hand, underfitting may occur if the model fails to capture important patterns in medical attributes.

- **High Dimensional Data Issues**

Thyroid datasets may contain many features, some of which may be irrelevant or redundant. Without proper feature selection, classification performance may decrease.

- **Computational Complexity**

Deep learning models require more computational resources and longer training time compared to traditional algorithms.

- **Class Imbalance**

Medical datasets often contain more normal cases than abnormal cases. This imbalance may affect classification accuracy.

- **Scalability**
  As healthcare databases grow larger, some traditional models may struggle to handle increasing data efficiently.
- **Proposed System**

In the proposed thyroid detection system, the dataset is first pre-processed to remove missing values and irrelevant attributes. Data normalization is applied to maintain consistent input for the classification model. The processed dataset is then divided into training and testing sets for model development and evaluation [9], [11].

To improve performance, feature selection is performed using the Fisher Score method, which identifies the most relevant medical attributes for thyroid disease detection. This process reduces dataset dimensionality and improves classification efficiency [3], [12].

The selected features are provided as input to a Multi-Layer Recursive Neural Network (ML-RNN) for classification. Deep learning models are capable of capturing complex relationships between medical attributes and improving prediction accuracy in disease detection tasks [1], [4].

The performance of the proposed system is evaluated using cross-validation techniques. Standard evaluation metrics such as accuracy, precision, recall, F1-score, and error rate are used to measure effectiveness. The proposed approach aims to achieve higher accuracy and lower error rates compared with traditional machine learning methods [5], [14].

System Architecture
Below diagram depicts the whole system architecture.

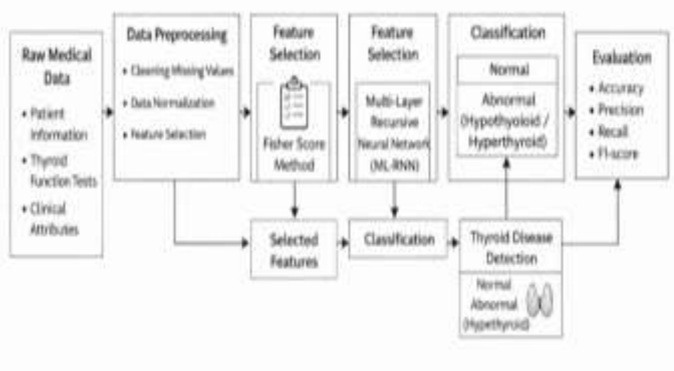

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

- **Data Collection and Preprocessing**

The first step in the system implementation involves collecting a reliable thyroid dataset containing patient medical records and laboratory test results. The dataset includes attributes such as T3, T4, TSH levels, and other clinical features. During preprocessing, missing values are handled carefully and irrelevant attributes are removed. Data normalization is applied to scale the features appropriately so that the classification model can learn effectively. Proper preprocessing ensures that the dataset is clean, consistent, and suitable for medical data analysis and prediction tasks [9], [11].

- **Feature Selection**

After preprocessing, feature selection is performed to identify the most relevant attributes contributing to thyroid disease detection. In this system, the Fisher Score method is used to rank features according to their significance. Selecting only important features reduces dataset dimensionality, improves computational efficiency, and enhances classification performance. Feature optimization techniques have been widely used in medical diagnosis systems to improve predictive accuracy and reduce redundant information [3], [12].

- **Training the ML-RNN Model**

The selected features are then used to train the Multi-Layer Recursive Neural Network (ML-RNN). The model learns patterns from the training data and identifies relationships between hormone levels and thyroid conditions. During training, the network adjusts its weights through multiple iterations to minimize classification error and improve prediction performance. Deep learning architectures have demonstrated strong capability in learning complex patterns from medical datasets and improving disease detection accuracy [1], [4].

- **Classification Module**

Once the model is trained, it is used to classify patient records into categories such as Normal, Hypothyroid, or Hyperthyroid. The classification module provides fast and reliable predictions based on input medical data. Similar deep learning-based classification systems have been successfully applied in thyroid disease detection and medical imaging analysis [5], [14].

- **Model Evaluation and Monitoring**

The performance of the trained model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques are applied to ensure that the model performs consistently on unseen data. Continuous monitoring can also be implemented to update the model when new medical patterns or patient data become available, thereby improving the reliability of automated thyroid diagnosis systems [8], [13].

VI .RESULTS AND DISCUSSION

Experimental Setup

To evaluate the effectiveness of the proposed thyroid disease detection system, experiments were conducted using the pre-processed thyroid dataset. The dataset was divided into training and testing sets, and the Multi-Layer Recursive Neural Network (ML-RNN) model was trained using features selected through the Fisher Score feature selection method. A cross-validation approach was applied to ensure reliable and unbiased performance evaluation of the model. The experimental analysis focuses on comparing the proposed model with traditional machine learning algorithms.

Performance Evaluation Metrics

The performance of the proposed model was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. These metrics are commonly used in medical diagnosis systems to measure classification effectiveness and reliability [8], [13]. Accuracy measures the overall correctness of predictions, while precision and recall evaluate the model's ability to correctly identify thyroid disease cases. The F1-score provides a balanced measure of precision and recall.

Model Performance Comparison

Table 1 presents the performance comparison between traditional machine learning models and the proposed ML-RNN model. The results show that the proposed model achieves the highest accuracy of 95.4%, outperforming conventional classifiers such as SVM (86.2%), KNN (84.7%), Decision Tree (82.9%), Random Forest (88.5%), and ANN (90.3%). The ML-RNN model also demonstrates higher precision, recall, and F1-score values, indicating better classification capability for thyroid disease detection.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	86.2	85.4	84.8	85.1
KNN	84.7	83.9	83.2	83.5
Decision Tree	82.9	82.1	81.6	81.8
Random Forest	88.5	87.6	87.2	87.4
ANN	90.3	89.7	89.1	89.4
Proposed ML-RNN	95.4	94.8	94.3	94.5

Accuracy Comparison Analysis

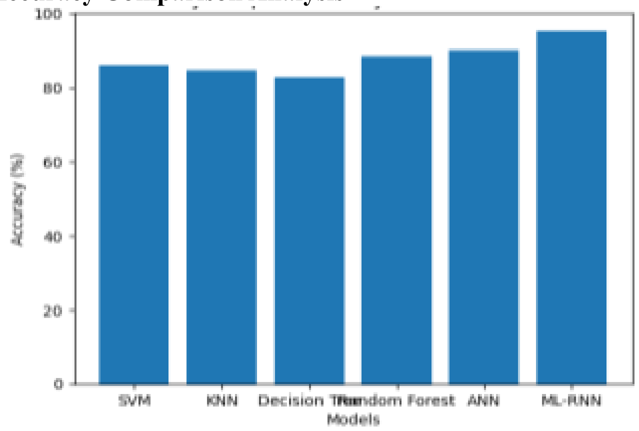

Fig 2. Accuracy Comparison of Thyroid Detection Models

The accuracy comparison graph (Fig. 2) visually illustrates the performance differences between the evaluated models. It can be observed that the ML-RNN model provides superior accuracy compared to traditional machine learning classifiers. This improvement is mainly due to the deep learning architecture's ability to capture complex nonlinear relationships between thyroid hormone levels and disease conditions.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve (Fig. 1) is used to evaluate the classification performance of the proposed model. The ROC curve demonstrates a strong classification capability, as the curve remains close to the upper-left region of the graph. This indicates a high True Positive Rate (TPR) and a low False Positive Rate (FPR), which are desirable characteristics for medical diagnostic systems.

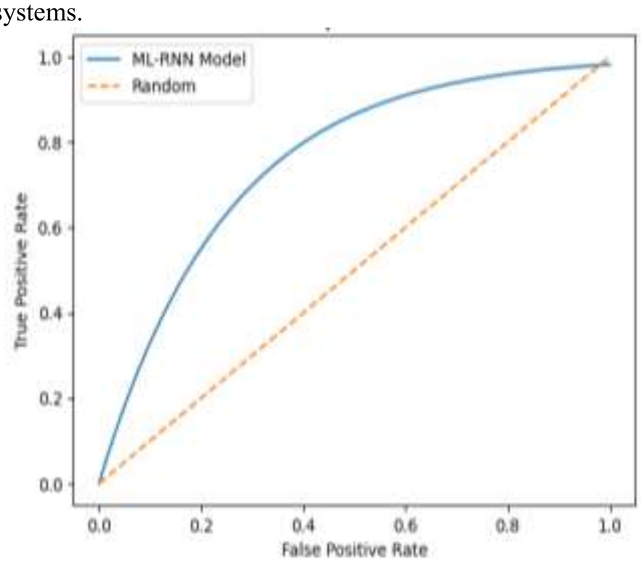

Fig 3. ROC Curve for Break Fault Prediction Model

Confusion Matrix Analysis

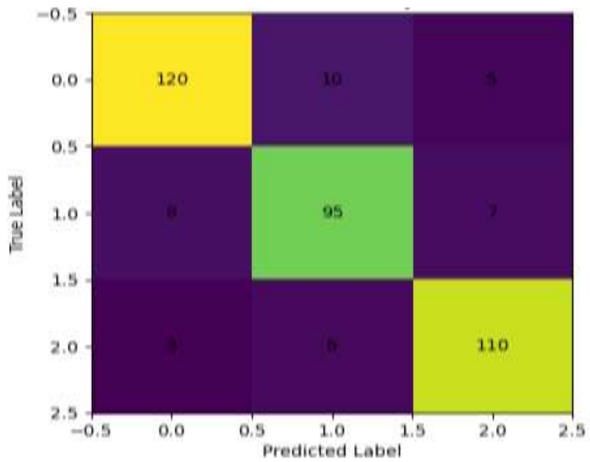

Fig 4. Confusion Matrix for ML-RNN Thyroid Classification

The confusion matrix (Fig. 3) provides detailed insight into the classification results of the ML-RNN model. The matrix shows the number of correctly and incorrectly classified instances for each thyroid condition, including Normal, Hypothyroid, and Hyperthyroid classes. The results indicate that most samples are correctly classified, demonstrating the model's effectiveness in distinguishing between different thyroid disease conditions.

VII.CONCLUSION AND FUTURE WORK

This project presents a deep learning-based approach for thyroid disease detection using a Multi-Layer Recursive Neural Network (ML-RNN). The thyroid dataset is pre-processed to remove inconsistencies and improve data quality. Feature selection is performed using the Fisher Score method to identify the most relevant medical attributes and improve classification efficiency [3], [12].The selected features are used to train the ML-RNN model, and the system is evaluated using metrics such as accuracy, precision, recall, and F1-score. Deep learning models have shown strong capability in capturing complex relationships in medical datasets, improving disease detection performance [1], [4].Experimental results show that the proposed model achieves higher accuracy compared with traditional machine learning algorithms such as SVM, KNN, and Random Forest, providing reliable thyroid disease detection and supporting early diagnosis [5], [14].

In future work, the system can be improved by using larger medical datasets and advanced deep learning techniques. The model can also be developed into a real-time clinical decision support system to assist healthcare professionals in diagnosing thyroid disorders more effectively [8], [13].

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