

Advancements in Neural Network-based Classification for Thyroid Disease Diagnosis: A Comprehensive Study

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Abstract—In recent years, neural networks have proven to be powerful tools for classification tasks across diverse domains, consistently achieving high accuracy. The primary goal of this study is to focus on using a neural network for thyroid disease classification, a particularly challenging scenario. In this paper, a powerful neural network model is developed and then carefully considered data preparation, model building, and training are presented. This study’s significance arises from its thorough investigation in the improvement of thyroid disease diagnosis, which will direct future efforts to design neural network architectures for increased accuracy in tasks akin to these.

Index Terms—Thyroid Disease Classification, Neural Network Models, Diagnostic Accuracy

I. INTRODUCTION

Thyroid diseases significantly impact global health and often go unnoticed because their signs can be minor and varied. Thyroid gland diseases (GDs) rank as the ‘first most common endocrine disorders in every part of the world’ after diabetes, as mentioned in the World Health Organization. [1][2] As essential controllers of body energy and growth, it’s important to recognize and treat thyroid problems early and accurately. Using machine learning, particularly neural networks, in health checks is a promising new way to better spot and classify thyroid diseases. [3]

This paper looks into how a specially made neural network can help in determining thyroid issues, evaluates its effectiveness, and discusses its impact

on health technology. By pointing out the shortcomings of existing methods, our study aims to enhance how these diseases are diagnosed, ultimately helping to take care of patients with thyroid issues better. This introduction leads into a thorough discussion of past research, preparing the reader to understand the recent advancements and the ongoing challenges in this area. The rest of the paper is organized as follows: After literature review, section III presents the gap analysis followed by methodology in section IV, and finally, the conclusion is presented in section V.

II. LITERATURE REVIEW

In this literature review, we explore the latest developments in using technology to predict thyroid diseases. These conditions are complex, so there is increasing interest in using technology to identify them more accurately and quickly. Our review examines different methods and findings from recent studies, laying the foundation to investigate how various techniques have addressed this health issue. We aim to clearly point out what these studies have contributed and their limitations, identifying crucial areas for more progress. This section prepares us for a detailed look at recent research that has influenced the field of thyroid disease classification, focusing on the possibilities for future enhancements.

Many research papers have been published in relation to prediction of thyroid disease using machine learning where each one has its own find-

ings and techniques. One of the recent studies by Peya, Chumki & Zaman (2021) suggested a strong predictive model that utilized machine learning classification algorithms which include K-Nearest Neighbor, Naive Bayes, and Decision Trees. Their work pointed out the outstanding precision levels achieved by the decision tree algorithm as it was observed at a high rate of 99.7%. [4]

The authors Riajuliislam, Rahim & Mahmud (2021) similarly dived into predicting early hypothyroidism by blending the feature selection process and classification algorithms. They used Recursive Feature Elimination (RFE) on the UCI thyroid dataset which led them to consistently achieving impressive 99% accuracy rates through different classification algorithms—underscoring their method’s effectiveness in uncovering cases of hypothyroidism at an early stage. [5]

Moreover, Chaubey et al.(2021) compared different classifiers such as logistic regression and decision tree for the thyroid disease detection using the UCI knowledge discovery database. It was observed that the kNN classifier showed better performance than other classifiers; it reached an accuracy rate as high as 96.87%. In totality, these works contribute to the ever-growing research sphere seeking optimization of accuracy and efficacy in thyroid disease classification through machine learning methods. [6]

III. GAP ANALYSIS

In our exploration of machine learning for thyroid disease classification, a significant gap stands out, which our research directly addresses. There is a pressing need for more transparent and interpretable models in this domain. Our study concentrates on enhancing the transparency of our neural network, allowing healthcare providers to comprehend and rely on its assessments. Bridging this divide is essential for progressing the discipline and ensuring that these innovations significantly benefit patient treatment.

IV. METHODOLOGY

A. Model Architecture and Training Parameters

Our strategy for classifying thyroid diseases leveraged a neural network implemented via the

Keras and TensorFlow library. The network’s structure comprised several dense layers: initially two layers, each with 128 neurons, followed by a third layer containing 64 neurons. For the output, a softmax activation function was employed to categorize the types of thyroid diseases. The Adam optimizer was used for training, and the model parameters were optimized using the sparse categorical cross-entropy loss function. We conducted the training over 10 epochs, during which the model weights were iteratively updated based on the training dataset. To provide a visual representation of the neural network’s architecture, Figure [1] illustrates the configuration of the dense layers employed in our classification model which was generated by ”ChatGPT Diagram Generator”.

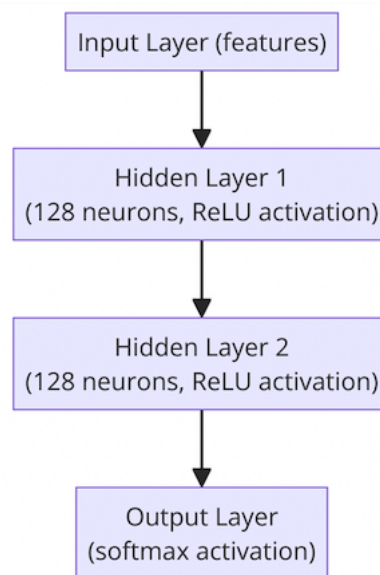


Fig. 1. Neural network architecture depicting the configuration of dense layers used for thyroid disease classification.

B. Dataset

The dataset utilized in our study comprised clinical features and diagnostic details pertinent to thyroid conditions from Kaggle.[7] To prepare the data, missing values were addressed by substituting the median for numerical attributes and the mode for categorical ones. The skewed dataset was balanced by resampling. Categorical variables were transformed into numerical formats using the Label Encoder method. Additionally, the StandardScaler

was applied to normalize the feature scales, facilitating uniformity and aiding in the model's convergence.

C. Loss Function

For our neural network, the sparse categorical cross-entropy loss function was chosen, which is apt for tasks involving multi-class classification. This function calculates the cross-entropy loss between the actual labels and the predicted probabilities, thereby steering the training process to reduce classification errors.

D. Evaluation metrics

Evaluation metrics are used to evaluate different aspects of the model's performance. The confusion matrix provides a summary of the predictions made by a classification model compared to the ground truth. It categorizes the classification results into four distinct categories as shown in figure 2.[8]

		Ground Truth	
		True	False
Prediction	True	True Positive (TP)	False Positive (FP)
	False	False Negative (FN)	True Negative (TN)

Fig. 2. Categories of classification results in a confusion matrix.

In medical diagnostics, focusing solely on accuracy might not provide a complete picture of a classification model's effectiveness. It's crucial to consider how well the model identifies true positive cases, particularly in healthcare settings. Therefore, it's vital to utilize precision and recall metrics. Precision calculates the ratio of accurately predicted positive cases to all predicted positives, and recall calculates the ratio of accurately predicted positives to all actual positives. In contexts like healthcare, where accurate detection of positives is critical, these metrics provide deeper insights into a model's capabilities beyond mere accuracy. This analysis incorporates

precision and recall, along with other metrics like accuracy and F1-score, to offer a detailed view of the model's performance in diagnosing thyroid conditions. The results of our model evaluation are as follows:

- Accuracy: 92.40%
- Precision: 92.67%
- Recall: 92.40%
- Recall: 92.33%

These metrics provide insights into the performance of our model and its effectiveness in classifying thyroid diseases.

V. CONCLUSION

Our study makes a significant contribution to the expanding field of machine learning applications in the classification of thyroid diseases. We implemented a neural network model trained on a thoroughly preprocessed dataset, which showed promising results in accurately diagnosing thyroid disorders using clinical and diagnostic data. This research underscores the importance of machine learning in aiding healthcare providers with the early detection and management of thyroid conditions, potentially enhancing patient outcomes and lowering healthcare expenses. Looking ahead, it is crucial to continue research into advanced modeling techniques, broaden datasets to be more inclusive and varied, and assess the practical application of these models in real-life settings. Such initiatives are essential for improving thyroid disease classification and advancing healthcare services overall.

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