Thyroid Disease Identification via EfficientNetB2: Leveraging Deep Neural Networks for Early Detection

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Abstract.

There are thyroid diseases called hyperthyroidism and hypothyroidism which can damage the human health, it affects the brain, the heart and the capability of having children. Early detection of such disorders helps patients heal more quickly and initiates treatment more effectively. In most cases, doctors request imaging and blood tests when making a diagnosis and both may be time-consuming and expensive. It is proposed that deep learning with an adapted version of EfficientNetB2 will enhance and streamline the process of diagnosing thyroid diseases. The model had been configured with two divisions: 0 (healthy) and 1 (thyroid illness) and photos of over 7,200 distinct thyroid conditions.

Keywords. Artificial Intelligence, Thyroid disease classification, EfficientNetB2, deep learning.

1. INTRODUCTION

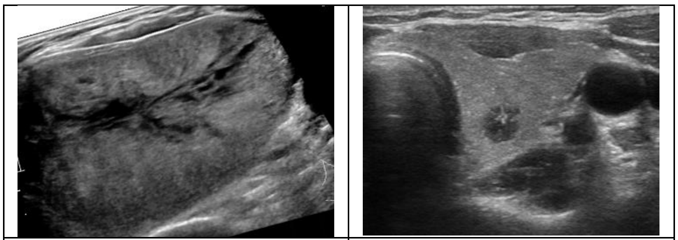
The thyroid gland controls most of the basic metabolic activities of the body. Hypothyroid and hyperthyroid are two kinds of thyroid disorders that left uncontrolled could have an adverse impact on your entire body. These diseases have been known to cause brain related problems, heart diseases and fertility issues, as the number of cases of these diseases is reported to be in the millions every year all over the world. Good management and therapy of thyroid problems through early and accurate detection are important to benefit patients and to control costs.

2. LITERATURE

Hypothyroidism, hyperthyroidism and thyroid cancer are common thyroid diseases. Machine learning (ML) and deep learning (DL) have made a great leap in the field of thyroid disease diagnosis. According to recent research, it is recommended to combine graphs with DL to generate clinical reasoning to enhance interpretability and decision-making [1]. Surveys on ML methods indicated the use of support vector machines (SVM), decision trees (DT), k-nearest neighbors (KNN), and random forests (RF) models that were effective in organizing clinical and laboratory data [2]. Accuracy, precision, recall, and F1-score are all performance metrics that are essential to assess these models. To find effective algorithms, classical ML studies examined sensitivity parameters and feature selection, which proved that well-tuned algorithms can effectively diagnose thyroid disorders [3].

3. INPUT DATASET

The paper capitalized on the extensive and high quality dataset available on the open-source Kaggle platform that included 7288 images classified as 0 (healthy) and 1 (thyroid problem) as depicted in Fig 1. Applying the same preparation techniques contributed to the EfficientNetB2 impressive thyroid classification.



(a)	(b_

Fig. 1 Dataset image for (a)Healthy and (b) Thyroid Disease image type

4. FINE-TUNED EFFICIENTNETB2 MODEL

The model was trained on ImageNet as a feature extractor with the upper layers cut off. A feature maps condensing layer (global max pooling) was followed by a custom classification head. The inputs to a dense layer of 256 units were made stable by batch normalization augmented with L2 kernel and L1 activity/bias regularization.

5. PROPOSED METHODOLOGY

According to the EfficientNetB2 study method, the proposed classifications of thyroid have four stages: data collection, data preparation, model construction and results exploration. Each of the major characteristics contributes to an effective and reliable method of thyroid classification.

Phase 1: Dataset Collection: The free data and professionally maintained databases made it possible to create a collection of images associated with thyroid disorders. All the examples in the dataset have corresponding labels of 1 thyroid illness and 0 healthy.

Phase 2: Model Architecture Design: The preparation of the data is about having the information set in such a way that it is sensible to make the model work on it. The images were all resized to meet the resolution requirement of EfficientNetB2 in the model.

Phase 3: Model Training and Validation: EfficientNetB2 was created with ImageNet and improved through the utilization of additional data. Adam optimizer and binary cross-entropy loss are used to find the optimum model parameters.

Phase 4: Model Evaluation and Analysis: Finally, the model was subject to rigorous tests using the test data. The performance of classification was assessed by examining accuracy, precision, recall, F1-score and the confusion matrix.

6. RESULTS

With an accuracy of 90% in detecting thyroid disease, the fine-tuned EfficientNetB2 model correctly categorised diseased cases and normal cases. Having equal F1-score, recall, and regularization, it does not overfit and provides reliable early detection during the initial run.

A. Classification Report Analysis

Table 1. Classification Report Analysis

Class	Precision	Recall	F1-Score	Support
0	0.86	0.93	0.90	164
1	0.94	0.88	0.91	201
Accuracy	0.90			365
Macro avg	0.90	0.91	0.90	365
Weighted avg	0.91	0.90	0.90	365

Table 1 shows, the EfficientNetB2 has a consistent degree of accuracy when it detects thyroid issues. Among all test cases, the model was accurate 90 percent of the time. The performance of all groups is good, as their level of accuracy, recall and F1-score are satisfactory.

B. Training and Validation loss Analysis

The loss curve of Fig. 2 provides significant new insights into the learning of the model after 15 epochs. Both the training and the validation loss are initially high, implying that the model starts out with poor predictions. The two losses, however, are indicative of a rapid fall; the training loss drops significantly and levels after the fourth epoch, which shows that it learns the data.

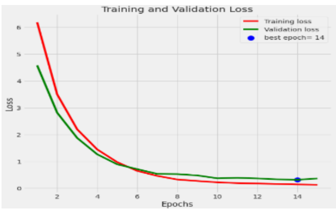


Fig. 2 Training and Validation loss Analysis

C. Training and Validation Accuracy Analysis

The Fig. 3 demonstrates an accuracy plot drawing conclusions on the model performance in terms of training and validation accuracy. Through epoch 14 the training accuracy rises rapidly and stalls at the highest point of 0.95, indicating that the model fairly well fits the training data.

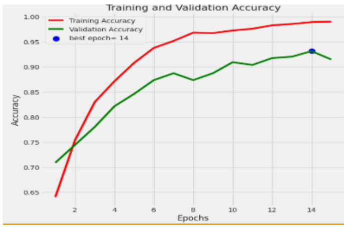


Fig. 3 Training and Validation Accuracy Analysis

D. Confusion Matrix Analysis

The confusion matrix, as illustrated in Fig. 4, demonstrates the relationship between the model results and the real observations. The method predictions are very close to the known health status of the patients of 153 healthy and 177 with thyroid disease.

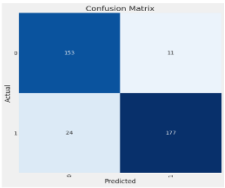


Fig. 4 Confusion Matrix Analysis

7. CONCLUSION

The study highlights the astounding accuracy of 90 percent in using an optimally tuned EfficientNetB2 model to autonomously detect and label thyroid diseases. Since it works efficiently, delivers high performance and saves time, the competency of EfficientNetB2 to excel clinically has resulted in it being an appropriate substitute to traditional practices. The outcomes of this investigation justify the development of AI in healthcare and are directed to assist in faster diagnosis, improved patient outcomes, and more effective healthcare.

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