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Intelligent Modelling for Thyroid Disorder Diagnosis

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ABSTRACT: In addition to providing new tools for clinical research, customized treatment, and medical diagnostics, artificial intelligence (AI) is revolutionizing healthcare. When diagnosing and tracking diseases, thyroid function tests are a valuable tool for doctors. It is obvious that artificial intelligence systems can help doctors and laboratory medicine specialists with assay design, process optimization, decision-making, test prescription, and interpretation. Several of these elements are reviewed in our essay. This paper also briefly addresses the problem of developing AI models relying on big data sets, which frequently necessitate distributed learning from multi-center contributions. Through the use of deep learning and image processing methods, this project uses a Streamlit web interface to develop a thyroid disease detection system. Using Deep Learning models, the system pre-processes, segments, extracts features, and classifies ultrasound pictures. It provides precise forecasts and performance indicators while classifying thyroid conditions and identifying cancers. A user-friendly web interface allows users to upload photos with ease and receive real-time diagnosis findings.

KEYWORDS: Artificial intelligence (AI), Deep learning (DL), Decision-making algorithm, Classification.

I. INTRODUCTION

Advances in computational biology are being used in the healthcare sector to store patient data collections and make predictions about medical conditions. There are numerous methods available for early illness diagnosis. Intelligent applications, or medical technology information, are not available to gather the necessary data sets for illness analysis [1], [2]. But in recent years, a technology known as Machine Learning (ML) optimization has emerged that is essential for forecasting and resolving complicated and non-linear problems. As much as possible, features from several datasets that are easily classified in healthy individuals and that can be selected in any illness detection approach are highlighted. Rather, misidentification may expose a healthy individual to needless treatment. The precision of predicting any diseases other than thyroid disorders is therefore of utmost importance.

Thyroid hormones are helpful for controlling the body's metabolism in a number of ways, including heart rate and caloric expenditure. The thyroid gland's output helps regulate the body's metabolism. The thyroid glands actively release the thyroid hormones triiodothyronine (T3) and levothyroxine (T4). These hormones play a crucial role in the formation of the overall monitoring system and in the regulation of body temperature. The two active hormones that the thyroid glands typically produce are T4 (sometimes referred to as thyroxine) and T3. These hormones have important roles in energy storage, temperature regulation, transmission, and protein management throughout the body. For these two thyroid hormones, T3 and T4, iodine is considered a major building block of the thyroid glands and is affected in a few particular issues that are very common [8, 9, 10, 11]. Hypothyroidism is caused by a lack of thyroid hormones, whereas hyperthyroidism is caused by an excess of thyroid hormones. Numerous conditions can result in hyperthyroidism and underactive thyroids. Medication can take many different forms. Patients undergoing thyroid surgery are at risk for iodine deficit, enzyme deficiencies, ionizing radiation, and persistent thyroid discomfort, which results in the production of thyroid hormones.

The intricacy of diagnosing certain thyroid disorders has prompted the creation of artificial intelligence (AI) tools to help doctors. This trend can be demonstrated by a variety of examples from the imaging and radiology fields.

One initial finding is that the treatment of thyroid nodules can be tailored and optimized through the use of AI-based automated diagnosis systems. AI-based solutions have been suggested as ways to address the complexity of the

fragmented risk stratification systems and increase the accuracy of ultrasonography-based conclusions for less experienced administrators in response to clinical requests to reduce unnecessary fine needle aspiration (FNA) (10).

The potential for staging thyroid tumor malignancy and the ability of deep-learning AI models to distinguish between benign and malignant thyroid tumors using unique clinical and ultrasonographic features represent the second observation (11). Using ultrasound images, cytopathology images, and genetic markers, artificial intelligence algorithms have been used to classify thyroid nodules (12). It is interesting to note that the AI model significantly reduced FNA and had diagnostic accuracy for malignancy that was higher than radiologists' (10). According to published data, neural networks were 84% accurate at differentiating between advanced and non-advanced thyroid carcinomas, with 87% and 92% positive and negative predictive values, respectively (13). Another crucial step in selecting the best course of treatment is the application of AI to classify tumors (11).

The thyroid is a tiny but crucial gland located in the neck that helps the body regulate heart rate and digestion [1]. The hormones that regulate metabolism, including heart rate and body temperature, are released by the thyroid organ. T4 and T3, two crucial hormones, are produced by it. These hormones control a variety of metabolic processes, including body weight and heart rate. Thyroid hormones, which are produced by the thyroid gland, assist regulate a number of organs through the blood. Thyroid hormone is produced inappropriately when the thyroid gland's function is compromised. Thyroid disease symptoms can include elevated blood pressure, abnormal pulse rate, and high cholesterol. Hypothyroidism, structural abnormalities, hyperthyroidism, tumors, and subclinical hyperthyroidism or subclinical hypothyroidism are the five common forms of thyroid disease. Medical professionals must examine the test results for hormones and other factors in order to detect thyroid disease, and hypothyroidism is diagnosed by testing a blood sample at a laboratory. The thyroid gland does not create enough thyroid hormone when a person has hypothyroidism. A number of symptoms, including fatigue, a weakened immune system, constipation, depression, a sluggish heartbeat, and weight gain, might be signs of hypothyroidism.

In order to normalize TSH and thyroxine levels, doctors modify the medication dosage based on the patient's circumstances. In hyperthyroidism, the thyroid produces too many hormones. Anxiety, irritability, agitation, fine, brittle hair, excessive sweating, hand tremors, heart palpitations, anxiety, skin thinning, and muscle weakness are all signs of hyperthyroidism. After the age of 60, hyperthyroidism is extremely prevalent. Thyroid surgery, radioiodine therapy, and medication are the three main ways that hyperthyroidism condition is treated.

Thyroid disease results from an imbalance in the thyroid gland's production of hormones, which the gland produces either too much or too little of for a variety of vital bodily activities. Numerous disorders affecting the thyroid might cause imbalances and malfunctions in other organs [2]. Goiter, heart disease, pregnancy issues, and the more serious myxoedema coma might result from improper treatment [3]. An estimated 40% of people are at danger of iodine deficiency, which aids in the production of thyroid hormone, and 200 million people globally suffer from thyroid illness, according to [4]. The two primary thyroid illness types that result in thyroid imbalance are hypothyroidism and hyperthyroidism. There are other thyroid disease types as well, and each has an effect on human health. Early diagnosis of the appropriate thyroid disease type is crucial to preventing such consequences and ensuring that therapy is tailored to the patient's needs.

Numerous tests that document distinct symptoms for thyroid disorders have been conducted in the past. A particular thyroid condition can be identified by these signs [5]. These tests and symptoms, for instance, can be used to identify and forecast thyroiditis, Graves' disease, Hashimoto's disease, thyroid goiter, thyroid cancer, nodules, etc. Numerous signs and characteristics can be used to classify thyroid illness. Numerous features pertinent to thyroid disorders are provided by current research. The names and descriptions of certain characteristics that can be used to predict thyroid disease are shown in Table 1; for instance, thyroid detection can be done using lithium, goiter, hypopituitary, Psych, TSH, T3, TT4, T4U, FTI, and TBG.

Numerous research have already examined thyroid conditions and related symptoms [6,7,8]. While some methods record tests and symptoms, others concentrate on data analytics. The accuracy and resilience of these methods differ depending on the disease detection method, such as statistical analysis, machine learning, or deep learning. Existing methods mostly rely on publicly accessible datasets and suffer from overfitting of the models. The majority of the datasets that are currently accessible have an imbalanced class problem, meaning that there are much less samples for the positive

(disease) class. A machine learning or deep learning model that uses such a dataset overfits the majority class and generates inaccurate predictions for the minority class. The fact that only a small number of thyroid disorders are utilized for classification is another drawback of current research; much of it concentrates on the binary-class problem, which renders those methods inappropriate for disease detection in the real world. The goal of this work is to address this problem by employing synthetic data samples to increase the number of minority class samples.

Thyroid disease can be accurately predicted using an effective machine learning technique. An optimization approach based on differential evolution (DE) is used to maximize the models' performance.

To find the optimal hyperparameters, DE works with the hyperparameters of different machine learning models. To significantly increase the accuracy of models for the identification of thyroid disease, the DE method is utilized to choose the ideal parameters for machine learning models.

The issue of class inequality is especially addressed in this paper. By performing data augmentation with conditional generative adversarial networks (CTGAN), the effects of class imbalance are lessened

II. BACKGROUND STUDY

Deep learning and machine learning techniques have been used in numerous previous studies to predict thyroid illness. To treat and recover as many patients as possible, it is very beneficial to predict thyroid disease in its early stages and classify it as either malignancy, hyperthyroidism, or hypothyroidism. Several thyroid illness classification and detection techniques have been described here in order to identify the recent research papers in the work that is being presented. A machine learning method for detecting B-Raf proto-oncogene, serine/threonine kinase (BRAF) mutations in cancerous thyroid nodules is presented by the authors in [9]. Ultrasonic pictures of 96 thyroid nodules were also included in the study. The existence of the BRAF mutation is detected using machine learning models like RF, LR, and SVM. A classification accuracy of above 60% is reported when using these models. To lower the false-negative rate for thyroid cancer, ultrasonic characteristics and fine-needle aspiration (FNA) were employed in a related investigation. Compared to other techniques like gradient descent and decision trees (DT), the RF model produced better outcomes. To select the cancerous thyroid nodule linked to the ultrasonic characteristics, the scientists used the least absolute shrinkage and selection operator (LASSO) and LR models in [10]. The RF model and a score system are utilized to categorize the malignant thyroid nodules. The accuracy of the logistic lasso regression (LLR) using RF was greater than 80%. The authors of [6] used various machine learning methods to analyze the data. Ten distinct classifiers are used to compare the outcomes. Using an additional tree classifier resulted in an accuracy of 84%.

SVM was employed in the study [11] to identify thyroid conditions. 83.37% accuracy has been reported. Furthermore, the model accurately differentiates between four thyroid conditions. The authors of [8] conducted experiments to use the DT model to predict and categorize thyroid illness. Additionally, in order to anticipate thyroid illnesses intelligently, researchers developed a machine learning-based tool called the Machine Learning Tool for Thyroid Disease Diagnosis (MLTDD). The accuracy of MLTDD is 98.7%. The most likely chemicals that trigger the thyroid hormone's homeostasis are predicted using machine learning methods such as LR, RF, SVM, GBM, and DNN in [12]. In [13], the authors used machine learning and deep learning techniques to study feature engineering. Bidirectional feature elimination using an additional tree classifier, forward feature selection, machine learning-based feature selection, and backward feature elimination were all implemented. The suggested method is able to predict binding protein, autoimmune thyroiditis, Hashimoto's thyroiditis, and non-thyroidal syndrome. The results show a 99% increase in accuracy when employing the RF classifier and supplementary tree classifier-based features.

In [14], a multi-kernel SVM for thyroid and cancer prediction is presented. When used for feature selection, the gray-wolf optimization enhances performance. The multi-kernel SVM used in the study yielded an accuracy of 97.49%. To increase performance for thyroid disorders, the authors of [15] used feature selection and image processing approaches to pick the key features from the database. multi-class hypothyroidism using machine learning and selected features approaches [15]. There are four types of hypothyroidism. According to experimental data, RF outperformed KNN, DT, and SVM algorithms in terms of accuracy, achieving 99.81%. In order to predict hypothyroidism, the study [16] examined three feature selection strategies employing DT, SVM, RF, naïve Bayes (NB), and LR. For feature selection, principal component analysis, univariate feature selection, and recursive feature selection were employed. When paired

with machine learning algorithms, recursive feature selection has been shown to perform better than alternative methods. Combining RFE with the DT, SVM, RF, naïve Bayes (NB), and LR algorithms yields an accuracy of 99.35%.

A multiple multi-layer perceptron (MMLP) model for classifying thyroid diseases was presented in the study [17]. According to reports, the MMLP can achieve 99% accuracy on huge datasets. The XGBoost method for thyroid illness classification and prediction was introduced in another work [18]. The effectiveness of the DT, LR, and KNN methods is contrasted with that of the XGBoost algorithm. Compared to the KNN method, the XGBoost algorithm increases accuracy by 0.02%. Artificial neural network (ANN), KNN, DT, and RF are machine learning-based approaches that are compared in [19]. A sizable dataset is used for the experiments. Additionally, during experiments, both original and sampled data are taken into account. With an accuracy rate of 94.8%, RF achieved enhanced performance.

Some studies concentrate on employing deep learning models for thyroid illness detection in addition to machine learning models. For instance, in [20], thyroid illness is predicted and categorized using a deep neural network (DNN). According to reports, DNN achieves 99.95% accuracy. In order to increase the accuracy of thyroid prediction, the authors compared a number of machine learning techniques in [21], including additional trees, CatBoost, LightGBM, ANN, KNN, SVM, RF, DT, XGBoost, and GaussianNB. The performance is assessed by looking at the F1 score, accuracy, recall, and precision. The research used an ANN classifier and reported 96% accuracy.

III. PROPOSED SYSTEM

The technology uses deep learning algorithms to diagnose thyroid problems more accurately. Accurate tumor predictions are ensured by sophisticated image processing methods such as feature extraction, segmentation, and noise filtering. By automating early thyroid illness diagnosis, the initiative improves diagnostic reliability and lowers human error. It accurately identifies thyroid problems by detecting tumor-related concerns from ultrasound pictures. To improve diagnosis and guarantee accurate thyroid disease classification, a variety of performance indicators can be employed. Since there are not many examples from the other classes, they are not covered in this study. We employed the CTGAN augmentation technique to balance the selected targeted dataset because it is unbalanced. Samples for the minority class are produced using this method. With a ratio of 0.8 to 0.2, data splitting is utilized to separate the dataset into training and testing sets, with 80% going toward training and 20% toward testing. Before submitting input to machine learning models, we first transform it into numeric form using a label encoder because these models operate on numeric data. In order to choose the optimal hyperparameter setting for models, we use a training set to train machine learning models and then use the DE optimizer to optimize the hyperparameters. Ultimately, we assess models based on their confusion matrix, F1 score, recall, accuracy, and precision.

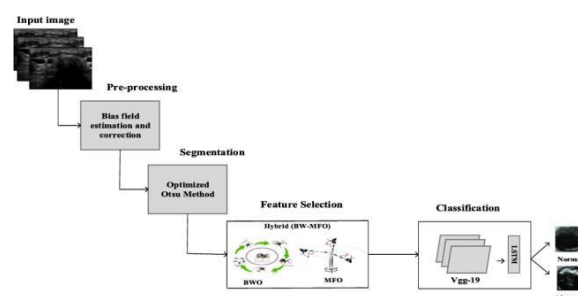


Figure 1 System Architecture

Dataset Analysis

The Kaggle repository provided the datasets utilized in this investigation. There are 31 features in each of the 9172 samples in the thyroid illness dataset. The collection includes a variety of records for the target classes and various thyroid illnesses. Health condition status and diagnosis classes are among the target classes. To choose the ideal amount of features for the classification of thyroid diseases, the significance of each feature should be assessed. Furthermore, these features fall under several kinds, such as string, int, boolean, and float. Ten classes are used by the suggested method: "-", "K", "G", "I", "F", "R", "A", "L", "M", and "N."

The dataset is unbalanced, according to the class counts. For instance, a large number of the dataset's samples are not utilized in any one class. To obtain the standard dataset for performance evaluation, data pre-processing is done. "No condition" is classified using the classification count. Data samples for other classifications, including binding proteins, general health, hypothyroid, hyperthyroid, anti-thyroid, replacement therapy, and many more, are also not categorized. Patients are classified as having "no condition" if they do not have thyroid illness. Serum thyroid levels are altered as a result of chronic disease, and concurrent non-thyroidal disease is typically observed in very sick individuals with chronic disease [35].

Of the 9172 records in the thyroid disease dataset, 6771 samples are from healthy individuals, while the remaining samples are from various thyroid conditions. For instance, there are 836 patients with concurrent non-thyroidal disease, 647 patients with hyperthyroidism, 733 patients with primary hypothyroidism, 859 individuals with compensated hypothyroidism, etc.

Data Pre-processing

The vacillations of a coil in the magnetic field generate intensity in homogeneity and a partial volume effect, which impact ultrasound images in real-time applications. To address this problem, bias field estimation and correction are used. The bias field, which is identified as a multiplicative module of an ultrasound image, displays the variation of gray level pixels of parallel issues in the spatial domain. Therefore, bias field correction and smoothing techniques are used in this project to improve the caliber of classification outcomes.

In this application, CTGAN is used to generate samples in order to perform data balancing. The normal class has the most samples in the dataset utilized for this study, whereas samples from the other classes are extremely sparse. CTGAN is used to produce 400–500 samples in order to balance the dataset. The number of samples before and after CTGAN data augmentation is displayed. Model overfitting, which occurs when a model is trained on a very unbalanced dataset, is prevented by dataset balancing.

Feature Extraction

Increase population variety to slow down the rate of convergence and avoid premature convergence. The suggested model has been linked to Vgg-19-LSTM with BWO and MFO, as was previously mentioned. The Mayfly and Black Widow Optimization algorithm hybridization is covered in length in this section, which mostly discusses a hybrid Meta heuristic algorithm. It can prevent early convergence in Mayflies by progressively increasing population diversity.

Furthermore, it successfully makes the local optimal possible. The mathematical models of the starting population's procreation, cannibalism, mutation, and convergence are presented in the section that follows. The Black Widow Optimization (BWO) method requires two sorts of populations, such as male and female, and initially executes the population at random. Offspring are created for the following generation based on this initiation. The calculation of the fitness value is important in this procedure; fata widow is the symbol for the fitness function.

In the group, each pair is autonomous and acts in parallel to mate and create a new generation. As previously said, they each handle mating from other spiders in the web. Consequently, they generated roughly 10,000 eggs during the real-time process. But only the strongest or most fit spider in the web makes it out alive. This algorithm uses an array to carry out the reproduction process; it continues to do so until a widow array containing random numbers becomes available.

Classification process

There are three different forms of cannibalism: sibling cannibalism, child cannibalism, and sexual cannibalism. The female spider consumes the male spider during or after mating in sexual cannibalism. Here, the approach gives careful consideration to fitness value. The second type of cannibalism occurs when a youngster consumes their parents in order to assess if the spiderlings are robust or weak. Similarly, sibling cannibalism occurs when a spider consumes its weaker sibling. This algorithm calculates the survivor rate by determining the cannibalism rate.

Thyroid Prediction

We created receiver operating characteristic (ROC) curves to compare the deep learning model's performance to that of nuclear medicine doctors. Significant variations in the area under the receiver operating characteristic curve (AUC) between the different diagnostic techniques were identified using the DeLong test. For both the deep learning models and nuclear medicine physicians, we presented κ values and F1 scores together with accuracy, sensitivity, specificity,

negative predictive value (NPV) and positive predictive value (PPV) with 95% CIs. The chi-squared test was used to assess the accuracy differences between clinical physicians and the DCNN model. $P < 0.05$ was deemed statistically significant in the statistical analyses, which were conducted using SPSS software (version 26.0), MedCalc (version 20.218), and R (version 4.2.2).

Result And Discussion

To the best of our knowledge, this is the first study to assess a deep learning approach as a thyroid nodule management tool. The ThyNet-assisted approach enhanced radiologists' diagnostic precision when examining images alone as well as when examining images and videos in a clinical context. Notably, the ACR TI-RADS classification combined with AI support enhanced both the positive and negative predictive values, potentially lowering the frequency of needless fine needle aspirations.

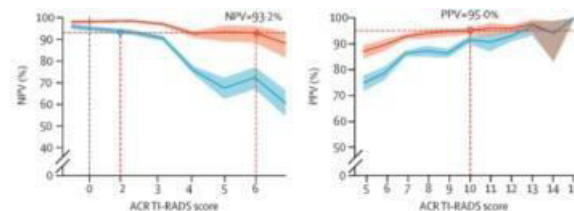


Figure 2 ThyNet Decision

The goal of this work was to create a deep learning AI-supported approach for thyroid nodule clinical decision-making. According to earlier research, deep learning algorithms performed better than medical personnel in a few clinical outcomes.^{3, 12, 21} However, using an AI diagnostic model alone is not feasible for clinical settings. These perfect algorithms cannot handle the noisy data found in medical workflows, which includes errors, omissions, and incompatibilities. Even though AI is said to perform better than humans, physicians should nonetheless oversee real-world judgments. As a result, this AI model's primary function is to increase diagnostic precision by supporting physicians in their treatment choices.

IV. CONCLUSION

Thyroid illness diagnosis and risk assessment are increasingly being aided by artificial intelligence. Clinical laboratories' effectiveness in process optimization and clinical decision support can be greatly enhanced by artificial intelligence companions. Artificial intelligence methods present new possibilities for TFT design and enhancement to in vitro diagnostic enterprises. Clinical diagnosis, laboratory test prescription, treatment pathways, and patient outcomes can all be improved by integrating AI into clinical pathways. AI will aid in the detection of molecular pathways, a better understanding of complicated thyroid illnesses, and the development of novel therapeutic approaches in the field of network medicine.

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