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Technique to Identify & Classify Thyroid Cancer Using Supervise & Supervise Learning

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Abstract
Background: Thyroid cancer is caused by thyroid gland, located in front part of neck below voice box called larynx. The thyroid gland is an endocrine gland, which controls hormones in the human body resulting the regulation of metabolism. It is one of the common cancer, which is about four per thousand people in the world. Thyroid cancer is seen more in women as compare to men as it is 1.9 and 6.1 per hundred thousand people in the world. From past ten years in India, it has been seen that the growth rate is increased up to 62 percent and 48 percent in women and men respectively.
Objectives: To develop and compare machine learning algorithm for thyroid cancer detection and prevention at early stage.
Methods: Artificial intelligence (AI) is continuously changing the shape of the healthcare industry. To categorize the cancer types in thyroid disease, a machine learning-based support vector machine approach has been applied. The multiclass support vector machine is one of the best-performing approaches in this domain. The support vector machine

algorithm has been applied to the machine learning datasets offered by the university of California Irvine to evaluate (train, test, validate) the final AI model.

Results: The final AI model using the support vector machine technique shows the precision is 73 percent, recall is 81percent , and f1-score is 77 percent respectively. The result is very significant in this domain with overall 97 percent accuracy.

Conclusions: Thyroid cancer is among the most frequent types of cancer. It is really difficult to detect it at an early stage. Machine learning (ML) is an emerging method for thyroid cancer categorization and prediction. In this paper machine learning-based multiclass support vector machine approach has been used to categorize the types of thyroid cancer with a 97 percent accuracy.

Keywords: Thyroid cancer, Support vector machine, Machine Learning, Disease classification, Artificial Intelligence.

1. Introduction

Thyroid cancer is one of the most often diagnosed disorders in the medical field. Previously, most patients were disregarded since they had little symptoms at the time, but with technological advancements, even small malignant tumours may now be discovered. ML has vital role in changing the categorization and diagnostic patterns in this uncharted territory. Thyroid is an endocrine gland that secretes two important hormones: the first is thyroxine, which contains four atoms of iodine and is commonly referred to as T4. The second is triiodothyronine, which has three atoms of iodine and is commonly referred to as T3. T3 and T4 eventually combine to make thyroid hormone. The thyroid gland is a hormone gland in the human body that governs metabolism, growth, and development[1]. Thyroid cancer arises when cells change or mutate. The abnormal cells in your thyroid begin to multiply and, when there are enough of them, form a tumour. Women are more likely than males to have thyroid cancer. The thyroid cases in Women is observed more than men in their forties and fifties, while men are more likely to develop it in their sixties or seventies. Whites are more likely to get follicular thyroid cancer than blacks, and women are more likely to have it than males. Thyroid cancer may strike anyone at any age[2]. Papillary thyroid cancer, for example, is more likely in those between the ages of 30 and 50. If diagnosed early, thyroid cancer is one of the most treatable kinds of cancer. Researchers have found four primary types. The earliest and most prevalent kind of thyroid cancer is papillary thyroid carcinoma. It has been reported in up to 80% of all thyroid cancer patients. It progresses gradually but often to the surrounding tissue in ones neck. Nonetheless, you have a good chance of total recovery. Follicular thyroid carcinoma is the second most dangerous type, and it accounts for 10% to 15% of all cancerous growth in the United States. It has the potential to spread to your lymph nodes and blood vessels. The third form is medullary carcinoma, which accounts for around 4% of all thyroid cancer occurrences. Because it produces calcitonin, a hormone that doctors check for in blood test results, it is more likely to be found early. Anaplastic thyroid cancer is the fourth and most severe variety because it spreads rapidly to other parts of the body. It is unusual and the most difficult to treat. Because the signs of thyroid cancer are so modest, it cannot be detected in its early stages. However, when the tumour develops, patients may have neck pain, throat pain, swallowing difficulties, voice changes, and coughing. Thyroid cancer has no known origin; however, it may be caused by inherited genetic problems, a lack of iodine, or radiation exposure. Currently, the treatment methods include the physical examination, Blood test, ultrasound, sample tissue inspection, and other imaging examinations Like CT-Scan, MRI, and nuclear imaging, which uses a radioactive version of iodine[3]. Genetic testing is also one of the parameters of diagnosis. Some people with medullary thyroid carcinoma may have hereditary transformations associated with other types of endocrine cancer[4].

2. Related Work

Guo, Y., Zhang, Z., and Tang, F. (2021) introduced a unique non-linear feature selection strategy based on support vector machines that tackles multi-class type difficulties. This is accomplished by combining a multi-class support vector machine with a fast element reduction analysis. The engaged classifier creates numerous determination functions that split each type. The suggested framework chooses attributes that work nicely for all types, guiding to a reduce time complexity with enormous optimization problems [5]. Verburg and Reiners (2019) propose a new approach for assessing ultrasound pictures with artificial intelligence that has comparable sensitivity and enhanced specificity when compared to expert radiologists' judgement[6]. Thomas et al. (2020) provided a technique for evaluating the malignancy risk of thyroid nodules using ML and AI[7]. Abdolali et al. (2020) published a comprehensive review on the significance of artificial intelligence in thyroid cancer imaging diagnosis[8]. Wang et al. (2019) used an object detection model to perform automated thyroid nodule detection[9]. Ali and Ayturk (2008) demonstrated the use of an expert system to diagnose thyroid disorders with 95.33 percent accuracy[10]. Peng et al. (2021) used a deep learning model to help with pituitary gland nodule identification and management in a multicentre diagnostic trial[11]. Nguyen et al. (2019) proposed combining information from the spatial and frequency domains to classify thyroid nodules using artificial intelligence[12]. Choi et al. (2017) propose a computer-aided diagnostic method based on AI for the initial clinical assessment of pituitary gland nodules on ultrasonography[13]. Esce et al. (2021) suggested an artificial intelligence-based technique for predicting papillary thyroid carcinoma[14]. Ghali et al. (2020) proposed using artificial intelligence-based algorithms and multi-linear regression to predict thyroid regulating hormone balance in humans[15]. Irina and Liviu (2016) propose a data mining technique for classifying thyroid diseases. The study focuses on the categorization of thyroid illness in two common types of thyroid condition (hyperthyroidism and hypothyroidism) in the population[16]. Li et al. (2021) examined and summarised AI developments in extracting and analysing semantic, appearance, and minute information to uncover the fact about thyroid cancer[17]. Wildman-Tobriner et al. (2019) proposed a mechanism for data and imaging analysis relating thyroid that substantiate the “American College of Radiology” while enhancing specificity and retaining sensitivity. It also simplifies attribute allocation, which may increase usability[18]. Mourad et al. (2020) show that general and present medical data may be safely converted into predictive strength to assist clinicians in making educated and optimum treatment decisions, with 94.5 percent accuracy in differentiating patients in terms of prognosis[19]. Yang et al. (2019) employed a machine learning algorithm using disease-specific survival data from the “National Cancer Institute's Surveillance, Epidemiology, and End Results Program” to combine clinical parameters to increase prognostic accuracy[20]. Xuesi et al. (2020) create a unique thyroid gland imaging datasets and they utilises those optimal resolution picture to help clinical diagnose of thyroid cancer[21]. Using Convolutional Neural Networks, Chandio et al. (2020) offer a decision support system for classifying initial variations in the morphological appearance of nuclei[22]. Taylor et al. (2019) employ an unsupervised machine learning technique that yields extensive sub-cellular facts regarding chemical changes associated with the differentiation of ordinary and malignant thyroid cells[23]. According to Masuda et al. (2021), machine learning utilising texture examination has a good role in identifying lymph nodes in diseased one with thyroid cancer and probable metastatic lymphoma examinations[24]. The RF model developed in this study, according to Liu et al. (2021), may reliably predict bone metastases in thyroid cancer patients, providing doctors with more tailored therapeutic suggestions. ML can increase the creation of bone transfiguration forcast models in sick people with thyroid cancer[25]. Turki (2018) evaluated machine learning classifiers on actual clinical data linked to thyroid cancer and other related cancer utilising area under ROC curve and accuracy. The experimental findings suggest that SVM performs well [26]. Liu et al. (2022) established a relatively high accuracy random forest model for forecasting lower QoL in thyroid cancer patients three months after surgery. These discoveries should be used in clinical settings to improve health care[27]. Eun and Baek (2021) gave an overview of the Artificial Intelligence enabled computer added design systems now employed for thyroid glands, as well as upcoming discovery for smart systems for individualised and optimal thyroid disease care [28]. Xi, Wang, and Yang (2022) presented a smart approach to determine malignant thyroid glands using original clinical dataset[29]. Razia and Rao (2016) presented a study of ML algorithms for diagnosing thyroid illness [30]. Yijun et al. (2020) created prediction models in papillary thyroid cancer sick people by integrating clinical characteristics[31]. Liu et al. (2022) predict thyroid cancer lung metastasis and provide a helpful and substantial reference for physicians' decision-making in advance[32]. Asif et al. (2020) offer a thorough investigation on the action of several machine learning classifiers in the pinpointing of thyroid illness[33]. Kim et al. (2021) used ML classifiers to predict 71.40 percent of recurrences by identifying 3 rules that defined all patients with recurrence in the model developing team[34]. Olatunji et al. (2021) created ML-based techniques that can deliver an alarming system for preliminary phase[35]. Gopinath and Shanthi (2013) developed a computerized diagnostic approach for detecting thyroid cancer signs in fine-needle aspiration cytology (FNAC) small photos with good sensitivity and specificity using statistical surface attribute and a Support Vector Machine algorithm [36]. Zhang et al. (2019) claimed that ML methods based on ultrasound imaging, notably the random forest algorithm, will be effective than radiologists in detecting malignant thyroid nodules [37]. Ouyang et al. (2019) provided a comparison of nonlinear machine-learning methods that perform similarly to linear algorithms in identifying the of malignant tumour risk in thyroid nodules [38]. After studying the ultrasound imaging data, Xiangchun et al. (2019) proposed a deep convolutional neural network (DCNN) framework to increase the diagnosis of thyroid cancerous gland[39]. Lee and Park (2022) gave reviews of multiple ML methods that may be acceptable for various types of data for the early detection of thyroid illness utilising numeric data, genomic data, radiomic data, and ultrasound data [40]. Yadav and Pal (2020) introduced ML strategy for the search of hidden patterns in thyroid illness [41]. Zhao et al. (2021) proposed that a machine learning supported two types method vision technique will help Radiograph experts to detect thyroid diseased gland more efficiently and significantly minimise the rate of needless fine-needle aspiration biopsy in thyroid ill glands clinical care[42]. Verma, Popli, and Kumar (2022) reported a machine learning research on thyroid disease[43].

3. Methods

3.1 **About Machine learning Model**

To classify the thyroid cancer ML based support vector machine approach has been considered. The SVM(Support Vector machine) is a type of supervised ML model. Which is very helpful in dealing with classification problems. This paper presenting the multiclass classification with SVM is used to classify the instances into one of three or more classes. The multiclass support vector machine is one of the best performing method in this domain. The support vector machine algorithm has been applied to UCI data set for training, testing and validating the ML based classification model.

3.2. **Data collection for thyroid disease**

The data-sets of thyroid cancer is collected from “Machine learning repository of university of California Irvine”. It has 3221 samples. The data sets is collected and saved into three different csv file namely allhyper.csv, allhypo.csv, sick.csv. Later it has been loaded into Google Collaboratory for further analysis.

3.4. **Model Description**

The SVM is used to differentiate four thyroid states: hyperthyroid, hypothyroid, euthyroid-sick, and euthyroid (negative). The SVM is a geometric method for performing classification and regression tasks. The basic goal is to discover a hyperplane that clearly classifies the data points, where hyperplanes are decision boundaries that aid in data classification. A data point is assigned to a different class if it lies on either side of the hyperplane. There are several alternative hyperplanes, but the one with the greatest margin, or distance, between the data points of the classes is best. This maximum marginal distance ensures that future data points are classified correctly. SVMs are commonly used for binary classification, or distinguishing between two classes. The strategy entails training a single classifier per class, with samples from that class serving as positives and all other samples serving as negatives. It basically divides a multiclass classification issue into numerous binary classification tasks.

4. Results

4.1 **Data Preparation**

The following parameters has been selected from the data sets for classifying the types of thyroid cancer.

Parameters	Variable type
Age	
TSH	
T3	
TT4	Quantitative

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T4U	
FTI	
Sex	Qualitative
On Thyroxine	
Query on Thyroxine	
On Antithyroid Medication	
Sick	
Pregnant	
Thyroid Surgery	
I131 Treatment	
Query Hypothyroid	
T3 Measured	
TT4 Measured	
T4U Measured	
FTI Measured	
Category	

Table 1: List of parameters

	Age	Sex	On Thyroxine	Query on Thyroxine	On Antithyroid Medication	Sick	Pregnant	Thyroid Surgery	I131 Treatment	Query Hypothyroid	...	TSH	T3 Measured	T3	TT4 Measured	TT4	T Measur
0	41	F	f	f	f	f	f	f	f	f	...	1.3	t	2.5	t	125	
1	23	F	f	f	f	f	f	f	f	f	...	4.1	t	2	t	102	
2	46	M	f	f	f	f	f	f	f	f	...	0.98	f	?	t	109	
3	70	F	t	f	f	f	f	f	f	f	...	0.16	t	1.9	t	175	
4	70	F	f	f	f	f	f	f	f	f	...	0.72	t	1.2	t	61	

5 rows x 27 columns

Figure 1: Data before pre-processing

	Age	FTI	FTI Measured	Goitre	Hypopituitary	I131 Treatment	Lithium	On Antithyroid Medication	On Thyroxine	Pregnant	...	T3 Measured	T4U	T4U Measured	TSH	TS Measure
0	41.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	1.30	1.0	2.5	1.0	125.
1	23.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	4.10	1.0	2.0	1.0	102.
2	46.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.98	0.0	1.9	1.0	109.
3	70.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.16	1.0	1.9	1.0	175.
4	70.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.72	1.0	1.2	1.0	61.

5 rows x 27 columns

Figure 2: Data after pre-processing

The data cleaning and pre-processing has been done for the removal of useless data (missing values, Null values, NaN). In this paper the principal component analysis(PCA) method has been used for dimensionality reduction and interpretation of the variation in high dimensional interrelated datasets. The pre-processing and classification of typed of thyroid cancer has been shown in figure 3.

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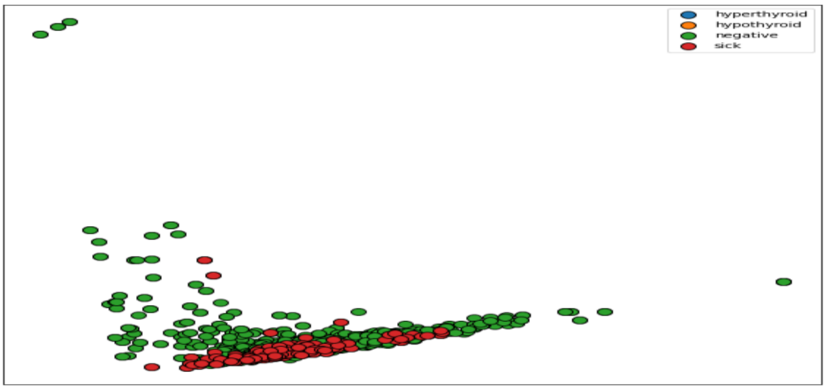

Figure 3 : Data Classification of types of thyroid cancer

4.2 Implementation

Implementation has been done in Google Collaboratory as it offers wide range of support for python and their libraries. The pandas, numpy, matplotlib, and scikit learn libraries were utilised in the implementation of this study. SVMs are commonly used for binary classification, or distinguishing between two classes. The strategy entails training a single classifier per class, with samples from that class serving as positives and all other samples serving as negatives. It basically divides a multiclass classification issue into numerous binary classification tasks. The model has been evaluated and the mean score and the confidence interval of the score estimate are generated in term of initial model accuracy as 0.70 (+/- 0.63) as shown in figure 4.

```
Model Scoring Evaluation Results
The mean score and the confidence interval of the score estimate are:
Accuracy: 0.70 (+/- 0.63)
```

Figure 4 : Model evaluation and initial accuracy

After initial evaluation of model the model has been trained and best model has been saved for further prediction. The classification report has been generated as shown in figure 5. The model classify the data-sets successfully into four different classes: Hyperthyroid, Hypothyroid, Euthyroid-sick, and Euthyroid (negative). The precision, recall, f1-score and support has been obtained and their macro average and weighted average has been calculated as 0.73, 0.81, 0.77, and 806 respectively. One the other hand their confusion matrix has been drawn as shown in figure 6. The final machine learning model using support vector machine approach shows the precision as 73 percent, recall as 81 percent and F1-score 77 percent respectively. Finally, the overall accuracy of model is 97 percent, which is very significant in this domain.

Classification Report

	precision	recall	f1-score	support
hyperthyroid	0.09	0.16	0.12	19
hypothyroid	0.00	0.00	0.00	55
negative	0.86	0.95	0.90	689
sick	0.00	0.00	0.00	43
accuracy			0.81	806
macro avg	0.24	0.28	0.25	806
weighted avg	0.73	0.81	0.77	806

Figure 5: The classification report

```
[ ] # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred, labels=classes)
    print(cm)

    [[653  27   9   0]
     [ 14   3   2   0]
     [ 52   3   0   0]
     [ 43   0   0   0]]
```

Figure 6: The Confusion matrix

5. Discussion

Thyroid cancer is among the most common types of cancer. Identifying it at early stage is very difficult. Machine learning is one of the emerging solution for classification and prediction of thyroid cancer. In this paper machine learning based multiclass support vector machine approach has been used to categorise the types of thyroid cancer with 97 percent accuracy. There is huge gap in theoretical and practical aspects of thyroid cancer. Industrial application of AI has huge demand in healthcare sector. The application of AI is changing and continues to change the domain of healthcare analytics. The proposed model can be extended with introduction of big data, image segmentation and deep learning approaches.

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