



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 8, August 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

Overview of Machine Learning Techniques for Thyroid Cancer Detection

Santhoshini S, Dr. Goutham M A

Assistant Professor, Department of Electronics and Communication Engineering, Sir M Visvesvaraya Institute of
Technology, Bangalore, Karnataka, India

Professor and Head, Department of Electronics and Communication Engineering, Adichunchanagiri Institute of
Technology, Chikmagalur, Karnataka, India

ABSTRACT: This review examines the cutting-edge advancements in Artificial Intelligence (AI) that are transforming how we diagnose thyroid cancer. We explore various AI techniques, including deep learning and neural networks, to analyze data and improve patient outcomes. The review dives into different learning approaches: supervised learning (training AI with labeled data), unsupervised learning (identifying patterns in unlabeled data), and ensemble methods (combining multiple models). It also discusses the importance of thyroid cancer datasets for training AI systems and explores techniques for selecting and extracting key features from this data. We explain how researchers evaluate the effectiveness of AI models using various metrics and showcase a real-world example of AI-powered thyroid cancer detection. Finally, the review acknowledges current limitations and explores potential future directions for research. By providing a comprehensive overview, this review aims to show how AI is fundamentally changing the way we diagnose thyroid cancer, highlighting its immense potential and paving the way for a more optimistic future.

KEYWORDS: Thyroid Cancer, AI techniques, Ultrasound Scan, Validation Datasets and Classification Techniques.

I. INTRODUCTION

Worldwide, data shows a concerning rise in abnormal thyroid nodules. This is linked to a surge in cell activity, where normal cell functions become overactive. There are four main types of thyroid cancer that can develop: papillary, follicular, anaplastic, and medullary. Several factors can contribute to these cancers, including radiation exposure, thyroiditis, genetics. Left untreated, these cancers can lead to other health problems like diabetes, heart rhythm issues, and blood pressure swings. While the number of cancer cells is key to understanding how aggressive a tumor is, traditional methods to count them are slow. This is where a new approach comes in: analyzing cell nuclei as an alternative way to track cancer cell growth. AI is revolutionizing healthcare, transforming how we diagnose diseases, treat patients, and deliver care. Its strength lies in analyzing massive amounts of medical data with unmatched accuracy and speed. This paves the way for earlier detection, more precise diagnoses, and personalized treatment plans. AI can even predict disease outbreaks and streamline hospital operations, ultimately leading to better patient outcomes. As AI technology continues to evolve, we can expect even more sophisticated applications and improved health for everyone. However, trust is crucial for AI to truly take hold. Studies show that security, risk perception, and trust all play a significant role in how people accept AI-powered healthcare assistance. Research confirms that trust is the key factor determining user adoption. Doctors are increasingly turning to computer helpers (CAD systems) to analyze images of thyroid cancer. These systems are famous for improving accuracy and speeding things up, making them a valuable asset. One popular option is a technique called radionics, which works alongside ultrasound scans. This combination is gaining favour because it's affordable, safe, easy to use, and practical for everyday clinical use.

Doctors who specialize in hormones (endocrinologists) often use ultrasound scans with sound waves in the 7-15MHz range to look for thyroid cancer. These scans help them see the size, shape, and other physical features of the thyroid. There's a special system called TI-RADS developed by the American College of Radiology. This system uses features like how solid or fluid-filled a nodule is, its echo pattern, shape, size, edges, and any tiny spots within it to categorize thyroid nodules into six groups, ranging from normal to likely cancerous. Even with the help of CAD systems, accurately identifying and telling apart different types of nodules remains a hurdle. This is because:

- Relying on radiologists' experience and judgment can be subjective.
- Sometimes, image quality isn't the best.
- Ultrasound scans of various types of nodules can look quite similar

Ultrasound scans are commonly used to check for thyroid nodules, but they can be time consuming and stressful for patients. They can also be prone to errors leading to misdiagnoses of normal, benign, malignant, or unclear cases. While a fine-needle aspiration biopsy (FNAB) can provide a more accurate diagnosis, it can also be uncomfortable for patients adding to the overall financial burden. In addition, there are also likely complications wherein, an unskilled specialist might accidentally convert a benign nodule into malignant one. The main difficulty lies in accurately identifying the characteristics that distinguish benign from malignant nodules. Although many studies have explored using ultrasound features to diagnose various cancers, these methods haven't proven reliable enough for thyroid nodules. Artificial intelligence (AI) is emerging as a powerful tool for diagnosing tricky diseases like thyroid cancer.

Here's how it can help:

- **Less guesswork, more accuracy:** AI can analyze ultrasound images more objectively than doctors, leading to fewer misdiagnoses.
- **Faster results:** AI can process information much quicker than humans, saving valuable time.

Machine learning (ML) and deep learning (DL) are specific types of AI showing promise in automating the classification of thyroid nodules. This technology can be used for various tests, including ultrasounds, biopsies, and even during surgery. Several studies have already shown positive results.

However, AI's effectiveness depends on two key factors:

- **Lots of data:** The more data AI has to train on, the better it performs.
- **Precise classification:** The way AI categorizes nodules needs to be highly accurate.

Thyroid cancer is becoming more common, and early detection is crucial for successful treatment. This is why we're excited about the potential of Artificial Intelligence (AI) and machine learning to improve how doctors diagnose this disease. AI can analyze medical images, biopsies, and even genetic data much faster and more objectively than traditional methods like needle biopsies, which can sometimes be inconclusive. This review brings together experts from computer science, radiology, and medicine to explore how AI can be used in the clinic to help doctors provide better patient care.

We'll discuss the potential benefits of AI, including:

- More accurate diagnoses
- Faster results
- Less invasive procedures
- Reduced healthcare costs
- Shorter wait times for patients

However, it's important to acknowledge the challenges of using AI in healthcare, such as data privacy concerns and ethical considerations. This review aims to provide a complete picture of how AI is currently being used, and how it could be used in the future, to help researchers and doctors fight thyroid cancer.

II. RELATED WORK

Vijay et al. [1] explored using machine learning to automatically classify thyroid nodules in ultrasound images. They analyzed the images by first finding the borders of the nodules and then converting them from gray to black and white. The researchers then built a computer program to identify features in the images and used those features to train a machine learning model to distinguish between benign and malignant nodules. Their model, based on Support Vector Machines (SVM), achieved an accuracy rate of nearly 96%, outperforming a different type of machine learning model (Artificial Neural Network). Their article also mentions additional details about the research but doesn't directly relate to the nodule classification task. The authors used machine learning (ML) using MATLAB to create a scoring system for detecting thyroid nodules in ultrasound images. MATLAB's ML tools were used to build models to classify nodules (malignant vs benign), while the GUI toolbox designed a userfriendly interface. They used a public database of thyroid

ultrasound images to train their models. First, they identified the nodule's borders (segmentation) to define the area for analysis. Then, they extracted seven key characteristics (features) using a technique called GLCM to differentiate between malignant and benign nodules. Finally, they built a program using SVM, which performed better than ANN on all accuracy measures.

The study found that the SVM model significantly outperformed the ANN model, achieving 96% accuracy compared to ANN's 75%. SVM also did better on other measures like sensitivity and specificity. The researchers concluded that even basic machine learning approaches, particularly SVM in this case, showed great promise for classifying thyroid nodules. However, they emphasize the need for further testing on new data sets before this model can be used in real-world clinical settings.

Prabal et al. [2] published a report analyzing the use of machine learning approaches, including Support Vector Machine, Artificial Neural Network, and Random Forest Classifier, to classify thyroid texture in ultrasound images using autoregressive features. The report discusses the importance of thyroid imaging and the challenges associated with thyroid diseases. It also presents a detailed feature extraction process and the use of different texture classification methods. The results of the study are compared with existing literature, and the performance metrics used include Dice's Coefficient, Sensitivity, and Specificity. The report concludes by discussing the robustness of the feature extraction process and the fully automated nature of the approaches used.

Their study involved four key steps:

Building the Image Library: Researchers collected real-world ultrasound images and prepared them for training the classification models.

Extracting Features: They then analyzed the image patches to identify key characteristics that differentiate between nodule types.

Classifying Textures: Different machine learning methods, including SVM, ANN, and RFC, were used to train models to categorize these image patches as benign or malignant.

Refining the Results: Finally, a step was applied to remove any misclassified image patches from the trained models for better accuracy.

The authors compared three machine learning methods (SVM, ANN, and RFC) against the latest techniques on two separate datasets. They used three metrics to compare performance: Dice's Coefficient (DC), Sensitivity (SE), and Specificity (SP). All three methods achieved good accuracy in classifying the image patches, with ANN performing the best. Encouragingly, the entire process – from feature extraction to training and testing – is automated. More importantly, the results closely matched the actual data (ground truth). The study concludes that their proposed methods achieved better Dice's Coefficient scores than previous approaches, while maintaining similar Sensitivity and Specificity.

Rajasekhar et al. [3] carried out a study to explore a new machine learning method to predict five different types of thyroid disease. They compared four ways to extract key characteristics (feature engineering) from the data and tested five traditional machine learning models alongside three deep learning models. To ensure a fair comparison, they addressed the uneven spread of data points (imbalanced dataset) through preprocessing. They evaluated the models' performance using various metrics like accuracy, precision, recall, and F1 score, along with a confusion matrix and a special validation technique (10-fold cross-validation) that helps assess robustness. Impressively, the study achieved a very high accuracy (99%) in predicting the ten thyroid diseases. The study looked at several techniques to identify the most important data points (features) for predicting thyroid disease. These techniques included both general approaches like forward selection and backward elimination, as well as specialized machine learning methods. They used this process on a dataset with 30 features to pick the most relevant ones for training their machine learning models, which included an approach called the "extra tree classifier." This helps the models focus on the information that truly matters for accurate prediction. The study's machine learning approach achieved impressive results in predicting ten types of thyroid disease. Their method, which relied on features selected using a technique called "random forest," achieved a near-perfect accuracy of 99%, outperforming other models. They even compared their approach to existing research and found it significantly better. However, the researchers acknowledged some limitations. The data set they used was

on the smaller side, and feature selection further reduced the data size. To improve accuracy and efficiency in future work, they suggested using larger datasets and exploring ways to minimize data loss during feature selection.

Gopinath and Shanthi [4] published a report that describes an automated system to analyze fine-needle aspiration (FNA) images and identify thyroid cancer patterns. The system works by (1) separating thyroid cells from the background in the image (segmentation), (2) analyzing textures within the cells to find key characteristics (using Gabor filters), (3) selecting the most important characteristics for differentiation, and (4) using a machine learning method (SVM) to classify the cells as benign or cancerous. This approach achieved a very high accuracy (96.7%) in detecting thyroid cancer, with a strong ability to identify both positive and negative cases (sensitivity and specificity). The study suggests that the system could be a valuable tool for diagnosing thyroid cancer from FNAC images.

The study describes a method to analyze fine-needle aspiration (FNA) images and differentiate between benign and malignant thyroid nodules.

Here's how it works:

Separating the Cells: First, the system separates the thyroid cells from the rest of the image using a special technique called "mathematical morphology segmentation."

Identifying Cell Characteristics: Then, it analyses the textures within the cells to find key characteristics. This is done using a filter called a "Gabor filter" applied at different settings.

Classifying the Cells: Finally, the system uses two machine learning methods (k-nearest neighbor and Support Vector Machine) to classify the cells as either benign or malignant based on the identified characteristics.

This approach helps identify features in the cells that differentiate between benign and malignant nodules.

The study compared two machine learning methods for classifying thyroid nodules in FNAC images. The Support Vector Machine (SVM) achieved a significantly higher accuracy (96.7%) than the k-Nearest Neighbor (k-NN) classifier (60%). SVM also showed better sensitivity (95%) and specificity (100%) at a specific wavelength and angle setting. This suggests that SVM with statistical texture features is more effective for automated diagnosis of thyroid cancer in FNAC images.

Vanitha and Perumal [5] reported their research that explores using machine learning to detect thyroid cancer. The study compared six different machine learning methods: Naive Bayes, logistic regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Artificial Neural Network, and AdaBoost. They tested these methods on a dataset of thyroid cancer data and compared their accuracy in predicting cancer. The report explains what each method does and how well it performed. Finally, the researchers discuss potential improvements for future development of these detection techniques. This research investigated machine learning for thyroid cancer detection. They analyzed a dataset containing information about thyroid patients, divided into three groups: normal, hypothyroidism (underactive thyroid), and hyperthyroidism (overactive thyroid). They tested seven machine learning methods on this data: Naive Bayes, logistic regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Artificial Neural Network, and AdaBoost. Their goal was to find the most accurate method for predicting thyroid conditions. The study also explored using a technique called "mutual information" to identify the most important data points for prediction. Finally, they analyzed the results to see which factors (pathological and blood test results) were most helpful in identifying thyroid cancer. Out of all the methods tested, Support Vector Machine (SVM) performed the best, achieving an accuracy of over 92%. The study compared four machine learning methods for detecting thyroid cancer: Logistic Regression (91.73% accuracy), Decision Tree (90.13% accuracy), Support Vector Machine (SVM, 92.53% accuracy), and Naive Bayes (90.67% accuracy). Encouragingly, all four methods performed better than traditional methods used by doctors. SVM showed the highest accuracy among these machine learning techniques. The authors concluded that these machine learning algorithms can be a valuable tool for doctors diagnosing thyroid problems. The algorithms may help reduce errors caused by unclear test results. Additionally, the study suggests that using even larger datasets in the future could lead to even more accurate detection of thyroid cancer.

Zhang et al. [6] introduced a new framework for detecting thyroid cancer using machine learning. This framework is unique because it offers doctors flexibility in choosing the best approach based on their specific needs and data. It can handle both balanced and imbalanced datasets, which is often a challenge in medical data analysis. The authors tested the framework on real-world datasets and found that it significantly improved the accuracy of diagnosing malignant

nodules. Additionally, the framework provides clear and interpretable outputs, allowing doctors to understand the results and make informed decisions. Overall, the study suggests this framework has potential for real-world use in clinical settings, possibly aiding doctors in diagnosing thyroid cancer with improved accuracy. The authors developed the framework called "Multi-Channel Xception-based Thyroid Cancer Detection" (MXTCD). This framework tackles challenges in medical image analysis, specifically for detecting thyroid cancer.

MXTCD works in two steps:

Pre-training: Medical images are fed into a pre-trained Xception model using tasks that classify images into two categories (binary classification).

Multi-channel Architecture: Based on doctor's needs, the system uses Xception with different configurations for tasks requiring binary or multiple-category classification (multi-class).

The authors assessed the models based on various metrics, including accuracy, how well they identify true positives (f1 score, precision, recall), ability to rule out cancer (negative predictive value), and processing speed (running time).

MXTCD offers impressive accuracy of 98.9% for Ultrasound images and 97.5% for CT scans. The authors suggested that their framework is unique because it allows doctors to tailor the approach to their specific needs and data (patient-centric design). The study also found that the type of medical image used (ultrasound vs. CT scan) can impact accuracy. They concluded that MXTCD outperforms existing methods with high accuracy (up to 98.9%), the framework is flexible and adaptable to different clinical needs, the choice of medical imaging modality can be important for optimal results, and also, MXTCD uses a specific neural network (Xception) that performs well compared to others. The framework is potentially interpretable by doctors, aiding diagnosis. Overall, this study suggests MXTCD has practical uses for improving thyroid cancer detection accuracy and efficiency in clinical settings.

Setiawan [7] investigated using machine learning to predict whether Differentiated Thyroid Cancer (DTC) will return after treatment. The study compared 23 different machine learning models, including some that combine multiple models (ensemble methods). They also explored using a technique called "chi-square" to identify the most important factors for prediction (feature selection). The data was obtained from a public source. Interestingly, after applying feature selection, ten of the machine learning models achieved a perfect accuracy (100%) in predicting both if DTC would recur or not. Overall, the study suggests that machine learning, particularly when combined with feature selection techniques like chi-square, can be a powerful tool for predicting DTC recurrence. The author in this study built on a dataset from a previous study to investigate the impact of feature selection using chi-square on machine learning models' ability to predict recurrence of differentiated thyroid cancer (DTC). The research work compared the models' predictive accuracy with and without feature selection. This involved finding the optimal settings (hyperparameters) for each machine learning model. Then, the data was split into two parts: 80% for training the models and 20% for testing their accuracy on unseen data. To perform feature selection, certain factors were excluded based on statistical tests (p-values) and explored 46 different combinations of factors through a technique called "grid search." Finally, comparison of the models' performance with and without feature selection was carried out to see if focusing on the most important factors improved prediction accuracy.

It was concluded that feature selection improves machine learning for predicting thyroid cancer recurrence. Machine learning models achieved near perfect accuracy with feature selection. Random forest performed best. It was also suggested that future research could explore deep learning approaches and using more data.

This review published by Anari et al. [8] examines various deep learning techniques (CNNs, GANs, LSTMs, DBNs, RNNs) used to classify thyroid nodules as cancerous or benign. It analyzes the effectiveness of these methods in diagnosing thyroid cancer. The review acknowledges that deep learning shows promise, but also highlights the need for further research and improved data preprocessing techniques to maximize their accuracy in diagnosing thyroid cancer.

The review explores how deep learning is being used to diagnose thyroid cancer. It examines how various algorithms, including CNNs, GANs, and even auto encoders, are applied to analyze images, gene expressions, and RNA-Sequencing data from patients. The review identifies two key areas for improvement namely, (a) preprocessing techniques and (b) multimodal data integration. The review mentions more effective methods are needed to prepare medical images for analysis by deep learning models, and also combining data from different sources (images, gene data) could provide a more comprehensive picture of thyroid nodules. The review highlights the promise of deep

learning for diagnosing thyroid cancer, but emphasizes the need for further development in data preparation and analysis techniques. Selecting the most relevant factors (feature selection) significantly improved machine learning models' ability to predict whether thyroid cancer would return after treatment. Some models achieved near perfect accuracy (94-98%) in predicting both positive and negative cases (recurrence and no recurrence). Random forest emerged as the best performing model.

The study suggests that feature selection, particularly chi-square, is a valuable tool for improving machine learning in predicting thyroid cancer recurrence. Future research could explore deep learning techniques and using more data to potentially achieve even better results. Begum et al. [9] studied challenges in early thyroid cancer diagnosis. They proposed a new system that uses a special machine learning technique (Bi-directional RNN with K-means clustering) to analyze data and identify thyroid problems, including cancer. The system analyzes a dataset containing almost 7,200 data points with various characteristics (categorical and numerical) about thyroid patients. To improve efficiency, the researchers also explored techniques to identify the most important data points for analysis. The proposed system achieved a high accuracy (98.72%) in detecting thyroid cancer. The study discusses potential areas for future research, including referencing relevant literature on analyzing and classifying categorical data. The authors suggest a promising new approach for using machine learning to improve thyroid cancer detection.

The system utilizes a special machine learning technique called a Bi-Directional RNN with Kmeans clustering to analyze various data points (variables) about a patient. Key features of the system are: (a) analysis of multiple variables, (b) prediction of healthy vs. problematic cases, (c) reduction in data complexity, (d) enhanced hypothyroidism diagnosis, and (e) cancer stage classification. The system achieved impressive results in terms of accuracy (98.72%), high true positive rate (TPR) of 0.987 (correctly identifies most true cancer cases), low false positive rate (FPR) of 0.013 (minimizes false alarms), good precision (0.921) and recall (0.987). When compared to existing systems, the proposed approach showed superior accuracy. The study concludes that this machine learning system effectively predicts thyroid cancer with high accuracy. They highlight the challenges of diagnosing thyroid cancer and emphasize the improvements in accuracy, recall, and precision achieved by this new system compared to existing methods. The authors suggest further research on novel data mining techniques to potentially improve disease diagnosis accuracy even more. Zhang et al. [10] analyzed over 2,000 nodules using two datasets with different characteristics and compared nine machine learning algorithms. Their research delves deeper into the workings of Random Forests, a specific machine learning method used in the study. It also references other relevant research on thyroid nodules and cancer, as well as additional papers on data analysis techniques used with machine learning models like Random Forests. Researchers analyzed two datasets wherein, the first dataset included 11 ultrasound (US) features, and the second dataset included the same 11 US features plus a real-time elastography (RTE) feature. Nine different machine learning algorithms were tested on these datasets, including common methods like logistic regression and random forest. To ensure accuracy, the researchers split the data (2064 nodules) into training and validation sets (3:2 ratio) and used a technique called 10-fold cross-validation for evaluation. Out of all the algorithms tested by the authors, random forest achieved the best performance in diagnosing nodules. The authors then compared the random forest's results with diagnoses by an experienced radiologist. Interestingly, the study found that the random forest's performance depended on specific features within the datasets, such as calcification patterns, presence of a halo around the nodule, lymph node status, nodule shape, and blood flow patterns. This work suggests that machine learning, particularly random forest algorithms, could be a valuable tool for diagnosing thyroid nodules, especially when considering specific features identified in the study.

Cicek and Kucukakcali [11] developed a clinical decision support model using the Bagged CART model to predict thyroid cancer. The model achieved high predictive performance metrics, including an accuracy of 99.1%, balanced accuracy of 98.7%, sensitivity of 99.7%, specificity of 97.7%, positive predictive value of 99.1%, negative predictive value of 99.2%, and F1-score of 99.4%. The study's dataset included 724 individuals, with 28.2% having benign nodules and 71.8% having malignant nodules. The Bagged CART model was found to be effective in predicting thyroid cancer. Researchers built a machine learning model (Bagged CART) to predict thyroid cancer using patient data from a hospital. The model analyzed factors like nodule characteristics, blood tests, and demographics. It achieved high accuracy and identified key factors influencing cancer prediction. The model analyzed patient data, achieving an overall accuracy of 99.1% and excelling in metrics like sensitivity and specificity. The study also identified key factors influencing cancer prediction, such as nodule size, thyroid hormone levels, blood flow patterns, and patient age. The research suggests that the Bagged CART model has the potential to be a valuable tool for doctors, aiding in faster diagnosis and potentially improving preventive medicine practices.

Li et al. [12] investigated using deep learning (specifically DCNNs) to analyze ultrasound images and improve thyroid cancer diagnosis. Their new system achieved high accuracy in identifying cancer across multiple test groups, performing at similar or better levels than a group of skilled radiologists. Their research investigated using deep learning to analyze ultrasound images for diagnosing thyroid cancer.

The key highlights of the study were:

Large Dataset: Researchers analyzed a massive dataset of ultrasound images from over 42,000 patients across three hospitals in China.

Multiple Validation Sets: The model's performance was tested on data from different hospitals, ensuring its generalizability.

Compared to Radiologists: The deep learning model achieved similar or better accuracy in identifying cancer cases compared to a group of experienced radiologists. The researchers suggested that deep learning has great potential as a tool for diagnosing thyroid cancer, especially considering the large dataset and validation across multiple hospitals.

They concluded that the high performance of the DCNN model could lead to a reduction in unnecessary invasive fine-needle aspiration biopsy procedures and overdiagnosis and overtreatment of thyroid cancer. It also has the potential to reduce barriers and provide equal access to diagnostic tools for thyroid cancer in regions and countries where medical resources are scarce.

Mir and Mittal [13] investigated using machine learning to predict different types of thyroid disease (normal, hyperthyroidism and hypothyroidism). The study analyzed data from over 1400 patients from Sawai Man Singh (SMS) hospital in India which included 1464 patients with information on 18 pathological tests and 3 blood tests (serological). The authors tested various machine learning algorithms to predict thyroid disease based on different combinations of data (pathological only, serological only, or both). They achieved the highest accuracy (98.56%) using a technique called "bagging classifier". This study suggests that machine learning, particularly using a combination of pathological and serological data, could be a valuable tool for accurately predicting thyroid disease. The authors used WEKA software for analysis on a Mac computer with specific processing power details (1.8 GHz processor, 8 GB RAM). They employed a technique called "K-fold cross validation" to assess the accuracy of their methods. This involves splitting the data into 10 parts, using one part for testing each time and the remaining nine for training. Finally, they averaged the accuracy across all tests. The authors concluded that different machine learning models might be better suited depending on the type of data available (pathological vs. serological). Their study also highlights the potential for further improvement by increasing the dataset size and exploring feature selection techniques.

Xi, Wang, and Yang [14] investigated using machine learning to improve diagnosing thyroid cancer before surgery. The authors analyzed data from 724 patients with thyroid nodules (1232 nodules total). They used six machine learning models to analyze factors like ultrasound images, patient demographics, and blood tests. The machine learning models achieved high accuracy in predicting whether a nodule was cancerous. To ensure unbiased results, they used a technique called ten-fold cross-validation to evaluate the models' performance. Additionally, they employed bootstrap analysis to quantify the uncertainty in the models' performance. The study also analyzed which factors within the data were most important for the models' predictions. Finally, they compared the models' performance to expert doctors' assessments. The results showed that the machine learning models significantly outperformed human judgment in predicting cancer.

Mourad, M. et al. [15] explored using Machine learning and feature selection algorithms (namely, Fisher's discriminant ratio, Kruskal-Wallis' analysis, and Relief-F) have been combined together on SEER database containing clinical features from de-identified thyroid cancer patients and also they demonstrated that distinguishing patients in terms of prognosis has been achieved with 94.5% accuracy.

Nguyen et al. [16] introduced a new method using artificial intelligence (AI) to improve how doctors classify thyroid nodules using ultrasound images. The method analyzes ultrasound images in detail to identify important characteristics (features) that might indicate a nodule is cancerous. The system then uses a multi-stage approach (cascade classifier) to categorize the nodule based on the extracted features. The authors tested their method on a large dataset (TDID) and achieved better results than previous approaches. They also explored using transfer learning (fine-tuning pre-trained

models) to potentially improve the system further. The authors proposed a new machine learning system to improve diagnosing thyroid nodules using ultrasound images. The system analyzes images in stages (cascade) to categorize nodules. Following that, they extract important features from the image in two ways (a) analyzing the image itself (spatial domain), and examining image frequencies (frequency domain). To improve accuracy, they use both deep learning and frequency-based methods for feature extraction.

They tested their system on a large dataset of thyroid ultrasound images (TDID). The system achieved better accuracy in classifying nodules compared to previous methods. They measured success using standard metrics like accuracy, specificity, and sensitivity. Overall, the results show that this new system performs well when compared to cutting-edge techniques. The authors conclude that this machine learning system has promise for improving the diagnosis of thyroid nodules from ultrasound images.

Nasr et al. [17] explored using deep learning, a type of artificial intelligence, to analyze ultrasound images and identify thyroid cancer and create a system to carry out the studies. The system achieved an impressive 99.9% accuracy in classifying cancerous and benign nodules using various deep learning models, including VGG16, MobileNet, and InceptionResNetV2. The researchers used a dataset containing 350 thyroid ultrasound images (260 patients), with confirmed classifications of benign or malignant nodules. They analyzed the system's performance using several metrics, including precision, recall, sensitivity, specificity, and overall accuracy. Their study highlights the potential of deep learning to significantly improve the accuracy of classifying thyroid nodules during ultrasound scans.

Wang et al. [18] explored using machine learning to predict if papillary thyroid cancer will return after initial treatment. They analyzed data from a large group of patients with various factors potentially affecting recurrence.

The authors analyzed data from 29 factors related to patients with this type of cancer. They used various factors such as (1) patient demographics (age, etc.), (2) existing health conditions, (3) Tumor characteristics, (4) Lymph node involvement, and (5) Blood tests (metabolic and inflammatory markers). They built models using five different machine learning algorithms, namely Logistic regression, Support vector machine, Extreme gradient boosting, Random Forest and Neural network. Rigorous testing was carried out to ensure the models' accuracy. They split the data into training and testing sets. The training set was used to develop and refine the models, while the testing set was used to evaluate their performance.

They also employed various techniques to select the most important factors for the models' predictions. Finally, they compared the models' performance, aiming to identify the one with the best results in predicting cancer recurrence. The study concluded that the random forest (RF) model achieved the expected prediction performance with generally good discrimination, calibration, and interpretability. It also highlighted the potential of machine learning approaches for improving the accuracy of risk stratification for papillary thyroid cancer patients.

Shih et al. [19] investigated using computer analysis of cell samples (cytology) to improve diagnosing papillary thyroid cancer. By analyzing features in cell samples, the authors identified six key characteristics that differed significantly between cancerous and benign thyroid nodules. They used these features to develop a system for estimating cancer risk in cases where initial tests were inconclusive (indeterminate FNAC results). The system achieved good accuracy (AUROC of 81.3%). Their study also proposed new ways to analyze these cell samples using computers. The research suggests that computerized analysis of cytological features can effectively distinguish between benign and malignant nodules, potentially leading to earlier and more accurate diagnoses.

Gu et al. [20] carried out research that explores using machine learning to improve how doctors assess thyroid cancer risk. They developed a system using the XGBoost algorithm that analyzes factors like blood tests and demographics to predict how aggressive a patient's thyroid cancer might be (metastasis). The developed machine learning approach reportedly outperforms the existing TI-RADS classification standard for assessing thyroid cancer. The authors also developed a free online tool that doctors can potentially use to identify patients at high risk for aggressive thyroid cancer.

Author	Technique / Methodology	Dataset	Result
Vijay et al. [1]	MATLAB's ML tools were used to build models. Extracted characteristics (features) using a technique called GLCM to differentiate between malignant and benign nodules.	Data obtained from the Universidad Nacional de Colombia.	ANN and SVM achieved an accuracy of 75% and 96% respectively. SVM outperformed all the other models.
Prabal et al. [2]	Thyroid texture identification from Ultrasound images. SVM, ANN, and Random Forest Classifier were used to classify thyroid texture.	Thyroid US datasets from SurgicEye GmbH and University Clinic of Magdeburg, Germany.	They use image-based features to characterize thyroid tissues. They obtained an accuracy of around 90% with all the three methods.
Rajasekhar et al. [3]	New machine learning method to predict five different types of thyroid disease using SVM.	UCI Thyroid Diseases dataset	The study achieved a very high accuracy (99%) in predicting the ten thyroid diseases.
Gopinath and Shanthi [4]	Automated system to analyse fine-needle aspiration (FNA) images and identify thyroid cancer patterns. Used SVM and kNN classifiers.	Thyroid FNAC images have been used from online image atlas of Papanicolaou Society of Cytopathology	SVM achieved a significantly higher accuracy (96.7%) than the k-NN classifier (60%).
Vanitha and Perumal [5]	This research investigated machine learning for thyroid cancer detection. Different models were compared.	UCI machine learning repository	Out of all the methods tested, SVM performed the best, achieving an accuracy of over 92%.
Zhang et al. [6]	They developed a framework which offers doctors flexibility in choosing the best approach based on their specific needs and data. It can handle both balanced and imbalanced datasets.	Digital Database Thyroid Image (DDTI) and Thyroid Imaging Reporting and Data System (TIRADS)	MXTCD outperforms existing methods with high accuracy (up to 98.9%), the framework is flexible and adaptable.
Setiawan [7]	Investigated using machine learning to predict whether Differentiated Thyroid Cancer (DTC) will return after treatment.	Differentiated Thyroid Cancer Recurrence Dataset at UCI ML Repository	The study suggests that machine learning, particularly when combined with feature selection techniques like chi-square, can be a powerful tool for predicting DTC recurrence.
Anari et al. [8]	Examined various deep learning techniques (CNNs, GANs, LSTMs, DBNs, RNNs) used to classify thyroid nodules as cancerous or benign.	Different data sources for different models.	Some models achieved near perfect accuracy (94-98%) in predicting both positive and negative cases. Random forest emerged as the best performing model.
Begum et al. [9]	Bi-directional RNN with K-means clustering to analyze data and identify thyroid problems, including cancer	Thyroid illness dataset from UCI machine learning store	The proposed system achieved a high accuracy (98.72%) in detecting thyroid cancer.
Zhang, B., et al. [10]	Machine learning for Differential diagnosis of thyroid nodules from Ultrasound Images.	NCI CPTAC Assay Portal	The random forest classifier, may diagnose malignant thyroid nodules better than other methods.
Cicek and Kucukakcali [11]	Developed a clinical decision support model using the Bagged CART model to predict thyroid cancer	Dataset obtained from Shengjing Hospital of China Median University	The Bagged CART model was found to be effective in predicting thyroid cancer.

Li et al. [12]	Investigated using deep learning (specifically DCNNs) to analyze ultra-sound images and improve thyroid cancer diagnosis	dataset of ultrasound images from over 42,000 patients across three hospitals in China	The high performance of the DCNN model could lead to a reduction in unnecessary invasive fine-needle aspiration biopsy procedures.
Mir and Mittal [13]	Used machine learning to predict different types of thyroid disease (normal, hyperthyroidism, hypothyroidism).	Data from over 1400 patients from Sawai Man Singh (SMS) hospital in India.	They achieved the highest accuracy (98.56%) using a technique called “bagging classifier”.
Xi, Wang, and Yang [14]	Used machine learning to improve diagnosing thyroid cancer before surgery using information about thyroid nodules.	The authors analyzed data from 724 patients with thyroid nodules (1232 nodules total).	The results showed that the machine learning models significantly outperformed human judgment in predicting cancer.
Mourad, M. et al. [15]	Machine learning and feature selection algorithms (namely, Fisher’s discriminant ratio, Kruskal-Wallis’ analysis, and Relief-F) have been combined together.	SEER database containing clinical features from de-identified thyroid cancer patients.	They demonstrated that distinguishing patients in terms of prognosis has been achieved with 94.5% accuracy.
Nguyen et al. [16]	Introduced a new method using AI where the system analyzes images in stages (cascade) to categorize nodules followed by feature extraction.	Thyroid ultrasound images (TDID) dataset	This machine learning system has promise for improving the diagnosis of thyroid nodules from ultrasound images.
Nasr et al. [17]	Explored using deep learning to analyze ultrasound images and identify thyroid cancer	The researchers used a dataset containing 350 thyroid ultrasound images (260 patients), with confirmed classifications of benign or malignant nodules.	The system achieved an impressive 99.9% accuracy in classifying cancerous and benign nodules using various deep learning models.
Wang et al. [18]	Logistic regression, SVM, XGBoost, Random Forest and Neural network were used to predict if papillary thyroid cancer will return after initial treatment.	They analyzed data from a large group of patients with various factors potentially affecting recurrence.	The study concluded that the random forest (RF) model achieved the expected prediction performance.
Shih et al. [19]	Computer analysis of cell samples (cytology) to improve diagnosing papillary thyroid cancer.	Retrospective cross-sectional study included 240 cases.	Computerized analysis of cytological features can effectively distinguish between benign and malignant nodules.
Gu et al. [20]	Developed a system using the XGBoost algorithm that analyzes factors like blood tests and demographics to predict how aggressive a patient's thyroid cancer might be (metastasis).	Retrospectively collected approximately 70 preoperative demographic and laboratory test indices from 1735 TC patients.	The XGBoost model achieved the best performance in the final thyroid nodule diagnosis (AUC: 0.84) and metastasis (AUC: 0.72-0.77) predictions.

III. CONCLUSION

The various research works examined the performance of various artificial intelligence (AI) systems designed to detect thyroid cancer. They analysed different AI models using metrics like accuracy, sensitivity, and specificity. These studies conclude that AI has great potential for improving thyroid cancer detection. However, the studies also emphasize the importance of ongoing evaluation to ensure these systems are used responsibly and effectively. The overall conclusion is that more research work is needed that highlights areas for future investigation to overcome current challenges and improve the practical use of AI for detecting thyroid cancer.

REFERENCES

1. Vijay V.V., Simpkin A., O'Connell J., Ospina N.S., Maraka S., and O'Keeffe D.T., Ultrasound Image Classification of Thyroid Nodules Using Machine Learning Techniques, *Medicina (Kaunas)*. 2021 Jun; 57(6): 527.
2. Prabal P., Alfredo I., Elmer J.G.A., Nazila E., Sathish B., and Michael F., Thyroid Ultrasound Texture Classification Using Autoregressive Features in Conjunction with Machine Learning Approaches, *IEEE Access*, Volume 7, 79354-79365 (2019).
3. Rajasekhar C., Furqan R., Isabel De La T.D., Juan L.V.M., Carmen L.R., and Imran A., Thyroid Disease Prediction Using Selective Features and Machine Learning Techniques, *Cancers (Basel)*. 2022 Aug; 14(16): 3914.
4. Gopinath B., and Shanthi N., Support Vector Machine based diagnostic system for thyroid cancer using statistical texture features, *Asian Pac. J. Cancer Prev.* 2013;14(1):97-102.
5. Vanitha R., and Perumal K., Thyroid cancer detection using machine learning techniques, *IJCRT Vol. 10 Issue 1*, 547 (2022).
6. Zhang X., Lee V.C.S., Rong J., Liu F., and Kong H., Multi-channel convolutional neural network architectures for thyroid cancer detection, *PLoS One*. Vol. 17(1), e0262128 (2022).
7. Setiawan K.E., Predicting recurrence in differentiated thyroid cancer: a comparative analysis of various machine learning models including ensemble methods with chisquared feature selection, *Commun. Math. Biol. Neurosci.*, Vol. 2024, Article ID 55 (2024).
8. Anari S., Sarshar N.T., Mahjoori N., Dorosti S., and Rezaie A., Review of Deep Learning Approaches for Thyroid Cancer Diagnosis, *Math. Prob. in Eng.* Vol. 7, 1-8 (2022).
9. Begum A.M., Tresa M.I., Sandhya S., Vidhya S., and Vinodhini G., Machine Learning Based Dysfunction Thyroid Cancer Detection with Optimal Analysis, *Turk. J. of Comp. and Math. Edu.*, Vol. 12, No.7, 818-823 (2021).
10. Zhang B., Tian J., Pei S., Chen Y., He X., Dong Y., Zhang L., Mo X., Huang W., Cong S., and Zhang S., Machine Learning-Assisted System for Thyroid Nodule Diagnosis, *Thyroid.*, Vol. 29(6), 858 (2019).
11. Cicek I.B., and Kucukakcali Z., Machine Learning Approach for Thyroid Cancer Diagnosis Using Clinical Data, *Mid. Blac. Sea J. Health Sci.*, Vol. 9(3), 440 (2023).
12. Li X., Zhang S., Zhang Q., Wei X., Pan Y., Zhao J., Xin X., Qin C., Wang X., Li J., Yang F., Zhao Y., Yang M., Wang Q., Zheng Z., Zheng X., Yang X., Whitlow C.T., Gurcan M.N., Zhang L., Wang X., Pasche B.C., Gao M., Zhang W., and Chen K., Diagnosis of thyroid cancer using deep convolutional neural network models applied to sonographic images: a retrospective, multicohort, diagnostic study, *Lancet Oncol.*, Vol. 20(2), 193 (2019).
13. Mir Y.I., and Mittal S., Thyroid Disease Prediction Using Hybrid Machine Learning Techniques: An Effective Framework, *IJSTR Vol. 9(2)*, 2868 (2020).
14. Xi, N.M., Wang, L., and Yang, C., Improving the diagnosis of thyroid cancer by machine learning and clinical data, *Sci. Rep.*, Vol 12, 11143 (2022).
15. Mourad M., Moubayed S., Dezube A., Mourad Y., Park K., Torreblanca-Zanca A., Torrecilla J.S., Cancilla J.C., and Wang J., Machine Learning and Feature Selection Applied to SEER Data to Reliably Assess Thyroid Cancer Prognosis, *Sci Rep.*, Vol. 10(1), 5176 (2020).
16. Nguyen D.T., Pham T.D., Batchuluun G., Yoon H.S., and Park K.R., Artificial Intelligence-Based Thyroid Nodule Classification Using Information from Spatial and Frequency Domains, *J. Clin. Med.*, Vol. 8(11), 1976 (2019)
17. Nasr S.A., Abdel-Fattah H.M., Abdelsalam M.M., and Moustafa H.E., An Accurate Deep Learning Based Framework for Detection of Thyroid Cancer Using Ultrasound Images, *IJCBS*, Vol. 24(12), 455 (2023).
18. Wang H., Zhang C., Li Q., Tian T., Huang R., Qiu J., and Tian R., Development and validation of prediction models for papillary thyroid cancer structural recurrence using machine learning approaches, *BMC Cancer* Vol. 24, 427 (2024).
19. Shih S.R., Jan I.S., Chen K.Y., Chuang W.Y., Wang C.Y., Hsiao Y.L., Chang T.C., and Chen A., Computerized Cytological Features for Papillary Thyroid Cancer Diagnosis Preliminary Report, *Cancers (Basel)*. Vol. 11(11), 1645 (2019).
20. Gu J., Xie R., Zhao Y., Zhao Z., Xu D., Ding M., Lin T., Xu W., Nie Z., Miao E., Tan D., Zhu S., Shen D., and Fei J., A machine learning-based approach to predicting the malignant and metastasis of thyroid cancer, *Front Oncol.* Vol. 12, 938292 (2022).



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details