

Machine Learning and Vision Transformers for Thyroid Carcinoma Diagnosis: A review

Yassine Habchi^{a,*}, Hamza Kheddar^{b,**}, Yassine Himeur^c, Abdelkrim Boukabou^d, Ammar Chouchane^e, Abdelmalik Ouamane^f, Shadi Atalla^c and Wathiq Mansoor^c

^aInstitute of Technology, University Center Salhi Ahmed, Naama, Algeria

^bLSEA Laboratory, Electrical Engineering Department, University of Medea, 26000, Algeria

^cCollege of Engineering and Information Technology, University of Dubai, Dubai, UAE

^dDepartment of Electronics, University of Jijel, BP 98 Ouled Aissa, 18000 Jijel, Algeria

^eUniversity Center of Barika. Amdoukal Road, Barika, 05001, Algeria.

^fLaboratory of LI3C, Mohamed Khider University, Biskra, Algeria

ARTICLE INFO

Keywords:

Thyroid carcinoma detection
Artificial intelligence
Deep learning
Biomedical images
Transformers

ABSTRACT

The growing interest in developing smart diagnostic systems to help medical experts process extensive data for treating incurable diseases has been notable. In particular, the challenge of identifying thyroid cancer (TC) has seen progress with the use of machine learning (ML) and big data analysis, incorporating transformers to evaluate TC prognosis and determine the risk of malignancy in individuals. This review article presents a summary of various studies on AI-based approaches, especially those employing transformers, for diagnosing TC. It introduces a new categorization system for these methods based on artificial intelligence (AI) algorithms, the goals of the framework, and the computing environments used. Additionally, it scrutinizes and contrasts the available TC datasets by their features. The paper highlights the importance of AI instruments in aiding the diagnosis and treatment of TC through supervised, unsupervised, or mixed approaches, with a special focus on the ongoing importance of transformers in medical diagnostics and disease management. It further discusses the progress made and the continuing obstacles in this area. Lastly, it explores future directions and focuses within this research field.

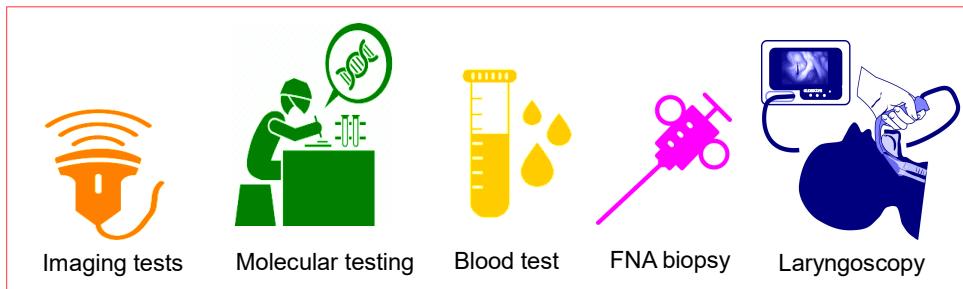
1. Introduction

The integration of AI into the healthcare sector represents a pivotal advancement, fundamentally altering the landscape of medical diagnostics, therapy, and patient management. The superior capabilities of AI, Incorporating the identification of patterns, forecasting analytics, and the process of making decisions, have led to the creation of systems that can interpret intricate medical data with greater accuracy and scale than ever before [1, 2]. Such advancements facilitate the early identification of diseases, enhance the accuracy of diagnoses, and support the customization of treatment plans for individuals. In addition, predictive models powered by AI are capable of foreseeing disease spread, boosting the efficiency of healthcare operations, and significantly improving outcomes for patients [3]. AI also has the potential to make healthcare more equitable by reducing disparities in service quality between rural and urban areas, thus improving access to premium healthcare services. As a result, the role of AI is significant in healthcare and is anticipated to grow as ongoing technological innovations lead to the creation of even more advanced applications, promising widespread benefits for patient health across the globe [4, 5].

Nonetheless, trust serves as a critical intermediary, impacting the extent to which factors related to AI affect user acceptance. Research has explored the roles of trust, risk, and security in determining the uptake of AI-powered support [6]. Empirical investigations within these studies have underscored the essential influence of trust in forming the basis of user acceptance.

Cancer is marked by the unchecked growth of cells across various parts of the body. These cells multiply erratically and can spread, damaging healthy tissue [7]. Such uncontrolled cell growth is triggered by changes or mutations in the DNA of these cells [8]. The DNA in cells comprises multiple genes, which provide the instructions necessary for a cell's function, growth, and division. When these instructions are erroneous, it can interrupt the normal functioning

*habchi@cuniv-naama.dz (Y. Habchi); hamza.khedar@gmail.com (H. Kheddar)
ORCID(s):

**Figure 1:** Approaches for identifying TC.

of cells and may result in the development of cancer [9–12]. thyroid cancer (TC), in particular, is recognized as one of the most common types of endocrine malignancies around the globe [13, 14].

Recent global epidemiological studies indicate a rise in abnormal thyroid nodules, linked to an upsurge in genetic cellular activity. This suggests an increase in normal cell functions, with anomalies classified into four primary types: follicular thyroid carcinoma (FTC), papillary carcinoma (PTC), medullary thyroid carcinoma (MTC), and anaplastic thyroid carcinoma (ATC) [15–18]. Elements like exposure to radiation, Hashimoto's thyroiditis, psychological factors, and genetic components, alongside advances in technologies of detection, appear these cancers. These factors can cause chronic health issues like diabetes and blood pressure instability. The cell cancer volume is a key to evaluating the aggressiveness and prognosis of TC's, with cell nuclei detection offering alternative markers for evaluating cancer cell proliferation. Computer-aided diagnosis (CAD) systems have gained prominence in TC analysis, improving diagnostic accuracy and reducing interpretation times [19, 20]. Radiomics, particularly through ultrasound (US) imaging [21], has emerged as an efficient diagnostic method. The American College of Radiology's thyroid imaging reporting and data system (TIRADS) categorizes thyroid nodules from benign to malignant [22–24]. Despite available open-source tools for nodule analysis, accurately identifying them remains a challenge, reliant on radiologists' experience and the subjective nature of visual image analysis [25].

Additionally, US imaging can be a lengthy and stress-inducing process, which may result in incorrect diagnoses. It is common to encounter classification errors among cases deemed normal, benign, malignant, or of uncertain nature [26–31]. For a more precise diagnosis, a fine-needle aspiration biopsy (FNAB) is often conducted. Yet, this technique can be uncomfortable for patients, and inaccuracies by the practitioner can mistakenly label benign nodules as malignant, leading to unnecessary costs [32, 33]. The main issue is the selection of nodule characteristics critical for accurately differentiating between benign and malignant cancer. Various research efforts have delved into the use of conventional US imaging to characterize different types of cancers, such as retinal [34, 35], breast [36–40], blood [41, 42], and TCs [43, 44]. Despite these efforts, there remains a lack of accuracy in the methods available for effectively categorizing thyroid nodules (see Figure 1).

The deployment of AI technology is crucial in diminishing subjectivity and boosting the precision of pathological assessments, particularly for complex conditions like thyroid diseases [45, 46]. These advancements enhance the the analysis of images obtained through US and expedite analysis times. ML and deep learning (DL) stand out as effective strategies for automating the differentiation of TNs in various contexts, including US, fine-needle aspiration (FNA), and during thyroid surgical procedures [47, 48]. The efficacy of these methodologies has been underscored in multiple research studies, as evidenced by [46, 49–53].

Current research efforts are delving into the utilization of innovative technologies for cancer detection, where the success of these methods depends on the amount of data accessible and the accuracy of the classification strategies. The drive to compile a review on "AI in the Diagnosis of TC" is motivated by the rising rates of TC, a critical concern in endocrinology where early and precise diagnosis significantly impacts patient outcomes. As AI and ML continue to evolve, their incorporation into various medical diagnostic fields, including imaging, pathology, and genomics, promises to enhance the accuracy and speed of detection processes. Traditional methods for diagnosing TC, like fine-needle aspiration biopsies, can often produce ambiguous outcomes, whereas AI presents an opportunity for more accurate and less invasive alternatives. This review seeks to integrate insights from pathology, computer science, ocrinologyand, and radiology, encouraging cross-disciplinary collaboration. It will also explore the clinical significance

of AI, offering recommendations for healthcare professionals on utilizing AI advancements for improving patient care, and pinpointing directions for future research endeavors. Additionally, the review will discuss the healthcare and economic system benefits, including cost savings and reduced wait times. Yet, it's essential to confront the challenges AI brings, such as ethical considerations and data privacy, to facilitate its responsible integration into healthcare practices. This review aims to provide an extensive examination of AI's current and future impact on the detection of TC, serving as a resource for both researchers and clinicians.

1.1. Contribution of the paper

This review explores the use of AI in identifying TC, emphasizing the shift towards improved diagnostic accuracy using AI techniques in healthcare, specifically for detecting TC. It begins with an overview of current frameworks and delves into AI strategies such as DL, artificial neural networks (ANNs), vision Transformers, conventional classification, predictive modeling, unsupervised learning (USL) like clustering, and ensemble methods like boosting and bagging. The significance of comprehensive datasets for AI success is discussed, alongside an analysis of TC datasets, feature selection, and extraction methods. It evaluates AI effectiveness in thyroid cancer dataset (TCD) through various metrics and concludes by highlighting future research directions to overcome challenges and enhance AI deployment in TCD. The review underscores AI's potential to revolutionize TCD, advocating for ongoing assessment to ensure ethical and effective use.

The main advancements presented in our paper are:

- A review of current frameworks coupled with a detailed investigation into diverse AI strategies, including supervised learning, conventional classification, DL, Transformers, probabilistic models (PM), and USL techniques. Additionally, ensemble approaches like bagging and boosting are scrutinized.
- An in-depth review of various TCDs, detailing their attributes and examining methods for feature selection and extraction used in different studies
- A detailed discussion on the benchmark criteria for assessing the efficacy of AI-powered approaches in identifying TC. These evaluation metrics cover a wide range, from regression and classification parameters to statistical, computer vision, and ranking parameters.
- A thorough critique and exploration of the challenges, limitations, prevalent trends, and unresolved questions in the domain.
- An analysis of future research priorities, highlighting specific areas that require more investigation to address current challenges and improve methods for detecting TC.
- A spotlight on the transformative impact of AI in enhancing TC diagnosis, stressing the importance of continual critical review to guarantee its ethical and effective application.

Additionally, the main contributions of this review, as differentiated from other reviews, are summarized in Table 1.

1.2. Bibliometric analysis

A bibliometric analysis was performed to delve into and evaluate the scientific studies reviewed in this paper. The continuous interest in AI-based TC research is depicted in Figure 2, with the publication count reaching 81 in 2022. Figure 2 (a) highlights the leading researchers in the field of TC-oriented AI research, focusing on those who have published within the past five years. Figure 2 (b) provides a snapshot of the enduring interest in AI-based TC research, showcasing a rising trend in the creation of AI solutions for TC since 2015. Figure 2 (c) maps out the countries that are major contributors to the research output in this area, with China and the United States showing a pronounced focus on AI-driven TC detection. Lastly, Figure 2 (d) illustrates the breakdown of publication types, with journal articles making up the bulk of the research (67.2%), followed by conference papers (19.3%).

1.3. Roadmap

The subsequent sections of this manuscript are organized as follows: Section 2 offers a detailed analysis of the frameworks currently employed in this field, outlining their advantages and disadvantages. In Section 3.2, various TCDs employed in AI-driven analyses are introduced, offering insights into their pertinence and distinctiveness. Section 4

Table 1

The notable advancements made by the suggested review in the categorization of TC when contrasted with similar research endeavors.

Ref	Year	Patient privacy	TC detec. schemes	AI apps	ML	DL	Trans	Feat	TCE	Prospective path					Metric
										IoMIT	RS	RL	PS	XAI	
[54]	2021	Yes	Yes	No	No	Yes	No	Yes	No	No	No	No	No	No	No
[55]	2021	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	No
[56]	2021	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	No	No	No	No	Yes
[57]	2021	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	Yes
[58]	2021	Yes	Yes	No	Yes	Yes	No	No	No	No	No	No	No	No	Yes
[59]	2022	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	Yes
[60]	2022	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	Yes	No
[61]	2022	Yes	Yes	No	Yes	Yes	No	Yes	No	No	No	No	No	Yes	Yes
[62]	2022	Yes	Yes	No	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes
Our -	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Abbreviations: Artificial intelligence applications (AI apps), Machine learning (ML), Deep learning (DL), Transformers (Trans), Features (Feat), TC example (TCE), Internet of medical imaging thing (IoMT), Recommender systems (RS), Reinforcement learning (RL), Panoptic segmentation (PS), Explainable artificial intelligence (XAI), Edge, fog and cloud networks based on AI (EFC-AI).

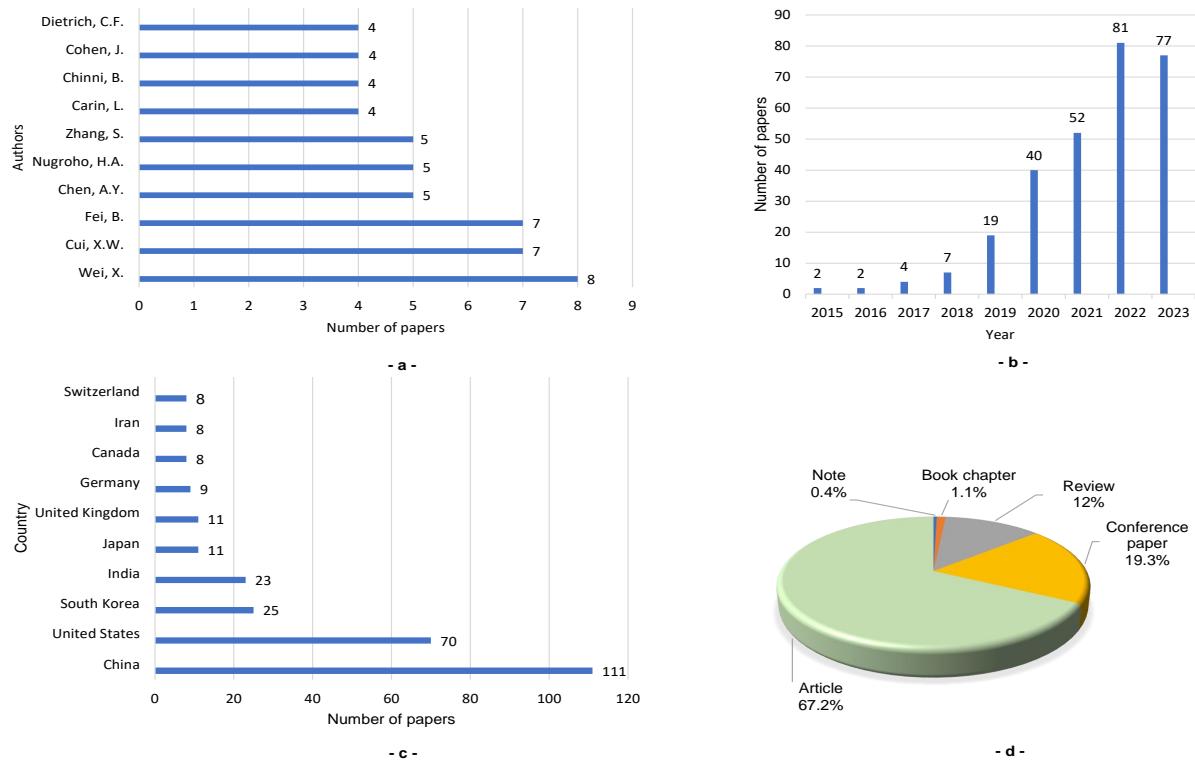


Figure 2: Bibliometric analysis in terms of (a). Documents by author; (b). Documents by year; (c). Documents by country; (d). Documents by type.

focuses on a pivotal aspect, 'Features,' detailing the techniques utilized for feature extraction and selection in AI models tailored for TCD. Following this, Section 3 presents a synopsis of contemporary methodologies for TCD employing DL and transformers, alongside an evaluation of their efficacy.

The ensuing part of our document delves into a meticulous critique and dialogue in Section 5.2, meticulously evaluating the obstacles, deficiencies, and segments requiring advancements within existing methodologies. Proceeding to Section 6, it delineates prospective trajectories for forthcoming research, underlining areas ripe for deeper exploration and innovation that could propel forward the efficacy of AI in diagnosing TC. The discourse culminates in Section 7, encapsulating the core insights and deliberations, thereby rendering a holistic conclusion to the subjects broached in earlier sections. This structured approach not only showcases our commitment to addressing the nuanced complexities

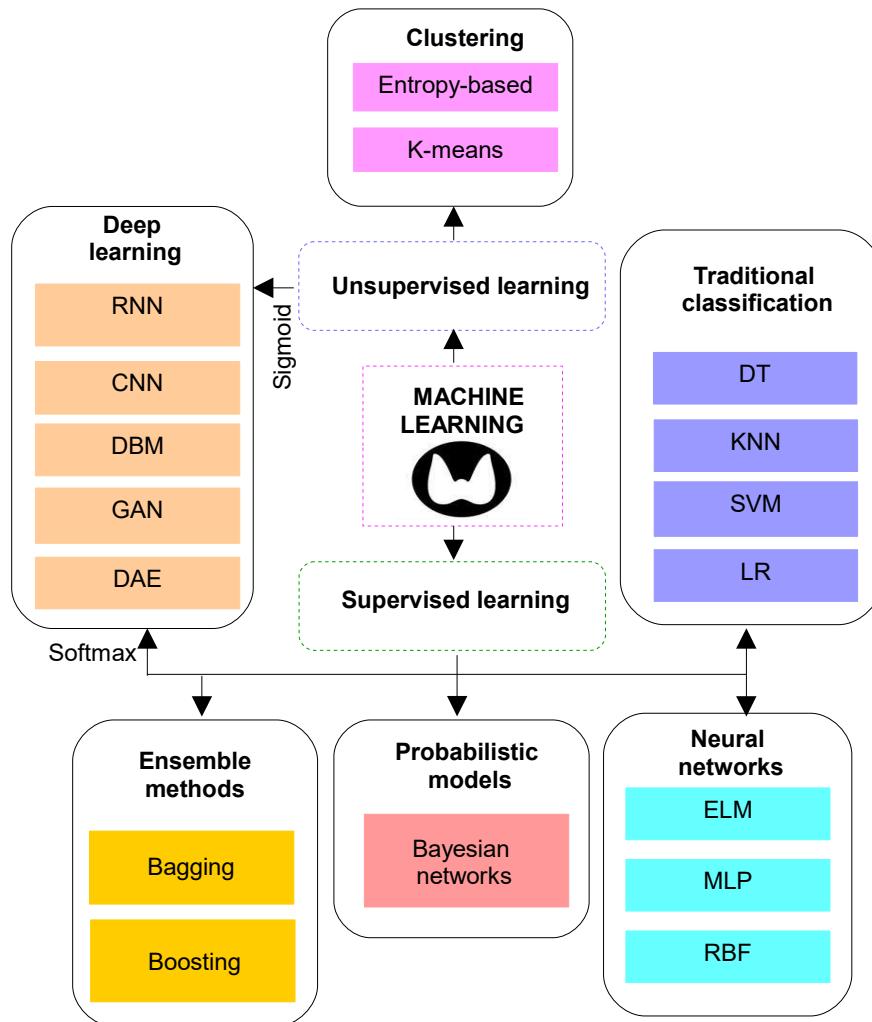


Figure 3: Classification of TCD strategies utilizing AI.

of AI application in medical diagnostics but also signals our dedication to fostering a forward-looking perspective on how these challenges can be navigated to harness the full potential of AI technologies in enhancing TCD.

2. Summary of current models and methods

In this section, we discuss the various AI-based methodologies utilized for diagnosing thyroid gland (TG) cancers. Figure 3 offers a visual depiction of the classification system we propose for methods of TC diagnosis leveraging AI.

2.1. Pre-processing

dimensionality reduction (DR) is a process applied in ML, mainly during the preprocessing and feature crafting stages, aimed at converting data from a high-dimensional space into a more manageable lower-dimensional space. This technique is valued for its efficiency and its capacity to reduce unnecessary data patterns while decreasing redundancy, serving multiple objectives. For example, DR was utilized in the diagnosis of thyroid disease (TD) through the analysis of cytological images [63].

Principal component analysis (PCA) operates as a sophisticated method for preprocessing, transforming samples (variables) into a smaller set of uncorrelated ones. This technique effectively reduces the volume of variables, thus

cutting down on redundant data, all the while striving to maintain the integrity of the data relationships. PCA is extensively used in the realms of cancer detection and distinguishing between malignant and benign thyroid cells. In research conducted by Shankarlal et al. [64], PCA was deployed to filter the most relevant set of wavelet coefficients from double-tree complex wavelet transform (DTCW) processed noisy thyroid images, which were then categorized using random forest (RF). In another instance, Soulaymani et al. [65] applied PCA to a dataset comprising 399 patients with three different TC types (undifferentiated, follicular, and papillary), allowing the classification based on variables like age, sex, type of cancer, and geographical location.

2.2. Purpose of AI-driven examination

This research centers on the use of AI for identifying TC. Comprehending the foundational objectives of each framework is essential for acquiring a more profound understanding of their reasoning [8].

(a) Classification of thyroid carcinoma: Entails the sorting of TCs according to their histopathological features, clinical manifestations, and prognostic outcomes. Various forms of thyroid carcinomas exist, each defined by unique characteristics. The principal categories are: (i) PTC: Representing the most prevalent form, PTC constitutes approximately 80% of all TC cases. It typically exhibits slow growth but has a propensity to metastasize to neck lymph nodes. Nonetheless, PTC generally responds well to treatment. (ii) FTC: Ranking as the second most frequent type, FTC has the capability to invade blood vessels and spread to distant body parts, although it is less prone to lymph node metastasis. (iii) MTC: Arising from the parafollicular or C cells of the thyroid, which secrete calcitonin, an increase in blood calcitonin levels may signal MTC. (iv) ATC: ATC is a highly aggressive and rare TC variant, characterized by its rapid spread to other neck regions and the body, making it challenging to treat. The stratification of thyroid carcinomas is vital for selecting the optimal treatment plan for individual patients, considering tumor dimensions, location, patient age, and general health. The evolution of AI and ML has significantly contributed to the automation and enhancement of thyroid carcinoma classification accuracy. Various models have been devised to categorize tumors based on medical imaging or genetic information.

For example, Liu and colleagues [66] highlight the fundamental importance of support vector machine (SVM) in the detection of cancer. In a similar vein, Zhang and their team [67, 68] introduce approaches utilizing deep neural network (DNN) to distinguish between malignant and benign thyroid nodules in US imagery. Moreover, the bi-directional LSTM (Bi-LSTM) model [69], shows noteworthy precision in the classification of thyroid nodules. These classification approaches create structured hierarchies crucial for organizing knowledge and processes in the field of TC.

(b) Segmentation of thyroid carcinoma: Entails pinpointing and outlining the area in an image that represents a thyroid tumor. The objective of this segmentation is to segregate the targeted regions, like the thyroid tumor, from adjacent tissues within medical images. This task can be achieved by manual annotation by an experienced radiologist or via automated techniques that employ ML algorithms [70, 71].

Segmentation plays a pivotal role in the detection of TC by enabling the accurate isolation and analysis of the thyroid gland, along with any potentially suspicious nodules or lesions present. Often detected through medical imaging modalities like US, computed tomography (CT) scans, or magnetic resonance imaging (MRI), TC requires the precise delineation of the region of interest (ROI) for sound diagnostic judgements. Segmentation not only facilitates the distinction of the thyroid gland from the surrounding tissues but also supports the precise quantification of nodule dimensions and volume, which are critical for evaluating the potential for malignancy. Furthermore, it enables the extraction of significant image attributes such as texture and shape, providing critical data for ML models or other analytical methods to improve diagnostic precision. Segmented images also enhance visual clarity, aiding radiologists and medical practitioners in the visual assessment and interpretation of areas of concern within the thyroid, vital for detecting abnormalities indicative of cancer. For longitudinal analyses, segmentation is invaluable in tracking changes in the thyroid and nodules over time, monitoring disease evolution or the efficacy of treatments. It also plays a role in accurately locating biopsy sites for suspicious nodules, guaranteeing targeted sample collection for cancer verification. In the context of treatment planning, segmentation is instrumental in assessing the tumor's size and its relationship to vital anatomical structures, thereby guiding therapeutic decisions. Moreover, the introduction of automated segmentation technologies streamlines clinical workflows by minimizing manual input and variability, empowering medical experts to dedicate more attention to complex diagnostic activities. Consequently, the segmentation process in TCD enhances precision, consistency, and confidence in diagnostics, markedly impacting patient management and outcomes.

AI methods, especially convolutional neural network (CNN) and the U-Net architecture, are becoming progressively popular for the segmentation of thyroid carcinoma. Their growing preference is largely due to their capacity to learn from and generalize across large datasets, significantly improving the accuracy and dependability of the segmentation procedure.

(c) Prediction of thyroid carcinoma:

Prediction in TC involves utilizing diagnostic tools and ML models to estimate the risk of development based on factors like genetic predisposition, gender, age, radiation exposure, and lifestyle choices. It's important to note that predictions indicate a heightened risk rather than a definite outcome. Medical practices often combine various predictive assessments to improve accuracy. For example, ML algorithms developed from medical records can help distinguish between benign and malignant nodules, facilitating early intervention. Studies, such as one utilizing ANN and logistic regression (LR) [72], and another employing a CNN to analyze over 10,000 microscopic images of TC [73], demonstrate the application of predictive techniques in identifying TC risk, showcasing advancements in AI-driven predictive modeling for more effective treatment strategies.

2.3. SL-based TC classification

Supervised learning (SL) is a ML approach where the ai algorithm outcomes is based on data that is explicitly labeled, in this discussion, related to medical information concerning TC. The primary aim of SL is to distinguish among different types of TC using data that is both labeled and illustrative.

This data could include US images, genetic indicators, radiomic features, patient demographics, or other pertinent details related to the diagnosis or prognosis of TC. The provided labels clarify whether each case is related to TC, and they may further specify details such as the type of thyroid carcinoma or the stage of cancer. In a classification task, an SL algorithm might be trained to differentiate between malignant and benign Thyroid nodules (TN) using distinct features derived from medical imaging data. The training data's labels indicate the nature of each nodule, thereby training the algorithm to classify new, unlabeled nodules accurately.

Similarly, the deployment of regression techniques in SL models, could be developed to forecast the progression or outcome of TC using diverse, patient-specific attributes. Here, the labels are associated with a continuous outcome variable, such as survival duration or a metric indicating disease advancement. It's vital to highlight that the efficacy of these methodologies is deeply dependent on the data's quality and comprehensiveness. The more accurate and complete the dataset, the more adeptly the algorithm can classify or predict new cases. Moreover, to validate the utility of supervised learning models in healthcare contexts, including the detection of thyroid carcinoma, it's essential to test these models on separate datasets and within real-world clinical environments to confirm their accuracy and reliability [74, 75]. In the following, a quick overview of frequently utilized ML algorithms is described.

(a) KNN and SVM: The k-nearest neighbors (KNN) algorithm stands as a non-parametric supervised learning method in ML, applied to both regression and classification tasks. It operates by utilizing k-nearest training samples for making predictions. In research conducted by Chandel et al., referenced in [76], the KNN technique was used for classifying thyroid diseases using variables like TSH, T4, and the presence of goiter. Furthermore, Liu and colleagues [77] applied a fuzzy KNN model for distinguishing among hyperthyroidism, hypothyroidism, and euthyroid (normal) cases. The need for analyzing larger datasets in future studies has been emphasized, as noted in [78].

SVM is a ML technique used for classification and regression tasks. In research presented by Ma et al. [79], an SVM-based method was developed to differentiate between benign and malignant thyroid nodules using a dataset that included 98 TN samples, with 82 benign and 16 malignant cases. Another study by Chang et al. [80] utilized six distinct SVMs for the classification of nodular thyroid lesions, focusing on identifying the most significant textural features for this purpose. The results indicated that the applied methodology was effective in achieving accurate classification. Furthermore, Dogantekin et al. [81] introduced a system that integrates Generalized Discriminant Analysis with a wavelet SVM (GDA-WSVM) for the diagnosis of thyroid nodules. This approach included steps for feature extraction, classification, and testing, showcasing its application in effectively diagnosing TC.

(b) Decision trees and logistic regression: decision trees (DT) learning is a technique in data mining that uses a model for predictive decision-making. In such a model, the outcomes are indicated by the leaves, and the branches represent the input features. This method has been utilized in detecting latent thyroid disorders, as evidenced by a range of studies, such as those referenced in [82], [83], [84], and [85].

In the research presented in [86], LR was employed to pinpoint specific characteristics of thyroid microcarcinoma among a group of 63 patients. This analysis utilized data from both contrast-enhanced ultrasound (CEUS) and traditional US evaluations. Furthermore, a significant study from northern Iran, detailed in [87], used LR to investigate a large dataset encompassing 33,530 cases of TC. LR is a widely used binomial regression model within the domain of ML.

2.4. USL-based TC classification

In the realms of AI and computer science, USL is the process of analyzing data that hasn't been previously labeled or annotated. Its primary goal is to uncover the underlying structures within datasets that do not have predefined labels. Contrary to supervised learning, which depends on labeled data for evaluating its effectiveness, USL operates without such direct guidance, presenting additional challenges in result assessment. Although USL algorithms are capable of addressing more complex problems than their supervised counterparts, they might also lead to increased uncertainty, sometimes creating unintended categories or incorporating noise rather than identifying clear patterns. Nonetheless, USL is considered an indispensable asset in AI, offering the potential to detect patterns within data that may not be obvious at first [88, 89].

2.4.1. Clustering

The objective of this strategy is to organize a dataset composed of TC information into distinct, uniform groups that share similar features. This process aids in the categorization of unlabeled data into malignant or benign sections. Due to its straightforwardness, this technique has received significant attention in numerous medical research areas, enhancing its applicability to tasks like detecting DNA copy number variations [90], identifying breast cancer [91], pinpointing cancer-related genes [92], diagnosing skin cancer [93], and discovering brain tumors [94]. Clustering methods also prove helpful in classifying cancer instances that are not clearly defined [95].

A research documented in [96] employed clustering to determine factors impacting the normal functioning of the thyroid gland. The use of PCA played a key role in organizing the clusters and simplifying the data structure. Additionally, an innovative automated clustering system for diagnosing TC was developed, as described in [97], which recommended appropriate medication treatments for hyperthyroidism, hypothyroidism, and normal cases. The study in [98] explored the use of fuzzy clustering on thyroid and liver datasets from the UCI repository, where fuzzy c-means (FCM) and possibilistic fuzzy c-means (PFCM) algorithms were employed and their performances compared.

(a) K-means (KM): The KM method is used for dividing data into partitions and tackles a combinatorial optimization challenge. It is commonly used in USL, categorizing observations into k distinct clusters. In the research presented by Mahurkar et al. [99], the study investigates the application of ANN and an improved K-Means algorithm to standardize raw data. This study employed a thyroid dataset from the UCI repository, comprising 215 total instances.

(b) Entropy-based (EB): In the study conducted by Yang et al. [100], a novel, parameter-free computational model called DeMine was introduced for the prediction of microRNA regulatory modules (MRMs). DeMine utilizes an information entropy-based methodology, comprising three primary steps. The process begins by converting the miRNA regulation network into a cooperative MRMs network. It then proceeds to pinpoint miRNA clusters, aiming to maximize entropy density within the specified cluster. The final step involves grouping co-regulated miRNAs into their appropriate clusters, thereby finalizing the MRMs. This technique enhances predictive precision and facilitates the identification of a broader array of miRNAs, potentially acting as tumor markers in cancer diagnosis.

2.5. DL-based TC classification

DL is a subset of ML and AI that focuses on the use of ANN for learning representations. ANNs are information processing units composed of interconnected non-linear units called neurons, effective in solving intricate problems through information storage and management. A neural network featuring several hidden layers where are often referred to as a DNN. The network's depth facilitates the extraction of increasingly abstract and advanced features as data moves through its layers. By leveraging large neural networks with several layers, DL can independently learn, create, and improve data representations, which is why it's known as "deep" learning. Within the realm of TC, DL is instrumental in several areas, including: (i) Classification of image: DL techniques, for example CNN, are trained to categorize thyroid US images, distinguishing between malignant and benign nodules by analyzing texture and shape, and other features [101–103], streamlining the process and assisting with the early identification of TC. (ii) Analysis of disease: DL is used to examine cytopathological or histopathological slide images, aiding in identifying and classifying cells

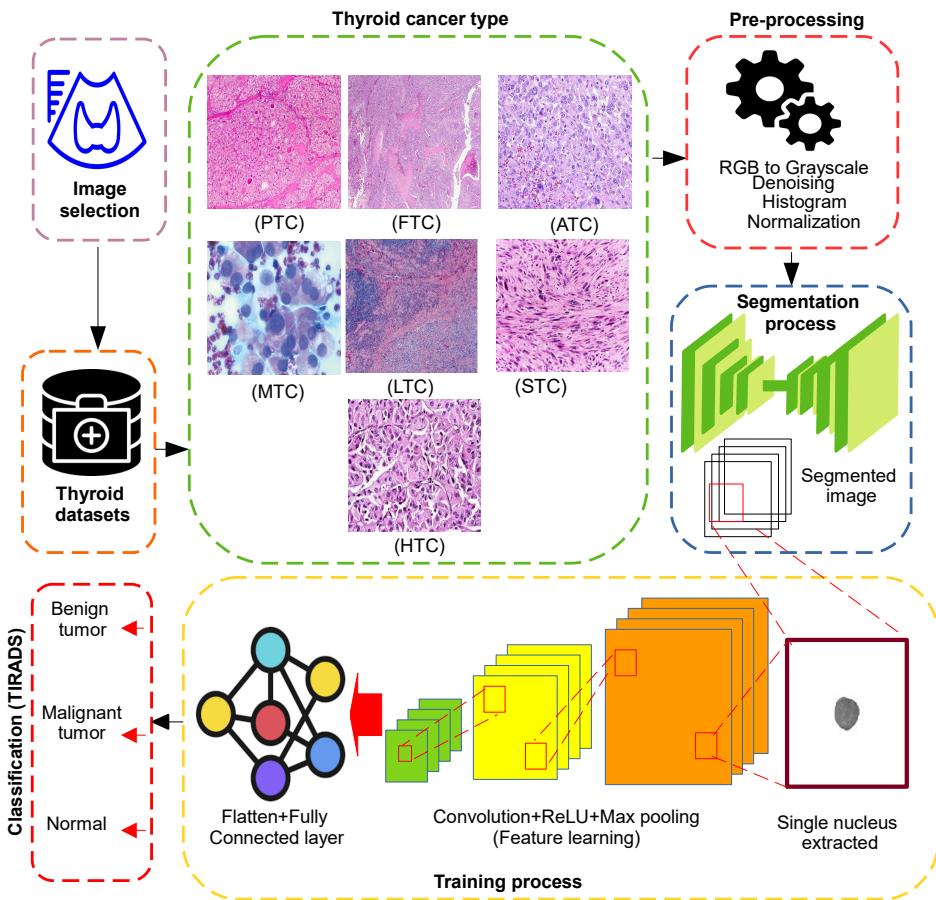


Figure 4: Comprehensive DL framework for detecting and classifying TC.

of cancerous. (iii) Analysis of genomic information: In this era DL models are capable of analyzing genetic variations linked to the risk of TC. (iv) Radiomics: DL models are adept at extracting Multidimensional information obtained from radiographic images, contributing to more accurate and individualized treatment strategies. (v) Predictive Analysis: By analyzing electronic health records and patient information, DL models can forecast the probability of an individual developing TC, facilitating early intervention. Figure 4 illustrates the diverse applications of DL in the field of TC diagnosis and management.

2.5.1. ELM and MLP

The extreme learning machine (ELM) model is distinguished by a single layer of hidden nodes that possess randomly assigned weight distributions. Crucially, the process of determining weights between the inputs and the hidden nodes to the outputs is executed in a solitary step, rendering the learning mechanism markedly more efficient than that of alternative models. The efficacy of the ELM approach in diagnosing TD has been corroborated through various research efforts, including those reported in [104], [105], [106], and [107].

The multilayer perceptron (MLP) is a type of feed-forward network that directs data processing sequentially from the initial point to the final layer of output. Within this architecture, each layer is made up of a different number of neurons. Rao and colleagues [108] devised an innovative approach for categorizing thyroid nodules employing an MLP integrated with a backpropagation learning mechanism. Their design comprised four neurons in the initial layer, three neurons in each of its ten concealed layers, and one neuron in the terminal layer. In a separate effort to enhance the precision of TD diagnosis, Hosseinzadeh et al. [109] utilized MLP networks. Their analysis compared the efficacy of MLP networks against the backdrop of existing research on TC classification, highlighting the superior

performance of MLP networks. Isa and associates [110] investigated the influence of MLP networks with various activation functions to determine the most effective function for the precise classification of challenging diseases, including thyroid disease and cancer of breast. The study assessed a range of activation functions, such as logarithmic, sinusoidal, neural, hyperbolic tangent, sigmoid and exponential functions. It concluded that the function of hyperbolic tangent, especially when utilized in conjunction with the backpropagation algorithm for training, proved to be the most efficient for classifying TD. This conclusion was also supported by the findings of Mourad et al. [111].

2.5.2. RBF and DAE

In the study by Erol et al. [112], ML methods were used for the TN classification. The research utilized both MLP and radial basis function (RBF) as activation functions. Notably, the RBF function outperformed the MLP in the accurate classification of thyroid nodules, underscoring the critical role of activation functions in function approximation. This research emphasizes their significance in the classification and prediction of time series data, especially concerning the diagnosis of TC.

Denoising autoencoders (DAEs) play a pivotal role in the identification of TC by adeptly deriving significant features from US or histopathological imagery. As a subset of ANN, DAE are primarily focused on the accurate reconstruction of inputted data. Their usage extends to tasks such as reducing dimensions and enhancing feature learning capabilities. The integration of DAEs into the workflow for classifying thyroid carcinoma typically unfolds in several phases: (i) initial data preprocessing, (ii) creation of perturbed input data, (iii) training the DAE, (iv) extraction of relevant features, and (v) execution of the classification procedure.

In the research presented by Ferreira et al. [113], a variety of six autoencoder models were utilized for the purpose of classifying PTC, incorporating strategies such as the stabilization of weights and network fine-tuning. The architecture of these autoencoders, especially the encoding layers, played an integral role in the effective integration of the network. In a related study by Teixeira et al. [114], both DAEs and their stacked configurations were applied to distill crucial features and pinpoint genes relevant to TC diagnosis.

2.5.3. CNN and RNN

CNNs, a branch of DL models, stand out for their remarkable capabilities in tasks such as image analysis and processing, including the classification of medical images. Their efficiency in managing data structured in grids, like images where the spatial relationship between pixels is crucial, makes them particularly suited for these tasks.

The focus on CNN-based techniques for TCD, especially in automating nodule identification and classification in US imagery [115], has grown significantly. The ConvNet model, known for its reliance on convolution operations vital for image recognition tasks [116], is a prime example of this effort. Various architectures of CNN such as VGG [103], AlexNet [117], LeNet [118], Squeeze Net [119], GoogLeNet [120], DenseNet [121], ResNet [122] and are celebrated for their inclusion of convolutional, pooling, and fully connected layers.

In a notable study by Li et al. [123], the efficacy of CNN models in predicting TC was investigated, utilizing a dataset of 131,731 US images from 17,627 patients. Xie et al. [124] implemented models such as Inception-Resnet, Inception, and VGG16 to differentiate malignant from benign tissues in 451 images of thyroid from the DDTI dataset, employing image augmentation to mitigate data limitations prior to classification. Moreover, Koh et al. [125] assessed the diagnostic accuracy of deep convolutional neural network (DCNN) models against that of expert radiologists for identifying thyroid nodules in US images, using a dataset of 15,375 images and showcasing the CNNE1 and CNNE2 models derived from DCNN for differentiating between malignant and benign nodules. Liang et al. [126] introduced a DL based on CNN for classifying and detecting thyroid and nodules of breast, comparing its performance with traditional US imaging results. Figure 5 depicts the recent advancements in classifying TC via CNN-based methods.

Recurrent neural networks (RNNs) belong to a category of ANNs characterized by connections between units forming a directed graph across temporal sequences. This structure allows them to leverage internal memory, making them adept at handling inputs of varying lengths. Consequently, RNNs excel in tasks that require understanding temporal dependencies, such as speech recognition, language translation, and time-series analysis.

Within the realm of thyroid carcinoma classification, RNNs offer promising capabilities for analyzing data that is sequential or time-sensitive. This includes observing the evolution of clinical symptoms over time, tracking changes in tumors using successive medical images or studying fluctuations in gene expression associated with the onset of TC. For example, Chen et al. (2017) utilized a hierarchical RNN structure to categorize thyroid nodules by analyzing historical US reports [127]. Their model comprises three layers of long-short-term-memory (LSTM) networks trained independently. The findings from their study suggest that this hierarchical RNN approach surpasses conventional

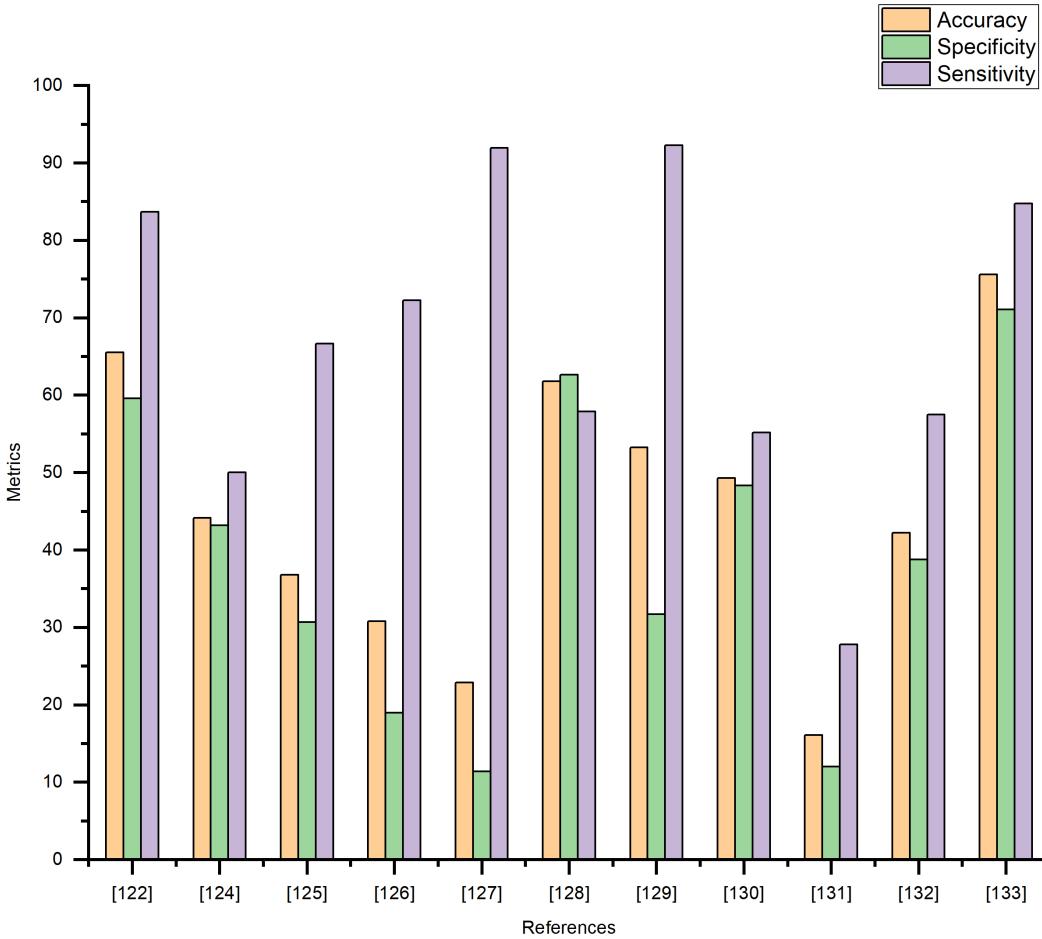


Figure 5: Synopsis of CNN-driven research in TC diagnosis with percentages for accuracy, sensitivity, and specificity.

models such as SVM + Unigrams, SVM + Bigrams, CNN, and LSTM in accuracy, computational efficiency, and robustness. These benefits are attributed to the RNNs's memory mechanisms, which permit the retention of information from previous states through feedback loops, thereby making RNNs highly effective for cancer detection applications.

2.5.4. RBM and GAN

Restricted Boltzmann machines (RBMs) feature a bipartite architecture with two layers: a visible layer for input data and a hidden layer for processing. The defining characteristic of RBMs is the absence of intra-layer connections, limiting connections to between-layer nodes only. This restriction simplifies the training process, as each node in one layer exclusively connects to all nodes in the opposite layer. Vairale et al. utilized RBMs to craft a customized fitness recommendation system for individuals with thyroid issues, demonstrating their practical application [128]. As generative models within the ANNs spectrum, RBMs are notable for their bidirectional nature and unsupervised learning capabilities, involving a visible layer of binary variables and a hidden layer of interrelated binary variables, with the learning mechanism heavily reliant on statistical methods.

ML framework is composed of two key elements: a generator and a discriminator. The generator's function is to convert a random input vector into a data point that fits within the space of the dataset. Conversely, the discriminator serves as a binary classifier, tasked with assessing whether input data, originating either from the training dataset or produced by the generator, is genuine. generative adversarial network (GAN) have found extensive applications in medical diagnosis, notably in the detection of TN [129, 130].

2.5.5. PM and EM

PMs, which include bayesian networks (BNs), are crucial in both computer science and statistics for depicting uncertainties and the complex interrelations among variables. In the domain of computer science, these models are integral for decision-making processes in ML, where they are used to quantify uncertainties and map out intricate dependencies among data points. Bayesian networks, a subset of probabilistic models, employ directed acyclic graphs to illustrate the relationships between variables, proving invaluable in scenarios that require reasoning in uncertain conditions, making predictions, and dealing with partial information. Within the realm of statistics, probabilistic models are essential for analyzing data, employing probabilistic principles to glean significant insights and estimate parameters, thus deepening our comprehension of multifaceted systems. Bayesian networks have been successfully applied in the medical field to differentiate between benign and malignant TN [131, 132], as well as in diagnosing diseases such as thyroid, hepatitis, and breast cancer [133].

In the realm of oncology research, tackling the intricacies of cancer datasets and enhancing the accuracy of detection frequently involves the use of ensemble methods. This strategy splits the dataset into several subsets, upon which a variety of ML algorithms are applied in parallel. The insights gained from these individual algorithms are subsequently merged to derive a comprehensive diagnosis. The main goal behind adopting ensemble methods is to forge a superior predictive model tailored for the detection of TC. Such an approach has been validated in multiple studies, including a significant one conducted by Chandran et al. [134], where the authors underscored the contribution of ensemble methods to a more profound data comprehension and heightened diagnostic accuracy.

2.5.6. Bagging and Boosting

Within the domain of TCD, Bagging stands out as a key ensemble learning strategy aimed at augmenting the precision and reliability of ML models. By mitigating variance and preventing overfitting, this technique is extensively used, particularly with decision trees, across various approaches. The primary objective of Bagging is to bolster the efficacy of weaker classifiers, making it particularly valuable in the context of screening for TC.

Bagging is a notable ensemble learning approach in TCD, aimed at boosting the accuracy and consistency of ML algorithms. This technique achieves its objectives by lowering variance and offering protection against overfitting. It finds broad application in a variety of methods, with a particular emphasis on decision trees. The main goal of Bagging is to improve the effectiveness of weaker classifiers in the context of TC screening. In their research, Chen et al. [135] presented feature bagging (FB) as an ensemble learning strategy designed to reduce the correlation between models in an ensemble. FB accomplishes this by training each model on randomly selected feature subsets from the dataset, rather than using the full set of features. The utility of FB is demonstrated in its ability to distinguish between benign and malignant cases of TC [136]. Within the scope of USL, meta-algorithms play a crucial role in reducing variance and improving the performance of weak classifiers, effectively converting them into robust classifiers [137].

In the context of boosting, Pan et al. in their study [138] employed a novel method called AdaBoost to identify TN, utilizing the widely recognized UCI dataset. The classification was performed using the random forest method, with PCA employed to retain data variance. Chen et al. [139], the Gradient tree boosting (XGBoost) algorithm was highlighted as a powerful implementation of gradient-boosted decision trees, with its application extending across multiple research areas. This includes usage in civil engineering [140], time-series analysis [141], sports and health monitoring [142], and the prediction of ischemic stroke readmission [143]. Specifically, in the context of TC, the XGBoost algorithm was employed by researchers to distinguish between benign and malignant TN [144], offering a solution to the problem of obtaining accurate diagnoses without the need for large datasets that DL models usually require.

Table 2 serves as an overview of various research initiatives aimed at identifying both benign and malignant forms of TC. It outlines the classifiers used, diseases focused on, datasets applied, research goals, and metrics for assessment. This table helps categorize the AI techniques applied in TCD, underlining their key roles in the domain.

3. Standardized assessment criteria and commonly used datasets

3.1. Metrics

In this segment, we explore the standard metrics commonly utilized for evaluating TD detection performance. These metrics act as critical benchmarks for measuring the success of methodologies, underscoring the significance of choosing the right metrics to assess ML models. A variety of DL metrics are used to determine the efficiency of

Table 2

Summary of studies on identifying benign and malignant TC, sorted by reference.

Ref.	AI Tech.		Classifier			Objective	DD	Dataset	APP	SV
	ML	DL	CNN	SVM	ELM					
[73]	✓	✓				C	TC	PD	Omics	10068 images
[65]	✓					C	TC	PD	NA	NA
[76]	✓			✓		C	TD	PD	US	7200 instances
[79]	✓			✓		C	TC	PD	US	92 subjects
[82]	✓			✓		C	TC	UCI	US	3739 patients
[84]	✓			✓		C	TC	NA	US	NA
[85]	✓			✓		C	TC	UCI	US	499 patients
[86]	✓			✓		C	TC	PD	US	63 patients
[87]	✓			✓		C	TN	PD	US	33,530 patients
[99]	✓			✓		C	TC	UCI	US	215 instances
[100]	✓			✓		C	TC	PD	US	734 cases
[104]	✓			✓		C	TD	UCI	US	215 patients
[105]	✓			✓		C	TD	UCI	US	215 patients
[106]	✓			✓		C	TD	PD	US	187 patients
[108]	✓			✓		C	TD	PD	US	7200 samples
[109]	✓			✓		C	TD	UCI	US	7200 patients
[112]	✓			✓		C	TD	PD	US	487 patients
[113]		✓				C	PTC	TCGA	US	18985 features
[114]	✓			✓		C	PTC	TCGA	Omics	510 samples
[123]	✓	✓	✓			C	TC	PD	US	17627 patients
[124]	✓	✓	✓			C	TC	PD	US	1110 images
[126]	✓	✓	✓			C, P	TN	PD	US	537 images
[127]	✓			✓		C	TN	PD	US	13592 patients
[128]	✓			✓		C	TD	PD	Fitness	94 users
[131]	✓			✓		C	TD	UCI	US	93 adult patients
[132]	✓			✓		C	TC	NA	US	37 patients
[135]	✓			✓		C	TN	PD	US	1480 patients
[145]	✓	✓	✓			C	TC	PD	Omics	482 images
[146]	✓	✓	✓			NA	PTC, FTC	NA	FNAB	NA
[147]	✓	✓	✓			C	PTC	PD	FNAB	370 MPG
[148]	✓	✓	✓			P	PTC	PD	FNAB	469 patients
[149]	✓	✓	✓			C	TC	DDTI	US	298 patients
[150]	✓	✓	✓			C	TC	PD	US	1037 images
[151]	✓	✓	✓			P	TN	PD	US	80 patients
[152]	✓	✓	✓			P	TN	PD	US	300 images
[153]	✓	✓	✓			C	TC	PD	US	459 labeled
[154]	✓	✓	✓			C	TD	ImageNet	US	2888 samples
[155]	✓			✓		NA	TC	NA	US	NA
[156]		✓				C	TC	PD	US	1358 images
[157]	✓			✓		C	TC	PD	Surgery	50 patients
[158]	✓			✓		C	TC	PD	US	89 patients
[159]	✓			✓		C	TD	PD	Cyt	447 patients
[160]	✓	✓	✓			C	FTC	PD	FNAB	57 smears
[161]	✓	✓	✓			NA	FTC	NA	FNAB	NA
[162]	✓	✓	✓			P	TC	TCGA	Hist	482 samples
[163]	✓	✓	✓			C	TC	PD	FNAB	1264 patients
[164]	✓	✓	✓			C	TN	PD	US	276 patients
[165]	✓			✓		C, P	FTC	PD	Hist	94 patients
[166]	✓			✓		C	FTC	PD	Hist	43 nuclei
[167]	✓			✓		C	TN	PD	US	467 TN
[168]	✓			✓		C	PTC	TCGA	Omics	500 patients
[169]		✓				PTC	TCGA	Omics	115 slides	NA
[170]	✓					C	TN	PD	Omics	121 patients

Abbreviation: Application (APP), Detected disease (DD), Thyroid cancer (TC), Subjects for validation (SV), Private data (PD), Classification (C), Prediction (P), Segmentation (S), Cytopathological (Cyt), Histopathological (Hist), Microphotographs (MPG).

the suggested method in identifying TD. It is important to note that certain metrics have been previously addressed in [171]. The other metrics, particularly designed for image processing applications in TD, are concisely outlined in Table 3. Figure 6 outlines the AI-based techniques for TCD.

Table 3: Summary of the metrics for classification and regression employed in assessing AI-driven methods for TCD.

Metric	Mathematical formula	Description
Classification and Regression		
Specificity	$\frac{T_N}{T_N + F_P} \times 100\%$	This metric represents the proportion of accurately predicted negative samples out of all the negative samples.
Root mean square error (RMSE)	$\left(\sqrt{1 - (ER)^2} \right) \times SD$	This is the standard deviation of the predicted errors between the training and testing datasets, and a lower value indicates the classifier's excellence.
Jaccard similarity index (JSI)	$\frac{ A \cap B }{ A \cup B } = \frac{T_P}{T_P + F_P + F_N}$	Paul Jaccard introduced this method to measure both the similarity and diversity among samples.
Volumetric overlap error (VOE)	$\frac{F_P + F_N}{T_P + F_P + F_N}$	Assess the likeness between the segmented area and the ground truth area. VOE quantifies the level of overlap between these two regions and is calculated as the ratio of the combined volume of the segmented and ground truth regions to the volume of their intersection.
Mean absolute error (MAE)	$\frac{1}{N} \sum_{i=1}^N a_i - p_i $	This measure indicates the average of the disparities between the real values and the predicted values.
Statistical		
Standard deviation (SD)	$\sqrt{\sum (x - \mu)^2 / N}$	It quantifies the degree of variability or spread within a dataset.
Correlation (Corr)	$\frac{\sum((x-\mu_x)(y-\mu_y))}{\sqrt{(\sum(x-\mu_x)^2)} \sqrt{(\sum(y-\mu_y)^2)}}$	It characterizes the extent of correlation or connection between two or more variables.
mean reciprocal rank (MRR)	$MRR = \frac{1}{ Q } \sum_{i=1}^{ Q } \frac{1}{rank_i}$	The MRR is a statistical measure used to assess the average reciprocal rank of outcomes for a set of queries, as explained in [172]. Here, "rank _i " denotes the position at which the first relevant document appears for the i-th query.
Kappa de Cohen	$k = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}$	This metric gauges the level of agreement between two assessors, considering chance as a baseline.
Computer vision		
Peak signal to noise ratio (PSNR)	$10 \cdot \log_{10} ((MAX_I^2) / MSE)$	It quantifies the proportion between the highest achievable signal power and the power of the noise that impacts the faithfulness of its portrayal. It assesses the excellence of a reconstructed or compressed image or video in relation to the original signal. This evaluation considers how much visual information is retained in the processed image or video, accounting for the image's spatial and frequency attributes.
Visual information fidelity (VIF)	$\frac{\sum_j I(C^j; F^j / s^j)}{\sum_j I(C^j; E^j / s^j)}$	Assess the likeness between two images (or videos) by subtracting the mean value from each signal and subsequently normalizing the signals by dividing them by their standard deviation. Finally, compute the cross-correlation between the two normalized signals.
Normalized cross-correlation (NCC)	$\frac{\sum_{i=1}^M \sum_{j=1}^N (I(i,j) - R(i,j))^2}{\sum_{i=1}^M \sum_{j=1}^N I(i,j)^2}$	An elevated structural content value indicates that the image possesses lower quality.
Structural content (SC)	$\frac{\sum_{i=1}^M \sum_{j=1}^N I(i,j)^2}{\sum_{i=1}^M \sum_{j=1}^N R(i,j)^2}$	This calculates the texture information within the image, where δ_{blac} represents the variance in luminance.
Noise visibility function (NVF)	Normalization $\left\{ \frac{1}{1 + \delta_{blac}^2} \right\}$	This approach sets distortion thresholds using contrast computations and wavelet transforms. VSNR is deemed excellent if distortions are below the threshold. It uses RMS contrast ($C(I)$) and visual distortion (VD) as defined in [173].
Visual signal to noise ratio (VSNR)	$10 \log_{10} \left(\frac{C^2(I)}{(VD)^2} \right)$	It relies on the contrast sensitivity function (CSF), with $A(u,v)$, $B(u,v)$, and $C(u,v)$ denoting the Discrete Fourier Transforms (2D TFD), as described in [174].
Weighted signal-to-noise ratio (WSNR)	$10 \log_{10} \left(\frac{\sum_{u=0}^{M-1} \sum_{v=0}^{N-1} A(u,v)C(u,v) ^2}{\sum_{u=0}^{M-1} \sum_{v=0}^{N-1} A(u,v) - B(u,v)C(u,v) ^2} \right)$	This metric assesses the precision of an ML model's predictions by quantifying the discrepancy between predicted and actual values relative to the range of actual values.
Normalized absolute error (NAE):	$\frac{\sum_{i=1}^M \sum_{j=1}^N I(i,j) - R(i,j) }{\sum_{i=1}^M \sum_{j=1}^N I(i,j) }$	It is a modified version of Mean Square Error (MSE), utilizing the Laplacian distribution instead of the Gaussian distribution. $L(I(i,j))$ represents the Laplacian operator.
Laplacian mean square error (LMSE)	$\frac{\sum_{i=1}^M \sum_{j=1}^N [L(I(i,j)) - L(R(i,j))]^2}{\sum_{i=1}^M \sum_{j=1}^N [L(I(i,j))]^2}$	

3.2. Datasets for TC

In the context of TC research, numerous datasets have been developed to support the testing and validation of ML algorithms and models. This step is crucial, given the significant challenge of compiling these datasets within the endocrine ML field. Table 4 lists examples of publicly available TCDs that are used for detecting TC.

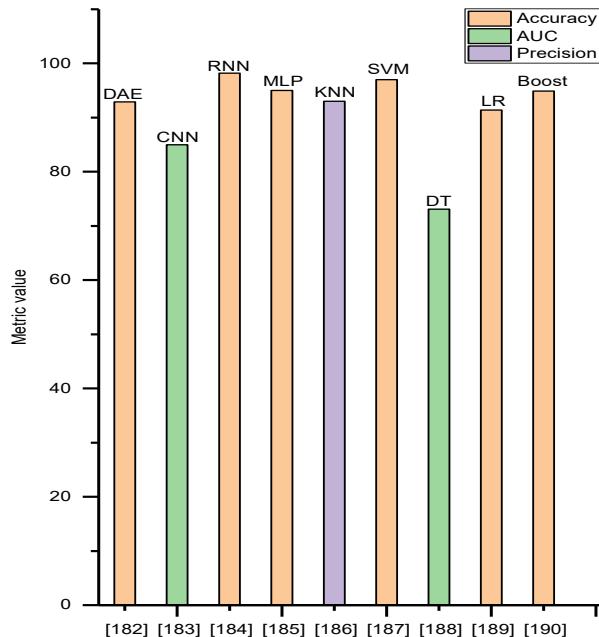
4. Features selection and extraction

This method evaluates the importance of different attributes by analyzing the relationships between features linked to cancer. In their research, Cui et al. [191] introduced a feature selection technique that leverages the Relief algorithm to enhance its performance.

Table 4

Instances of publicly available TCDs utilized in the identification of TC.

Ref.	TCD	Description	Link
[175]	THO	This dataset is designed to investigate the fundamental causes and effects of TD through the application of diverse omics approaches, including genomics, epigenomics, transcriptomics, proteomics, and metabolomics.	Visit THO datasets
[176]	TDDS	The dataset used for classification encompasses 5 features and 7200 instances, featuring a mix of 15 categorical and 6 numerical attributes. The classes within this dataset comprise hypothyroid, hyperfunction, and subnormal functioning.	Visit TDDS datasets
[177]	KEEL	The KEEL dataset offers a collection of benchmarks for assessing the performance of different learning approaches, including semi-supervised classification and USL. It encompasses 21 features, 7200 instances, and 3 classes.	Visit KEEL datasets
[178]	GEO	The GEO database serves as a repository for genomics data. It is specifically structured to archive gene expression datasets, arrays, and sequences within gene expression omnibus (GEO).	Visit GEO datasets
[179]	DDTI	The digital database thyroid image (DDTI) dataset acts as an essential tool for both researchers and novice radiologists aiming to create algorithm-driven CAD systems for analyzing TN. It contains 99 cases and 134 images.	Visit DDTI datasets
[180]	NCDR	The national cancer data repository (NCDR) functions as a repository for healthcare and research purposes, aimed at documenting every reported instance of cancer within England. The data originates from the Office for National Statistics.	Visit NCDR datasets
[181]	PLCO	The National Cancer Institute backs the prostate, lung, colorectal, and ovarian (PLCO) cancer screening trial, which focuses on identifying the primary factors influencing cancer incidence in both genders. This trial encompasses records from 155,000 participants and includes comprehensive studies on TC incidence and mortality.	Visit PLCO datasets

**Figure 6:** Summary of techniques for the TCD based in AI [182–190].

4.1. Selection methods

This part focuses on highlighting the methods commonly employed in the classification process. The primary goal is to identify and select relevant features that can enhance the accuracy of classification, simultaneously eliminating non-essential variables.

(a) Information gain (IG): This method simplifies the classification of TC attributes by assessing the probability of cancer presence through the comparison of entropy levels pre and post-evaluation. Generally, a greater gain value

signifies reduced entropy. Although IG provides numerous advantages, it also comes with specific limitations and challenges:

- **Advantages:** This approach enhances model performance by identifying relevant features, reducing data clutter, and improving accuracy. By simplifying the feature set, it makes complex models more manageable and speeds up both training and inference, which is vital for real-time applications. It helps prevent overfitting through the removal of non-essential attributes, leading to models that are simpler and easier to understand, thereby aiding in decision-making processes. Additionally, it lowers costs by focusing on critical data, allows for easier application to new datasets, and provides insights into the significance of features for a better understanding.
- **Disadvantages:** Typically, this method assesses features on an individual basis, which may lead to missed crucial interactions between them. It often favors categorical features over continuous ones, especially in the absence of proper discretization. This approach risks ignoring the broader context, potentially leading to a substantial loss of information. Moreover, it can show a preference for majority classes and may not be well-suited to certain model types. Handling data with many dimensions poses difficulties, and the arbitrary decision-making in setting thresholds can affect the results.

The IG technique has found extensive application in various aspects of cancer diagnosis. Its applications range from isolating genes that provide meaningful insights to enhance the precision of cancer classification, to determining treatment variables for breast cancer through entropy metrics. It has also been used for the systematic analysis and structuring of breast cancer-related medical data, compressing gene dimensions in datasets involving multiple cancer types, and removing genes that are either irrelevant or redundant in cancer studies. Moreover, the integration of IG with SVM, known as the IG-SVM method, has been adopted, where the IG outcomes serve as input for the LIBSVM classifier, illustrating its versatility in feature selection and enhancement of classification processes.

(b) Correlation-based feature selection (CFS): The CFS technique is commonly applied to examine the relationships between various cancer-related attributes. Although CFS offers a range of advantages, there are also notable limitations associated with its use in feature selection within ML:

- **Advantages:** CFS is valued for its straightforwardness, ability to identify linear correlations, capability to decrease dimensionality, and potential to boost model efficiency and clarity. This method supports quicker model training and prediction, exhibits robustness against outliers, and accommodates the incorporation of expert insights. Moreover, it enhances the effectiveness of other methodologies, provides opportunities for visualization and deeper understanding, lowers expenses, and enables the conduct of sensitivity analyses.
- **Disadvantages:** It's important to recognize that this approach may miss complex, nonlinear relationships between features and the outcome variable. Additionally, it can be vulnerable to multicollinearity, where features are highly correlated with each other, requiring additional preprocessing steps. Careful consideration of the specific issue and dataset at hand is crucial when applying this method.

The CFS algorithm has been widely incorporated into feature selection strategies to enhance classification outcomes across various studies. For example, Ashraf et al. employed it for analyzing datasets related to thyroid, hepatitis, and breast cancer from the UCI ML repository, as documented in [192]. A hybrid methodology that integrated learning algorithm tools with feature selection techniques for diagnosing diseases, including CFS as a key element, was introduced in [133]. In [193], researchers utilized CFS for feature selection within microarray datasets, successfully minimizing data dimensionality and pinpointing significant genes. A combined model that blended CFS with binary particle swarm optimization (BPSO) was developed in [194] for cancer classification, applied to 11 standard microarray datasets. Additionally, the CSVM-RFE technique, which integrates CFS, was applied in [195] to diminish the feature set in cancer research by removing non-essential elements. Moreover, CFS methodologies were utilized in [168] for the identification of key RNA expression features.

(c) Relief (RA): The Relevance Analysis (RA) is an effective technique used in feature selection, evaluating the discriminative power of features between classes through score assignment. RA has its own array of advantages and disadvantages:

- **Advantages:** Relief offers several benefits in feature selection, including its robustness against noisy data, capability to handle both continuous and categorical features, and ability to detect feature interactions without assuming their independence. It also reduces bias in datasets with imbalanced classes, eliminates the need for model training, and facilitates sensitivity analysis. These attributes make Relief an advantageous tool for feature selection in various data scenarios.
- **Disadvantages:** Relief exhibits significant computational complexity, affecting its applicability to large datasets. Its performance is sensitive to parameters, particularly the choice of the number of nearest neighbors (k), which can be challenging to optimize. The stability of Relief is also affected, with variations in the dataset leading to different selections of features. Furthermore, it is designed solely for use within supervised learning contexts, struggles with non-metric features, and necessitates adaptations for handling multiclass classification scenarios.

This method evaluates the importance of different features by exploring the relationships between variables related to cancer. In their research, Cui et al. [191] suggested a feature selection strategy that employs the Relief algorithm to enhance its effectiveness.

4.2. Extraction methods

(a) Principal component analysis (PCA): PCA has been widely recognized in numerous researches for its effectiveness in reducing data dimensionality and decoupling cancer-related features. PCA is praised for its ability to decrease dimensions and reveal patterns, although it may compromise on interpretability and is optimally used with linear correlations. For example, Shankarla et al. (2020) implemented PCA to refine feature selection for TC via the DTCW transformation [64]. Soulaymani et al. (2018) investigated PCA's capability in distinguishing various TC subtypes, such as papillary, follicular, and undifferentiated types [65]. Additionally, O et al. (2019) assessed PCA and linear discriminant analysis in the classification of Raman spectra for different TC subtypes [196]. Selaru et al. (2004) also utilized PCA on cDNA microarray data to explore the genetic underpinnings of breast cancers [197].

(b) Texture description: Texture analysis is a highly regarded technique for extracting related data in TC segmentation, classification, and prognosis efforts. The scientific community has developed various texture analysis methods, including wavelet transforms, binary descriptors, and statistical descriptors, among others. Specifically, the discrete wavelet transform (DWT) has garnered significant interest for its exceptional capability in data decorrelation. Although texture analysis is beneficial for distinguishing textures, it can be affected by changes in lighting conditions and does not inherently understand semantic content, which may limit its application in complex visual tasks. Wavelet-based methods have been extensively applied in detecting TC. For example, Sudarshan et al. [198] applied wavelet techniques to identify cancerous areas in thyroid, breast, ovarian, and prostate tumors. Additionally, Haji et al. [199] used texture data for the diagnosis of thyroid nodule malignancy employing a 2-level 2D wavelet transform. Further contributions to this field are documented in studies such as [200] and [201].

(c) Active contour (AC): The AC model, a versatile framework often used in image processing, was initially introduced by Kass and Witkin in 1987. AC is known for its ability to adjust to complex shapes, yet it faces challenges such as sensitivity to initial placements and issues with overlapping figures. Various strategies have been developed to address these challenges in contour segmentation using deformable curve models. These models have seen significant application in TCD, as evidenced by research conducted by [202], [203], and [204].

(d) LBP and GLCM: local binary patterns (LBP) are descriptors used in computer vision for identifying textures or objects in digital images. They are appreciated for their straightforwardness and ability to distinguish features effectively. However, LBP may be vulnerable to noise and often requires tuning of parameters for optimal performance. The LBP method was employed in TCD, as illustrated in a study by Yu et al. [200]. Furthermore, the integration of LBP with DL has been explored for distinguishing between benign and malignant TN, as seen in the studies by Xie et al. [205] and Mei et al. [206].

The gray-level co-occurrence matrix (GLCM) serves as a tool to depict the occurrence frequency of pixel value pairs at a predetermined distance within an image. It is particularly useful for texture analysis and the identification of distinctive features. Nevertheless, GLCM faces challenges such as sensitivity to image variations, high computational demands, and the need for careful parameter tuning. Song et al. [207] leveraged GLCM for feature extraction to differentiate among various types of TC. Additionally, Dincic et al. [208] employed GLCM in a comparative study to investigate the differences between patients with Hashimoto's thyroiditis-associated PTC and those with Hashimoto's thyroiditis only.

Table 5

Summary of features methods based on DL conducted in the diagnosis of TC.

Ref.	Year	Classifier	Features	Contributions
[210]	2017	KNN	FC/IG	Minimize data duplication and decrease processing duration. KNN addresses absent dataset values, while ANFIS receives the modified data as input.
[211]	2017	SVM	FC/CFS	Retrieve the geometric and moment characteristics, while specific SVM classifier kernels categorize the acquired features.
[111]	2020	CNN	FC/R	Utilize both ML techniques and feature selection algorithms, specifically Fisher's discriminant ratio, Kruskal-Wallis analysis, and Relief-F, for the examination of the SEER database.
[212]	2022	CNN	FE/PCA	This study mitigated the impact of imbalanced serum Raman data on prediction outcomes by employing an oversampling technique. Subsequently, the dimension of the data was reduced with PCA before applying RF and the Adaptive Boosting for classification.
[213]	2012	Boosting	FE/TD	Integrate CAD with DWT and extract texture features. Utilize the AdaBoost classifier to classify images into either malignant or benign thyroid images based on the extracted features.
[214]	2021	CNN	FE/AC	Improve image quality, perform segmentation, and extract multiple features, including both geometric and texture features. Each feature set is subsequently classified using MLP and SVM, leading to the classification of either malignant or benign cases.
[215]	2020	SVM	FE/LBP	Deep features are obtained through CNN, and they are merged with manually crafted features, which include histogram of oriented gradient (HOG) and scale-invariant feature transforms, to generate combined features. These combined features are subsequently employed for classification via an SVM.
[216]	2019	SVM	FE/GLCM	Apply a median filter to mitigate noise and outline the contours before feature extraction from thyroid regions, encompassing GLCM texture features. Subsequently, employ SVM, RF, and Bootstrap Aggregating (Bagging) to differentiate between benign and malignant nodules.
[209]	2019	SVM	FE/ICA	A multi-kernel-based classifier is employed for thyroid disease classification.

(e) ICA: In independent component analysis (ICA), data is decomposed into a set of independent contributing features to aid in feature extraction. ICA is adept at identifying statistically independent components, making it valuable for tasks like source separation. Its strengths lie in uncovering non-linear relationships and facilitating data compression. Nonetheless, ICA faces challenges due to assumptions about the data mixing process and can be difficult to interpret. ICA is applied for disentangling multivariate signals into their separate constituents. In the research conducted by Kalaimani et al. [209], ICA was used to isolate 29 attributes as independent and significant features for categorizing data into hypothyroid or hyperthyroid groups through a SVM.

A portrayal of the techniques derived from DL utilized in diagnosing TC is provided in Table 5.

5. TCD using vision transformers

5.1. Detection techniques

Transformer models are a type of DL model introduced in [217]. They have since become the foundation for many state-of-the-art natural language processing (NLP) and ML models. Transformers are designed to handle sequential data, making them suitable for various tasks beyond NLP as well. Transformers in TCD enable efficient analysis of medical data, including literature and patient records, offering high accuracy. They uncover patterns, risk factors, and diagnostic clues, aiding early detection. This technology enhances diagnosis speed, fuels data-driven research, and promises improved patient care and oncology advancements [218, 219]. Several studies have proposed the use of DL models, particularly transformer-based models, for detecting TC from US images. Here are some of these studies, for example, researchers in [220] developed a diagnostic system using DL (Deit, Swin Transformer, and Mixer-MLP) and metaheuristics to improve thyroid abnormality detection. They employed feature extraction and dimensionality reduction techniques, then evaluated multiple classifiers. The MEREC-TOPSIS MCDM method ranked the models, leading to the selection of the best-performing models for ensemble learning. The PCA+FOX optimization-based feature selection and random forest model achieved high accuracy on US and histopathological datasets, surpassing existing methods. This innovative approach eases the burden on healthcare professionals by enhancing TC diagnosis. The study [221], addressed the challenge of extracting important thyroid nodule characteristics from clinical narratives in US reports using NLP. A team of experts developed annotation guidelines and tested five transformer-based NLP models. Their GatorTron model, trained on a substantial text corpus, outperformed others, achieving the best F1-scores for extracting 16 thyroid nodule characteristics and linking them to nodules. This pioneering work enables improved

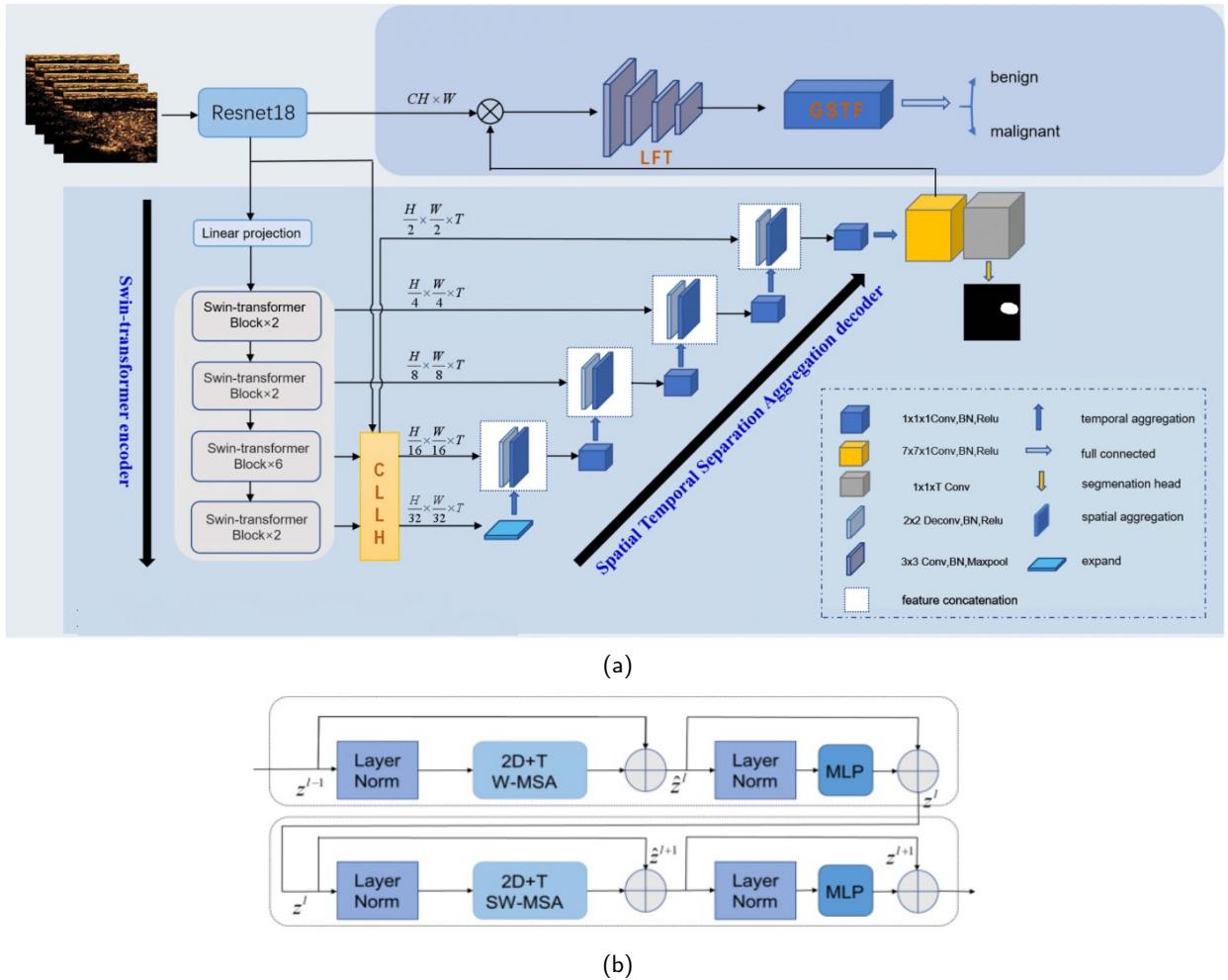


Figure 7: (a) The general framework of the suggested HEAT-Net, (b) Details of the swin-transformer block [223]

documentation quality of thyroid US reports and enhances patient outcomes assessment through electronic health records analysis. In [222], the study introduces a novel Boundary-preserving assembly Transformer UNet (BPAT-UNet) for precise US thyroid nodule segmentation. This network incorporates a boundary point supervision module (BPSM) for boundary refinement and an adaptive multi-scale feature fusion module (AMFFM) for handling various scales of features. Additionally, an assembled transformer module (ATM) improves boundary constraints and small object detection. Results demonstrated significantly improved segmentation accuracy compared to classical networks, achieving Dice similarity coefficients of 85.63% and 81.64% and HD95 values of 14.53 and 14.06 on private and public datasets, respectively. Chen et al. [223], introduces Trans-CEUS, a spatial-temporal transformer-based model for real-time microvascular perfusion analysis using CEUS as it shown in Figure 7. It combines dynamic swin-transformer and collaborative learning to accurately segment lesions with unclear boundaries, achieving a Dice similarity coefficient of 82.41%. The model also attains a high diagnostic accuracy of 86.59% for distinguishing malignant and benign TN. This pioneering research highlights the effectiveness of transformers in CEUS analysis and offers promising outcomes for thyroid nodule segmentation and diagnosis from dynamic CEUS datasets.

DL has been instrumental in medical image segmentation, particularly for thyroid glands in US images. However, existing models face issues like the loss of low-level boundary features and limitations in capturing contextual features. In response, a hybrid transformer UNet (H-TUNet) is introduced in [219]. It combines a 2D Transformer UNet with a multi-scale cross-attention transformer and a 3D Transformer UNet with self-attention to improve representation

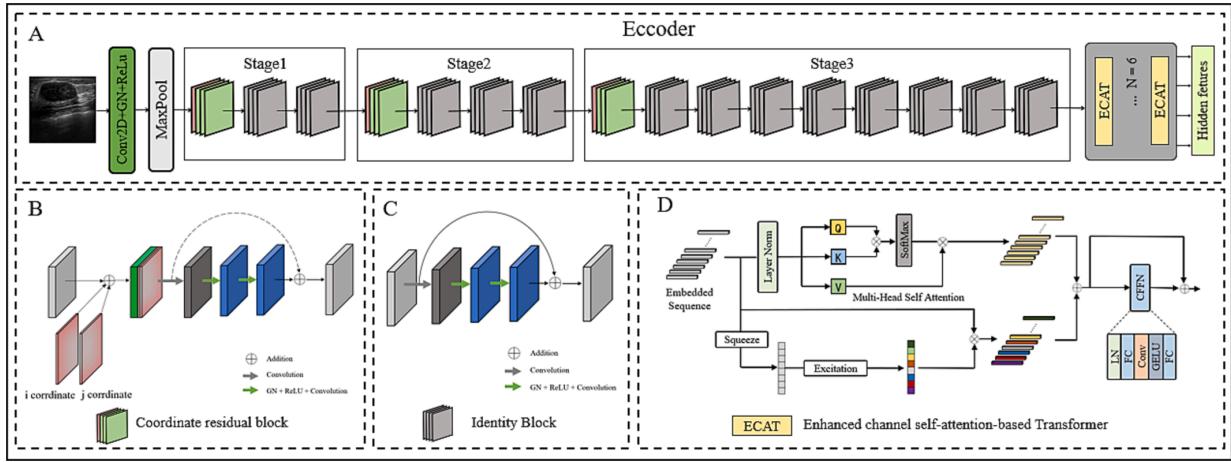


Figure 8: An example of the basic structure of encoder HEAT-Net for TC segmentation [226].

and contextual information. The end-to-end network was evaluated on thyroid segmentation datasets, outperforming other methods in benchmark tests. H-TUNet shows promise for thyroid gland segmentation in US sequences. Set classification involves predicting a single label from sets with multiple instances, like pathology slides or medical text data. State-of-the-art methods often use complex attention architectures to model set interactions. However, when labeled sets are limited, as in medical applications, these architectures are challenging to train. To tackle this issue, a kernel-based framework is introduced in [224], connecting affinity kernels and attention architectures. This leads to simplified "affinattention" nets, which are applied to tasks like Set-Cifar10 classification, thyroid malignancy prediction, and patient text triage. Affinattention nets deliver competitive results, outperforming heuristic attention architectures and other methods. jerbi et al. in 2023 [225], a DL approach, incorporating CNNs and vision Transformers, was employed to classify thyroid US images as either malignant or benign. A deep convolutional generative adversarial network (DCGAN) was used to address data scarcity and imbalance. Various models, including VGG16, EfficientNetB0, ResNet50, ViT-B16, and Hybrid ViT, were trained with both softmax and SVM classifiers. The hybrid ViT model, with SVM classification, outperformed others, achieving a 97.63% accuracy, showing promise for aiding doctors in diagnosing thyroid patients more effectively.

US is a valuable clinical screening tool, but segmenting lesions or organs in US images is challenging due to artifacts and low contrast. In this study [226], the authors introduce a novel U-shape segmentation model (Figure 8) combining CNN and transformer structures to integrate local and long-range information. It uses coordinate residual blocks (CdRB) to encode position data, channel-enhanced self-attention-based transformers (ECAT) for global feature enhancement, and a dual attention module (CDAM) for feature correlation and edge accuracy. The method outperforms state-of-the-art methods across various datasets, demonstrating adaptability and robustness in US image segmentation, potentially serving as a general segmentation tool.

The study [227] addresses the challenge of accurately diagnosing malignant TN through US imaging. Existing CAD methods often struggle to maintain precise shape information and capture long-range dependencies. The proposed Transformer fusing CNN Network (TCNet) utilizes a large kernel module (LKM) in a CNN branch for shape feature extraction and an enhanced Transformer module (ETM) in another branch for remote pixel connections. A Multiscale fusion module (MFM) integrates feature maps from both branches. Comparisons with other methods demonstrate TCNet's superiority and effectiveness in nodule segmentation. Hypoparathyroidism is a major concern post-TC surgery, affecting patients' quality of life. Identifying and locating parathyroid glands via US images before surgery can help protect them. In [228] a dual-branch contextual-aware network (DCA-Net) with Transformer is proposed to reduce hypoparathyroidism incidence. It combines a Transformer for global context extraction and a feature encoder branch for local feature aggregation. A channel and spatial fusion module (CSFM) integrates information from both branches. The DCA-Net effectively addresses detail loss, establishing global and local feature dependencies. Experiments with an US image dataset demonstrate superior performance compared to existing methods. The thyroid gland plays a crucial role in regulating the human body's functions, making the identification of TN from US images important for

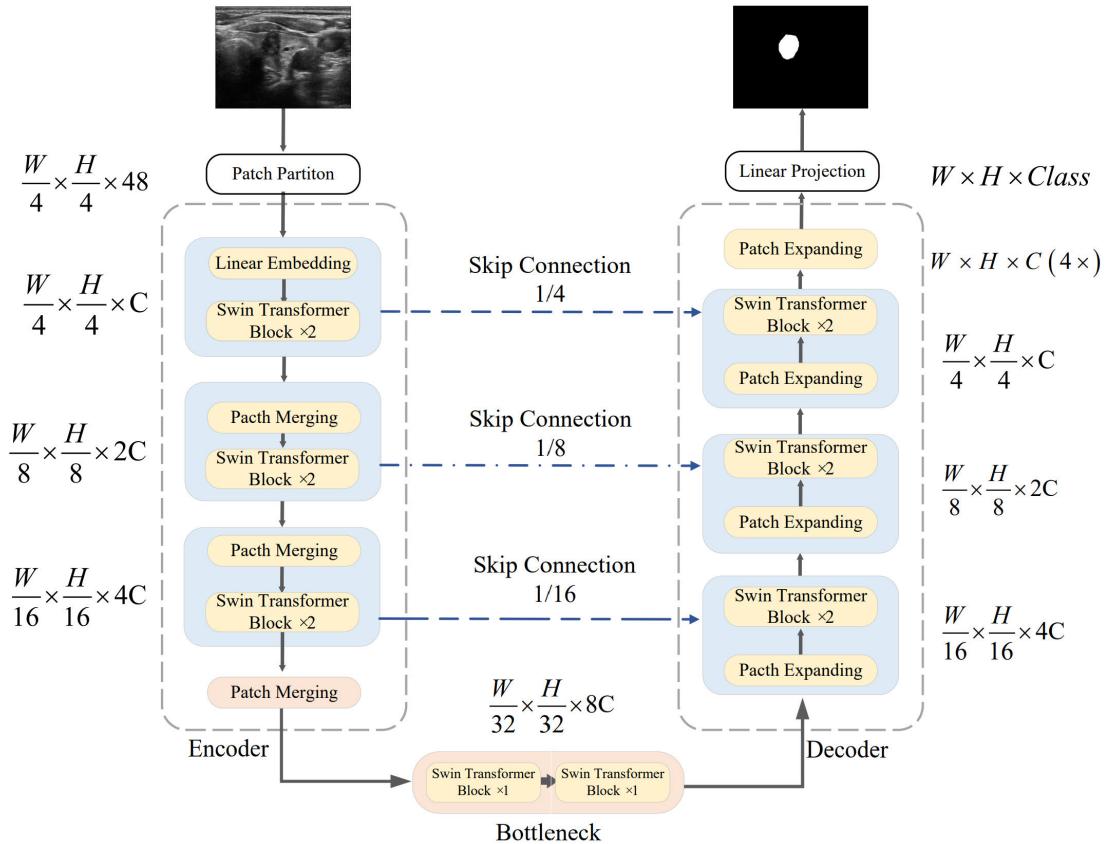


Figure 9: The Swin-Unet architecture [70].

medical diagnosis. However, the automatic segmentation of these nodules is challenging due to their heterogeneous appearance and background similarities. This study [70] presents a novel framework AMSeg based on Swin-Unet architecture presented in Figure 9, which employs multiscale anatomical features and late-stage fusion through adversarial training to address these challenges. Experimental results demonstrate the superiority of AMSeg in thyroid nodule segmentation, achieving high dice, Hd95, Jaccard, and precision values. This end-to-end network offers promise for clinical applications, potentially replacing manual segmentation methods.

In this study [229], the authors harnessed natural language processing with a bidirectional encoder representations from transformers (BERT) classifier to analyze unstructured clinical text data pertaining to recurrent papillary TC (PTC) diagnosis. The BERT model achieved exceptional performance, boasting a 98.8% accuracy in binary PTC recurrence classification. This approach streamlines the handling of unstructured patient information, eliminating the need for labor-intensive data refinement, and holds significant promise for training AI models in healthcare. The variability in features between benign and malignant TN, particularly in TI-RADS level 3, can lead to inconsistent diagnoses and unnecessary biopsies. To address this in [230], TC-ViT, a Vision Transformer-based model, utilizes contrast learning to enhance diagnostic accuracy and biopsy specificity. By incorporating global and local features, this model minimizes the distinction between nodules of the same category. Test results indicate an accuracy of 86.9%, outperforming classical DL models. TC-ViT offers automatic classification of TI-RADS 3 and malignant nodules in US images, promising improved computer-aided diagnosis and precise analysis. Optical coherence tomography (OCT) can aid in distinguishing normal and diseased thyroid tissue during surgery, but interpreting OCT images is challenging. In this study [231] explored various DL models for classifying thyroid diseases using 2D and 3D OCT data from 22 surgical patients with thyroid pathologies. The 3D vision transformer model achieved the best performance, with an

MCC of 0.79 (accuracy of 0.90) for normal versus abnormal classification. Custom models also excelled on open-access datasets. These findings suggest that combining OCT with DL can enable real-time, automatic identification of diseased tissue during thyroid surgery.

Accurate segmentation of thyroid nodules in US images is crucial for early TC diagnosis. Addressing the challenges posed by weak image edges and complex thyroid tissue structure, the study [232] introduces a local and context-attention adaptive network (LCA-Net). It combines local features from convolutional neural networks and global context from transformers, improving edge information capture. The model incorporates specific modules to handle different nodule sizes and positions, enhancing generalization. LCA-Net outperforms existing models on public datasets, demonstrating its potential for precise thyroid nodule diagnosis in clinical settings. In this study [233], the authors focus on improving the prediction of lymph node metastasis in papillary thyroid carcinoma by combining whole slide histopathological images (WSIs) and clinical data. They introduce a transformer-guided multi-modal multi-instance learning framework that effectively groups high-dimensional WSIs into low-dimensional feature embeddings and explores shared and specific features between modalities. The approach achieved an impressive AUC (area under the curve) of 97.34% on their dataset, outperforming state-of-the-art methods by 1.27%, highlighting its potential in improving precision medicine decisions based on multi-modal medical data fusion. Diagnosing lymph node metastasis in papillary thyroid carcinoma typically relies on analyzing large whole slide histopathological images (WSIs). To enhance accuracy, a novel transformer-guided framework is introduced in [234], leveraging transformers in three critical aspects. It incorporates a lightweight feature extractor, a clustering-based instance selection scheme, and a Transformer-MIL module for effective feature aggregation. The model further benefits from an attention-based mutual knowledge distillation (AMKD) paradigm. Experimental results on a WSI dataset outperform state-of-the-art methods by a significant margin, achieving a 2.72% higher AUC. Xiao et al. in [235] aim to address the challenges of diagnosing TC, particularly in cases where US images suffer from noise and artifacts, leading to a certain misdiagnosis rate in clinical practice. They highlight the need for further diagnosis using plain and contrast-enhanced CT scans. While plain CT provides valuable information, contrast-enhanced CT offers better contrast and can reflect organ margin erosion, a crucial symptom for TC diagnosis. However, the latter relies on the use of a contrast agent and exposes the patient to ionizing radiation. To mitigate these challenges, the authors propose an improved Unet architecture. Their approach involves using a convolutional Transformer module to learn global information from high-dimensional features. They also incorporate a texture feature module to extract local texture information from plain CT scans and integrate edge information obtained from superpixels as prior knowledge. The ultimate goal is to generate enhanced CT images with clear texture and higher quality, providing a valuable tool for TC diagnosis without the need for contrast agents and ionizing radiation. Histopathological images carry valuable information for tumor classification and disease prediction, but their size hinders direct use in CNNs. This study [236] introduces Pyramid Tokens-to-Token VIision Transformer (PyT2T-ViT), a lightweight architecture with multiple instance learning based on the vision Transformer. PyT2T-ViT uses Token-to-Token ViT (T2T-ViT) for feature extraction to reduce model parameters. It also incorporates an image pyramid to capture local and global features, significantly reducing computation. Experiments on thyroid pathology images yield superior results compared to CNN-based methods, balancing accuracy and efficiency. The authors in [237] aim to utilize multi-instance learning for the diagnosis of TC based on cytological smears. These smears lack multidimensional histological features, necessitating the mining of contextual information and diverse features for improved classification performance. To address these challenges, they introduce a novel algorithm called PyMLViT, which consists of two core modules. First, the pyramid token extraction module is designed to capture potential contextual information from smears. This module extracts multi-scale local features using a pyramid token structure and obtains global information through a vision transformer structure with a self-attention mechanism. Second, they construct a multi-loss fusion module based on the conventional multi-instance learning framework. To enhance the diversity of supervised information, they carefully allocate bag and patch weights and incorporate slide-level annotations as pseudo-labels for patches during training.

In Table 6, transformer-based models' performance (in %) for TC diagnosis is summarized.

5.2. TC diagnosis example

To exemplify the approaches adopted in the literature for TCD and the utilization of AI in classifying cancer types, we provide a simplified example. The pattern recognition process entails training a neural network to accurately classify input patterns into specific target classes. Following training, the network becomes capable of categorizing model. In this part, we demonstrate an example of categorizing TC into benign, malignant, or normal based on a collection of characteristics according to the TIRADS.

Table 6

Summary of transformer-based models' performance (in %) for TC diagnosis

Ref.	Transformer	Task	ACC	SEN	SPE	AUC	F1-score	Improvement
[220]	Swing	C	99.13	–	–	99.13	98.82	The diagnosis accuracy and the extract features of thyroid abnormality detection has been improved. The redundant features has reduced to avoid the overfitting.
[221]	BERT, RoBERTa, LongFormer, DeBERTa, and GatorTron	C	97.10	98.80	92.80	–	96.50	The proposed model can achieve satisfactory classification accuracy and identified a large number of characteristics comparable to experienced radiologists and can save time and effort as well as deliver potential clinical application value
[222]	BPAT-UNet	S	–	–	–	–	–	The proposed BPAT-UNet displays superior segmentation performance in visualization results and evaluation metrics
[223]	Trans-CEUS	S	86.59	–	–	–	–	Demonstrated significant improvement when compared to previous approaches, showcasing its effectiveness in the tasks of lesion segmentation and thyroid nodule diagnosis.
[219]	H-TUNet	S	–	–	–	–	–	The 2D and 3D Transformer UNet can distinguish the thyroid regions from other anatomies more effectively than the state-of-the-art segmentation models.
[224]	Network	C	–	–	–	91.3	–	Attention nets outperform complex attention-based architectures and other competing methods in tasks such as thyroid malignancy prediction.
[225]	ViTs	C	97.63	–	–	–	96.67	The SVM classification produces better performance than the Softmax classification for all of the models with the Hybrid ViT
[226]	CNN	S	–	–	–	–	–	The proposed method showcases excellent adaptability and robustness in US image segmentation and can potentially be a general US segmentation tool.
[227]	ETM	S	–	–	–	–	–	Extract the precise shape features of malignant thyroid and establish the remote connection between thyroid nodule pixels
[228]	Bottleneck	S	–	–	–	–	–	They proposed that DCA-Net can effectively mitigate the loss of details
[70]	Swing	S	–	–	–	–	–	The method can handle blurred and uneven tissue regions during the thyroid nodule segmentation process and enhanced prediction of accurate nodule edges.
[229]	BERT	C	–	–	–	–	88.00	Analyze unstructured clinical text information on diagnosis of the recurrent PTC efficiently.
[230]	ViT	C	86.90	87.10	86.10	–	92.4	Improve accuracy of diagnosis and specificity of biopsy recommendations. Minimize the representation distance between nodules of the same category
[231]	3D vision	C	90.00	–	–	–	–	Efficiently classifying thyroid diseases
[232]	LCA-Net	S	–	–	–	–	–	The superiority of the proposed LCA-Net for thyroid nodule segmentation
[233]	GMMIL	P	93.88	–	–	97.34	94.65	Experimental results on the collected lymph node metastasis dataset demonstrate the efficiency of the proposed method
[234]	Tiny-ViT	P	–	–	–	98.35	92.97	Improve predict lymph node metastasis from WSIs efficiently using a novel transformer-guided.
[235]	Convolutional	S	–	–	–	–	–	The Unet architecture has been optimized to create improved cross-sectional images with clearer texture and higher quality
[236]	T2T-ViT	C	86.60	–	–	–	–	The model parameters are reduced , and the model performance and computation are greatly improved compared with CNN.
[237]	PyMLViT	C	87.50	–	–	–	–	Optimize the training process of the network

Abbreviations: segmentation (S), Classification (C), Prediction (P), Guided multi-modal multi-instance learning (GMMIL).

In this case, we utilize a dataset obtained from the UCI ML Repository [238]. This dataset is instrumental in developing a neural network designed to categorize patients visiting a clinic into three distinct groups: normal, hyperfunctioning, or subnormally functioning. The dataset is structured into Thyroid Targets (TT) and Thyroid Inputs (TI) as detailed below: (i) TI consists of a $21 \times 7,200$ matrix that describes 7,200 patients through 15 binary and 6 continuous attributes. (ii) TT is a $3 \times 7,200$ matrix with class vectors, distributing each patient input into one of the three categories: (1) Hyperfunctioning, (2) Normal, not suffering from hyperthyroidism, and (3) Subnormal functioning.

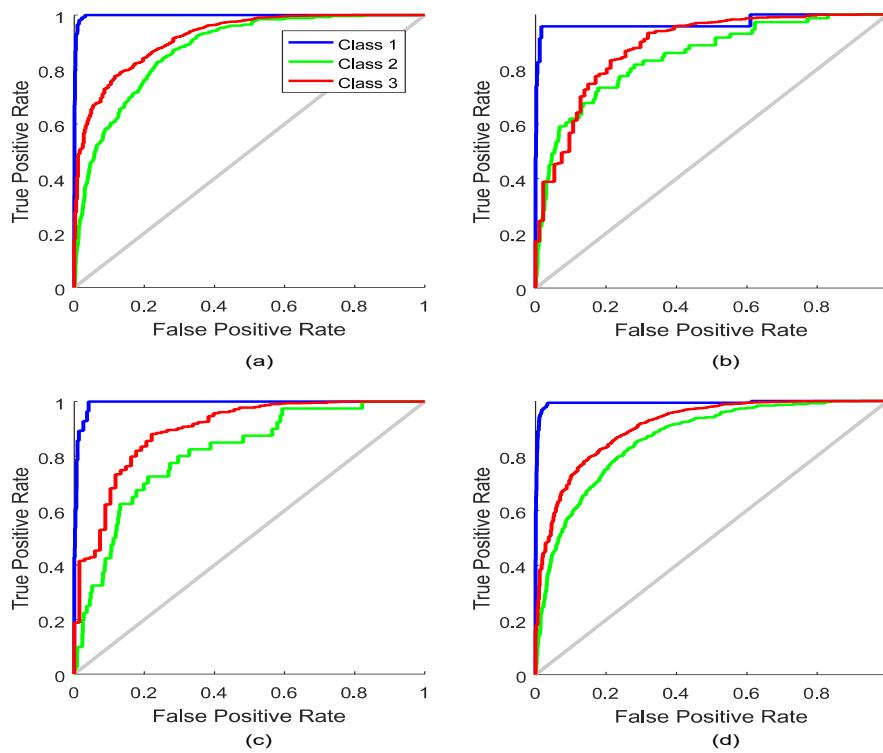


Figure 10: An example of TC classification USING ROC metric. (a). Training ROC; (b). Validation ROC; (c). Test ROC; (d). ALL ROC put the reference, mention first group what does it mean and the second group also, put (a) and (b) for each group

In this neural network setup, the dataset is divided into 5,040 samples for training, 1,080 samples for validation, and 1,080 samples for testing purposes. The network undergoes training to minimize the error between the thyroid inputs and targets until it achieves the desired target objective. If the error rate (ER) fails to decrease and training progress stalls, training with the training data is stopped, and the validation data is utilized for additional evaluation. Subsequently, the testing data is employed to assess the accuracy of the trained model.

In this illustration, we employ a network featuring 10 hidden layer neurons, 21 input features, and 3 output classes. Following the model simulation, the percentage error is computed, yielding values of 5.337% for training, 7.407% for validation, and 5.092% for testing. The overall recognition rate stands at 94.4%, with an overall error rate of 5.6%. The receiver operating characteristic (ROC) curve is presented in Figure 10. This example showcases the application of AI in TC classification, achieving a high recognition rate with the provided dataset. Figure 11 illustrates an instance of thyroid segmentation in US images utilizing k-means clustering, with three clusters selected for demonstration. K-means clustering is widely employed for such purposes.

6. Critical analysis and discussion

Data Accessibility and Precision Challenges: This document necessitates a thorough investigation and discussion on leveraging AI for thyroid carcinoma detection. While there's ample discourse regarding AI's potential in existing studies, a nuanced analysis is crucial to fully decipher its impact on healthcare, spotlighting both its advantages and drawbacks.

This segment commits to an exhaustive examination of AI models' proficiency in identifying thyroid carcinoma. We aim to scrutinize not merely their statistical precision but also their efficacy in practical clinical environments, and their contribution to the overarching clinical decision-making framework.

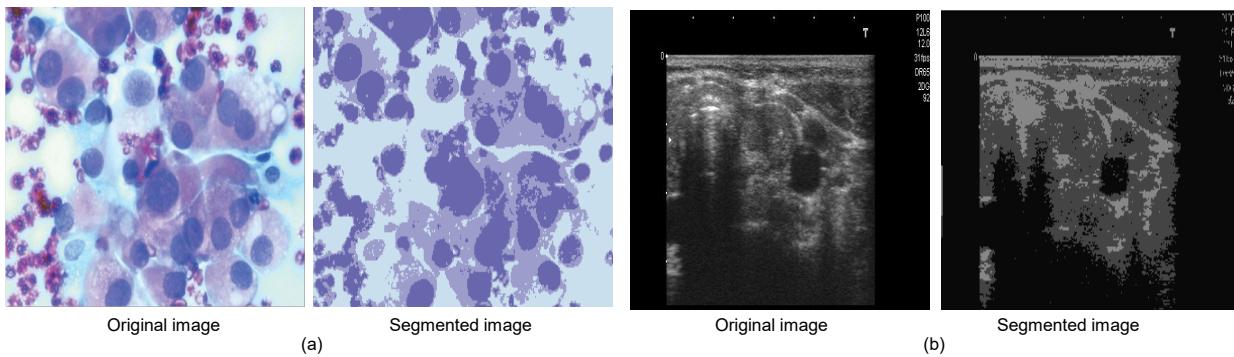


Figure 11: Thyroid segmentation example employing the K-Means method. (a) Imaging of medullary TC; (b) Ultrasound imaging of the thyroid.

Furthermore, this exploration delves into the potential biases embedded in AI models, seeking to unveil how they might inadvertently amplify existing healthcare inequities. By contrasting AI-enabled methodologies with conventional diagnostic tactics, we aspire to glean deeper insights into their relative effectiveness.

Recognizing the obstacles in integrating AI solutions into healthcare practices, including infrastructural, regulatory, and cultural challenges, is essential. In conclusion, we highlight the critical role of cross-disciplinary cooperation in seamlessly integrating AI into healthcare systems, thereby maximizing its beneficial impacts on patient health outcomes.

The reported metrics of AI models, such as accuracy, sensitivity, and specificity, can vary significantly across academic publications due to factors like the choice of dataset, data quality, and the methodological approach utilized. The performance of AI models in controlled experimental setups may not accurately represent their effectiveness in actual clinical scenarios. Variables including data discrepancies, lack of complete data, and evolving clinical conditions can substantially influence outcomes. Therefore, assessing a model's flexibility and reliability in diverse conditions is crucial. Table 7 provides an overview of the performance indicators for various AI-enhanced TCD frameworks, presented in percentage (%) terms, across multiple models and data sources. Additionally, Figures 12 and 13 display these performance indicators, also in percentage (%) terms, with a focus on private datasets and US imaging data, respectively.

Although AI methodologies have shown promise in TC diagnosis, they face challenges that hinder the development of efficient solutions, lead to increased expenses, and limit their broad application. For precise detection of TC, it's essential to collect and securely consolidate all relevant data in a single repository, unless adopting federated learning (FL) approaches, as Himeur et al. suggest [258]. Following this, algorithms capable of identifying all forms of TC must be developed. Comprehensive TCD should include an extensive array of training and testing images, diagrams of nodules, and detailed classifications of nodule characteristics across different sizes, as Shah et al. recommend [259]. It's crucial for these datasets to be continually updated with data from MRI, CT scans, X-rays, and other clinical images to assess TC accurately. Inclusion of demographic details such as race, ethnicity, gender, and age is also necessary. Establishing a centralized database accessible to all healthcare facilities for testing, validating, and implementing AI algorithms on the collected data is critical, following Salazar et al.'s guidance [260]. Additionally, a succinct overview of further limitations and challenges yet to be addressed is provided.

- The challenge of obtaining clean data and ensuring accuracy: In the realm of cancer diagnosis, especially TC, a major obstacle is the absence of detailed and well-annotated datasets that comprehensively document the disease's incidence and progression. Elmore et al. [261] point out that the limited detailed records on TC-related deaths make the process of collecting and authenticating data particularly difficult. Data availability is often restricted to individual healthcare providers, largely because there is no consolidated clinical database for TC to support data exchange across multiple organizations. Furthermore, the capability of AI algorithms to accurately diagnose TC is hampered by the limited presence of labeled cases that correlate with actual clinical outcomes, as underscored by Park et al. [262]. Although substantial datasets are essential for neural networks to generate accurate results, there is a need for selective data incorporation during the training phase to prevent the ingress of detrimental noise.

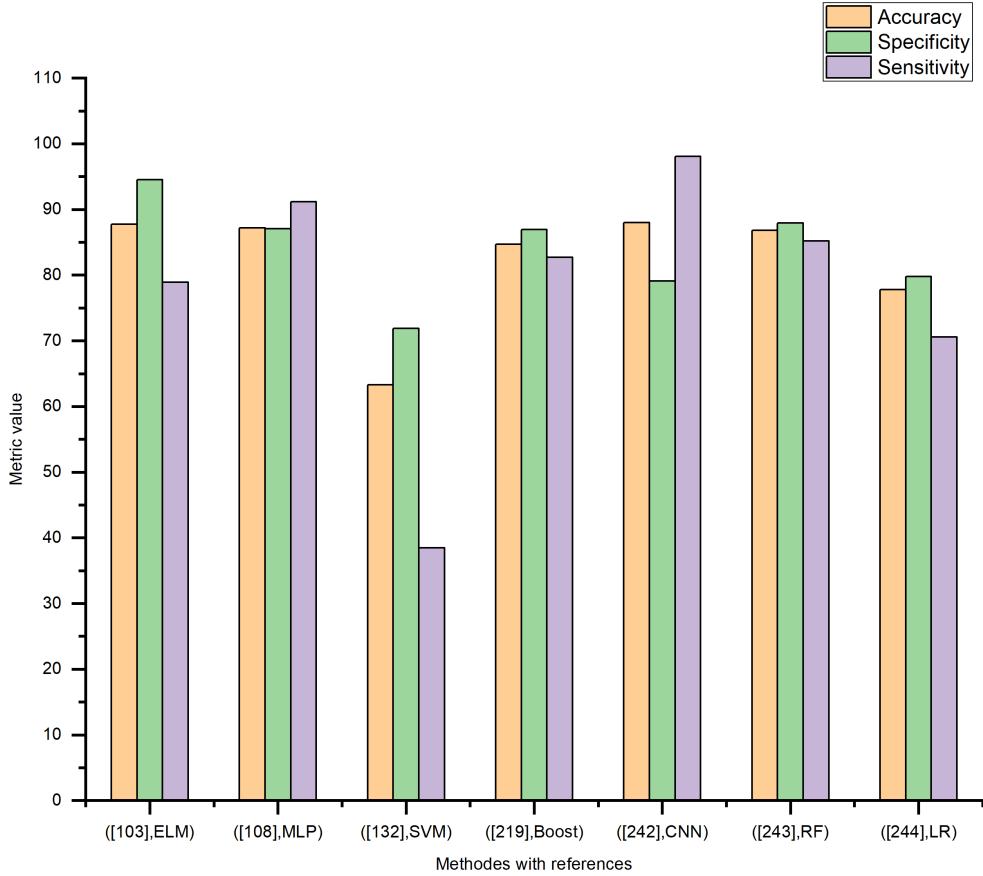


Figure 12: Performance assessment of TC frameworks in percentages (%) for private datasets

- Thyroid gland imaging: Within the domain of TC diagnosis, imaging modalities such as CT and MRI are available but often not preferred due to their high costs and limited availability under certain circumstances, as highlighted by Ha et al. [58]. US imaging is commonly used as an another physical exams technique, fine-needle aspiration biopsies, or radioisotope scans for its cost-effectiveness and accessibility. During an ultrasound examination, medical professionals can evaluate the thyroid gland by analyzing the nodules' echo patterns, along with their size, echogenicity, margins, and any calcifications present. However, it's crucial to acknowledge, as Zhu et al. [263] have noted, that the accuracy of ultrasound in differentiating between malignant and benign nodules can vary, and the images obtained may be prone to noise.
- Hyperparameters of DL models: Designing the effective DL algorithm is crucial for overcoming different challenges, especially in diagnosing TC. The task of precisely differentiating between malignant and benign tumors, is complex due to their significant similarities, as highlighted in the study by Wang et al. [264]. Addressing this challenge may require significantly increasing the number of DL layers for feature extraction. However, such an increase can lead to longer processing times, particularly with large datasets, which may delay timely cancer diagnoses for patients, as pointed out in the research by Lin et al. [57].
- Computation cost and storage limitations pose notable hurdles in algorithm development. Time complexity, a key measure in algorithm evaluation, assesses computational complexity by approximating the count of basic operations performed and its relationship with the size of input data. Typically represented as $O(n)$, where n is the size of the input, often measured by the bits required for its representation, this concept is thoroughly examined in the study by Al et al. [265]. Particularly in AI research related to TC or analogous cancer detection, researchers are tasked with finding algorithms that offer a harmonious blend of accuracy and computational efficiency. Their goal is to develop

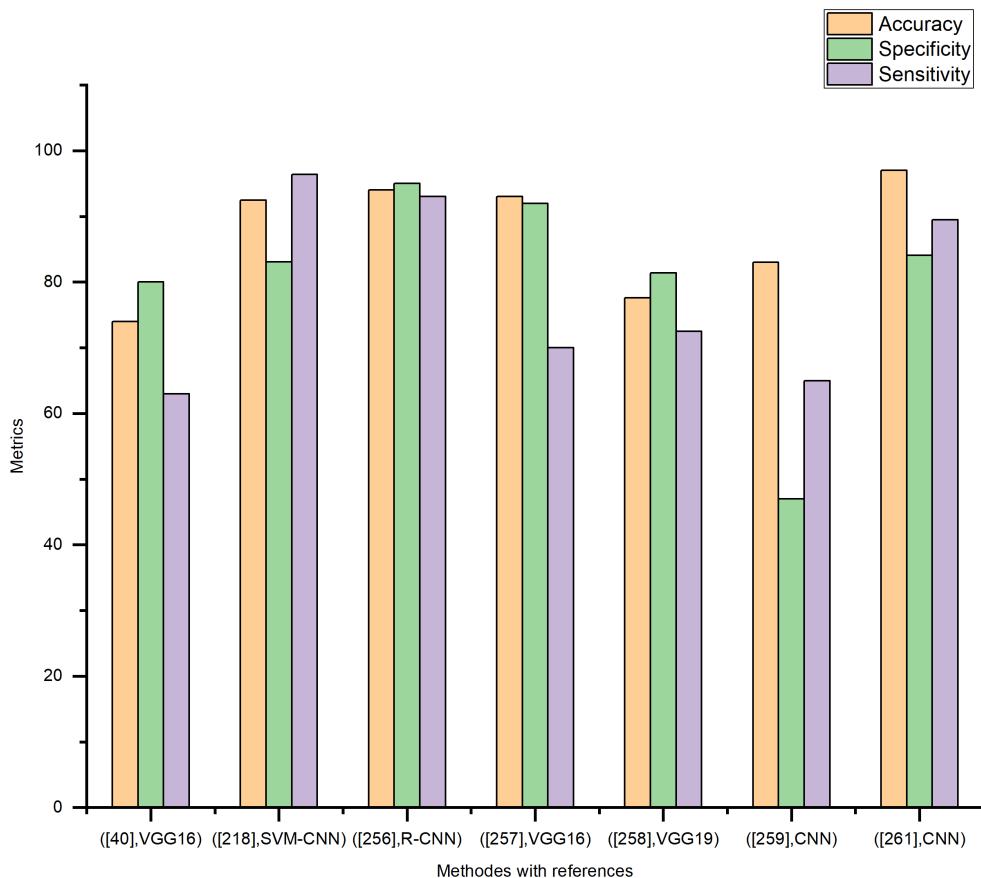


Figure 13: Performance assessment of TC frameworks in percentages (%) for ultrasound.

algorithms that can quickly process large datasets while maintaining precise results. Furthermore, the extensive amount of data used in these algorithms sometimes exceeds the storage capabilities, an issue underscored in the research by Lin et al. [57].

- **Imbalanced dataset:** Cancer element distribution within thyroid tissue cell categories often shows considerable imbalance, with cancerous cells usually forming a small fraction of the total tissue cell dataset. This results in a dataset that is heavily skewed, containing both cancerous and normal cells. Such imbalanced distribution of features in datasets for cancer cell detection can cause less than ideal performance of AI algorithms used for detection tasks, as observed in the study by Yao et al. [266].
- **Sparse labels:** Annotation is crucial in the detection of CT, particularly in differentiating normal cells from cancerous ones. However, this process can be both time-consuming and costly, largely because of the limited availability of annotated data. This shortage can result in inconsistent labeling, which may negatively impact the precision of AI algorithms that depend heavily on accurately labeled data. Consequently, these challenges may diminish trust and confidence in AI applications, as discussed in the study by Yao et al. [266].
- Presently, due to advancements in technology, especially in TC diagnosis, and the growing availability of medical and patient data, researchers face challenges in developing algorithms capable of efficiently handling a limited number of samples. These samples could be characterized by noise, lack of annotations, sparsity, incompleteness, or high dimensionality. As a result, there is a need for AI algorithms that are not only highly efficient but also able to process large datasets shared among healthcare providers and patients, or between specialist doctors, as underlined in the research by Sayed et al. [267].

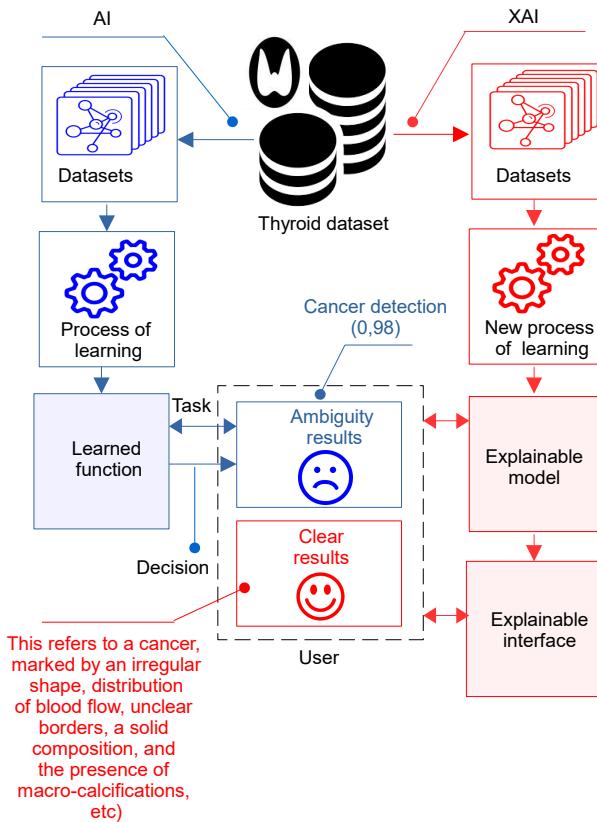
Table 7

Assessment of the effectiveness of different TC frameworks, measured in percentages (%).

Ref.	AI Model	Dataset	SEN	SPE	ACC	AUC
[31]	CNN	DICOM	-	91.50	-	-
[46]	RF	US	-	-	-	94.00
[102]	ThyNet	PD	-	-	-	92.10
[103]	VGG-16	CI	-	-	97.66	-
[120]	Fine-Tuning DCNN	PD	-	-	99.10	-
[123]	DCNN	SGI	93.00	86.00	89.00	-
[167]	DNN	ACR T	-	-	87.20	-
[239]	Ensemble DL	CI	-	-	99.71	-
[240]	k-SVM	US	-	-	-	95.00
[241]	ANN	US	-	-	-	69.00
[242]	SVM RF	US	-	-	-	95.10
[243]	ANN SVM	US	-	96.00	-	-
[244]	RF	US	-	-	-	75.00
[245]	CNN	DICOM	82.40	85.00	83.00	-
[246]	ResNet18-based	PD	-	-	93.80	-
[247]	multiple-scale CNN	PD	-	-	82.20	-
[248]	Alexnet CNN	PD	-	-	86.00	-
[249]	CNN (BETNET)	US	-	98.30	-	-
[250]	ResNet	T	-	75.00	-	-
[251]	Xception	CT images	86.00	92.00	89.00	-
[252]	Google inception v3	HPI	-	-	95.00	-
[253]	CNN	T	81.80	86.10	85.10	-
[254]	CNN	T	78.00	85.00	82.10	-
[19]	CNN	T	80.60	80.10	80.30	-
[255]	CNN	MRI	65.00	80.00	79.00	-
[256]	CNN	CT image	93.00	73.00	84.00	-
[257]	CNN	US	-	-	77.00	-

Abbreviations: Ultrasound (US), TIRADS (T), Cytological images (CI), Sono graphic images (SGI), Histo pathology images (HPI)

- Error Vulnerability: Despite AI's inherent autonomy, it is prone to making errors. For example, training an algorithm with TCDs for identifying cancerous regions can lead to biased predictions if the training datasets are biased. These biases may then lead to a series of erroneous results, which could go unnoticed for a significant duration. Identifying and correcting the source of these errors, once recognized, can be a laborious process, as explored in the research by Karsa et al. [268].
- The data form: Even with the significant advances in leveraging AI for TCD, ongoing challenges due to several persistent limitations remain. The growing need for varied medical imaging technologies results in the creation of large datasets crucial for AI algorithms. Nonetheless, efficiently managing and organizing this abundance of data has emerged as a daunting challenge. A primary issue exacerbating this challenge is the absence of adequate labeling, annotation, or segmentation of data, which complicates the process of data management, as underscored in the research by Kim et al. [269].
- Unexplainable AI: The application of AI in healthcare sometimes results in "black box" outcomes, where the decision-making process lacks transparency and sufficient justification. This lack of clarity can make healthcare practitioners question the dependability of the results, possibly leading to incorrect choices and treatments for patients with TC. In essence, AI systems can operate as black boxes, providing outcomes without explicit and comprehensible rationales, a concern highlighted in the research by Sardianos et al. [270].
- Lack of cancer detection platform: A significant barrier in detecting various cancers, including TC, is the absence of platforms that facilitate the replication and evaluation of previous research. This gap presents a considerable challenge that hampers the assessment of AI algorithms' performance, thereby hindering improvements [151]. The presence of online platforms that offer cutting-edge algorithms, extensive datasets, and expert insights is crucial for assisting healthcare practitioners, specialists, researchers, and developers in making the right decisions with reduced chances of error. Moreover, this kind of platforms are vital in augmenting clinical diagnoses, as they enable more thorough Examination and assessment [271].
- Data loss and contrast: The shift towards digital medical records is crucial, notably in cancer diagnosis using slide images. This latter facilitate the use of AI for pathologic examinations [272]. Nonetheless, medical digitalization

**Figure 14:** Diagram of XAI blocks.

encounters specific challenges. There exists the danger of losing critical information during the digital conversion process and potential inaccuracies due to data compression methods applied in autoencoder algorithms. Thus, selecting the right digitalization technology is essential to ensure the preservation of data fidelity and authenticity [273, 274]. The subtle contrast between the thyroid gland and surrounding tissues complicates accurate analysis and diagnosis of TC.

7. Future research directions

This segment delves into the anticipated developments of AI in identifying TC, scrutinizing forthcoming trends and advancements alongside their ethical repercussions. Ethical concerns encompass more than the immediate area of focus; issues regarding data privacy, responsibility, and fairness are also discussed. This part underscores research avenues poised to significantly improve TCD moving forward.

(a) Explainable Artificial Intelligence (XAI): Integrating AI into decision-making is crucial but faces challenges due to its complexity and lack of clarity. To mitigate these issues, explainable artificial intelligence (XAI) seeks to make AI models more transparent. This is particularly vital in healthcare, where understanding the rationale behind AI-generated outcomes is paramount. XAI has been applied to the diagnosis of intractable thyroid diseases, as evidenced in studies by Lamy et al. (2019) [275], Kobylinska et al. (2019) [276], Pintelas et al. (2020) [277], Lamy et al. (2020) [278], and Poceviciute et al. (2020) [279]. The differentiation between standard AI and XAI is showcased in Figure 14. Wildman et al. (2019) [163] proposed an XAI approach for detecting TC, enhancing the confidence of healthcare practitioners in AI predictions. XAI models clarify their reasoning, addressing the limitations associated with opaque "black box" algorithms. With XAI, healthcare professionals are equipped to make more accurate and confident decisions.

(b) Using Cloud, fog, and edge computing: The concept of edge networks merges edge computing with AI, allowing AI algorithms to operate closer to where data originates, a discussion brought forward by Sayed et al. (2023) [280]. This method enhances efficiency and cost-effectiveness for data-intensive applications, minimizing the requirement for extensive communication between patients and healthcare providers. By positioning data and storage closer to users in the healthcare field, this approach enables direct and swift access, a point highlighted by Alsalemi et al. (2022) [281]. To further improve the detection of TC within edge networks, fog computing is integrated. Fog computing introduces a distributed framework that bridges cloud computing and data generation sources, offering a versatile distribution of computational and storage capacities at key locations to boost overall system performance [282].

Cloud computing acts as a pivotal facilitator for the efficient functioning of AI-driven TCD systems, offering readily available access to data storage, servers, databases, networks, and applications for healthcare professionals, contingent upon internet connectivity. This integrated approach has proven its worth in medical scenarios, such as in the TC detection, as corroborated by several researches [283–293].

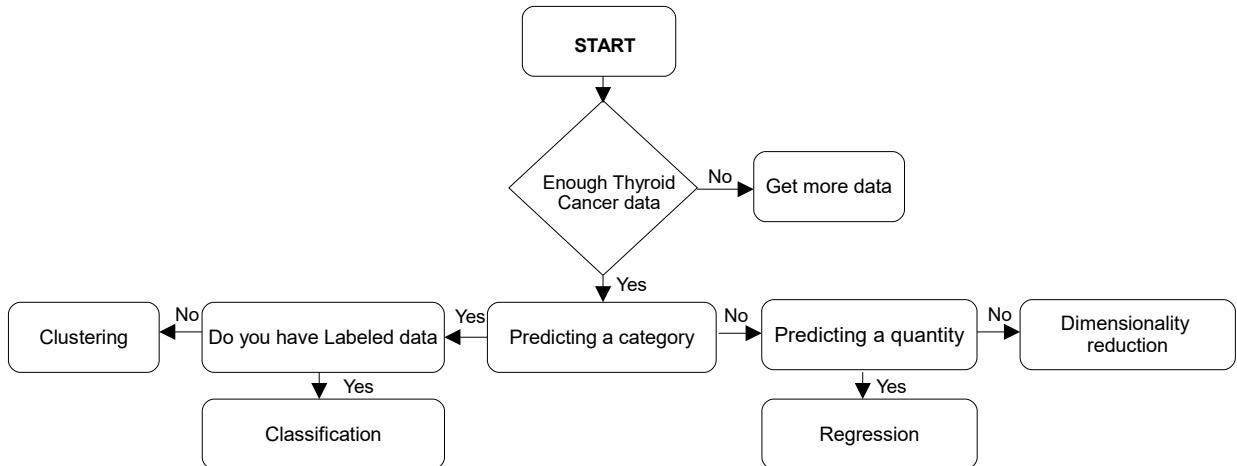
(c) Deep reinforcement learning (DRL): reinforcement learning (RL), a branch of ML [294], enables agents to navigate and make decisions in evolving environments by engaging in a learning cycle of trial and error, observation, and interaction. The interest in leveraging RL for diagnosing untreatable diseases and enhancing the support for medical decision-making processes has grown recently. For example, Balaprakash et al. (2019) [295] apply RL in cancer data classification, whereas Li et al. (2020) [296] explore the use of deep RL for lymph node set segmentation. In the approach by Li et al. (2020) [296], pseudo-ground truths are created using RECIST-slices, facilitating the simultaneous tuning of lymph node bounding boxes through the collaborative efforts of a segmentation network and a policy network.

(d) Deep transfer learning (DTL): transfer learning (TL) is recognized as an effective approach to reduce overfitting and improve the precision of diagnostic tools [297–299]. This technique applies knowledge acquired from one domain to solve related issues in another, such as shortening the duration of training and minimizing the amount of data needed [267, 300]. It is particularly useful in diagnosing TG. For example, the Enhance-Net model, described in [301], could act as a foundational model to boost the efficacy of a targeted DL model aimed at analyzing medical images in real-time. Furthermore, in [150], the research focuses on identifying pertinent characteristics of benign and malignant nodules using CNNs. By transferring insights from generic data to a dataset of US images, they achieve a fusion of hybrid semantic deep features. The application of transfer learning has also proven beneficial in categorizing images of thyroid nodules, as shown in [156]. Additional studies on this topic include [154, 302–305].

(e) Panoptic segmentation (PS): Accurately identifying and segmenting objects with varied and intersecting features continues to be a significant hurdle, especially in the medical field. To tackle this issue, several scholars have developed holistic and unified segmentation methods [306, 307]. Panoptic segmentation has received considerable attention, merging the principles of instance and semantic segmentation to detect and delineate objects efficiently. Semantic segmentation involves the classification of each pixel into distinct categories, whereas instance segmentation focuses on delineating individual object instances. AI has been applied to this framework through either supervised or unsupervised instance segmentation learning techniques, making it highly applicable to medical scenarios. The effectiveness of this integration in medical contexts has been highlighted in research works like [308, 309].

(f) IoMIT and 3D-TCD: The internet of medical imaging thing (IoMIT) has gained substantial interest in the healthcare industry in recent years. IoMIT seeks to advance the quality of healthcare services and minimize treatment expenses by facilitating the exchange of medical information between patients and healthcare providers via interconnected devices equipped with wireless communication technology. An instance of such integration is showcased in [310], where an AI-enhanced solution for the preemptive identification of TC within the IoMIT paradigm is introduced. This method employs CNN to refine the distinction between benign and malignant nodules, aiming ultimately at life preservation. Additional investigations pertinent to IoMIT include studies like those found in [311] and [312].

2D ultrasound is a prevalent technique for evaluating thyroid nodules, yet its static imagery might not fully capture the nodules' complex structures. Consequently, there's a growing interest in utilizing three-dimensional (3D) ultrasound, which offers a holistic view of the lesion by reconstructing nodule characteristics, thereby facilitating enhanced discrimination between different diagnostic categories [313]. The capability of 3D ultrasound to analyze intricate growth patterns, edges, and forms from various perspectives and depths allows for a more accurate assessment of thyroid nodules' morphological features compared to 2D ultrasound. Comparative research has confirmed the superiority of 3D over 2D ultrasound in achieving more precise evaluations [314–316].

**Figure 15:** Diagram of AI-algorithms choice for TCD.

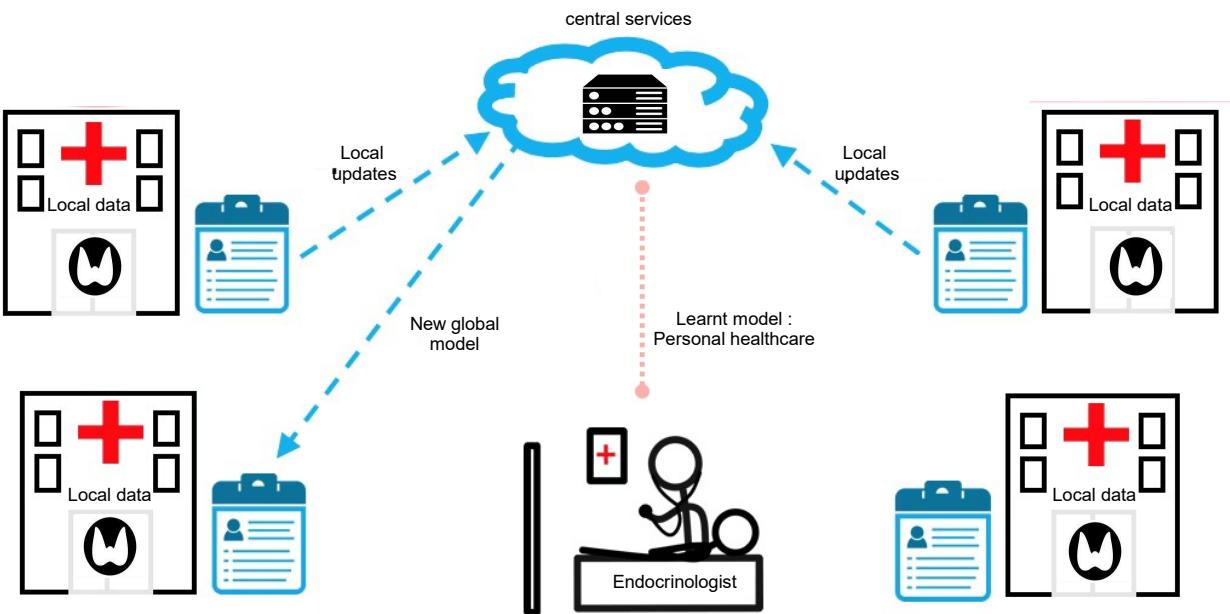
(g) AI-based thyroid surgical techniques: As surgical practices face complex challenges, the essential role of AI-driven robotic assistance is becoming increasingly recognized. AI has the capability to navigate clinical intricacies by processing and leveraging large volumes of data, offering decision-making support with precision that rivals that of medical experts [317]. Businesses are AI into surgical operations through the development of AI systems and the deployment of robots to aid surgeons in the operating room. These robots fulfill various functions, such as managing surgical tools, handling potentially contaminated materials and medical waste, conducting remote patient monitoring, and compiling patient information including electronic health records, vital signs, lab results, and video documentation [318]. It is therefore vital for surgeons to develop a comprehensive understanding of AI and its potential impacts on healthcare. While AI-enabled robotic surgery is still emerging, fostering interdisciplinary collaboration can accelerate the progress of AI technology, thereby improving surgical outcomes [319–322] [323–326].

(h) Recommender systems (RSs): The vast amount of information produced by online medical platforms and electronic health records presents a challenge for TC patients seeking specific and accurate data [327]. Additionally, the substantial costs associated with healthcare data management can complicate the task for physicians handling a broad spectrum of patients and treatment alternatives. The implementation of RS has been suggested as a solution to improve decision-making within healthcare, reducing the load on both patients and oncologists [328, 329]. Incorporating RS into digital health facilitates tailored recommendations, precise evaluation of large data sets, and stronger privacy measures, leveraging the capabilities of AI and ML technologies [330].

(i) Federated learning (FL): FL has gained traction in healthcare applications due to its capacity to enhance patient data privacy across different healthcare settings [258, 331]. The influence of environmental factors on human health, which can subsequently impact economic stability, is substantial. An increase in the incidence of thyroid gland disorders has been observed across diverse populations. ML plays a crucial role in addressing such health issues by leveraging collected data to train models capable of foreseeing severe health conditions. Considering the critical need for maintaining the confidentiality of patient information among various health institutions, FL stands out as an optimal framework for these purposes, as illustrated in Figure 16. Lee et al. [332] conducted a study comparing the effectiveness of FL with five traditional DL techniques (SE-ResNext50, SE-ResNet50, ResNext50, ResNet50, VGG19) in analyzing and detecting TCD.

(j) Generative chatbots:

Recent breakthroughs in AI, notably in creating generative chatbots and expansive language models like the GPT series, have marked a significant stride forward [333]. These advanced models, trained on vast datasets, can produce text that mimics human speech and engage in meaningful dialogues beyond basic scripted responses. As these models have evolved, their application spectrum has broadened, with healthcare becoming a key area of application. In this sector, these models are being explored for patient interaction, initial symptom evaluation, dissemination of health

**Figure 16:** The FL for healthcare.

information, and aiding healthcare workers in research and data analysis [4]. Integrating such technologies promises to enhance healthcare operations, patient experiences, and professional healthcare services, provided that necessary safety measures and ethical guidelines are observed [334].

Applying generative chatbots or models like ChatGPT directly for diagnosing TC (or any medical condition) would be imprudent and risky. Nevertheless, they can play supportive roles within healthcare environments [335]. For example, chatbots can initially collect information from patients about their symptoms, familial health history, and lifestyle factors. This preliminary data gathering can enrich the understanding of a patient's situation before they consult a healthcare practitioner. Additionally, chatbots can inform about TC, including its risk factors, symptoms, and prevention measures [336], empowering patients with knowledge about the condition and prompting those with relevant symptoms to seek professional advice. Although not a substitute for professional diagnostics, these tools can guide users through questions that pinpoint potential risks or symptoms, encouraging them to seek further evaluation from a healthcare professional [337].

After diagnosis, chatbots can inform patients about treatment options, side effects, nutritional advice, and answer frequently asked questions. They can also (i) remind patients about medication times, upcoming appointments, or regular self-checks, (ii) support relaxation techniques, offer mental health resources, or provide empathetic listening, and (iii) assist healthcare workers by offering instant access to information on TC, latest research, or treatment alternatives, serving as a real-time resource [338].

8. Conclusion

This investigation delves deeply into ML and DL, highlighting their growing prominence due to their enhanced precision over other methods. It comprehensively reviews various algorithms and training models, discussing their benefits and drawbacks. Specifically, DL techniques are celebrated for their application in a myriad of real-world scenarios, notably for their generalization capabilities and resilience to noise.

Nevertheless, significant challenges obstruct the full adoption of DL in detecting TC, with the lack of clean data and appropriate platforms being primary concerns. Tackling these data challenges with detailed precision is essential for creating effective and robust models for detecting more complex cancer stages.

Future research should aim at overcoming these hurdles and improving TCD methods. This study highlights the urgent need for increased research focus on TC diagnostics to match the high precision expectations of healthcare

practitioners. While cancer detection in two or three dimensions is progressing, the limited expertise in handling various geometric transformations and multi-dimensional data compromises the accuracy in diagnosing life-threatening diseases. Therefore, it is vital to innovate in distinguishing between cancerous nodule sizes. Such innovations could significantly speed up treatment, improve diagnostic precision, foster proactive epidemiological tracking, and reduce death rates.

Novel technologies like Explainable AI, edge computing, reinforcement learning, privacy-preserving mechanisms, and remote sensing are paving new paths in TCD research. These developments are crucial for medical professionals, simplifying the diagnostic process, reducing detection times, and enhancing patient confidentiality. Future research will explore the impact of these advanced technologies further. The objective is to create a major transformation in cancer detection approaches by crafting advanced, privacy-focused technologies for the identification of TC patients and extending into domains like telehealth.

References

- [1] Y. Himeur, S. Al-Maadeed, I. Varlamis, N. Al-Maadeed, K. Abualsaud, A. Mohamed, Face mask detection in smart cities using deep and transfer learning: lessons learned from the covid-19 pandemic, *Systems* 11 (2) (2023) 107.
- [2] A. Chouchane, A. Ouamane, Y. Himeur, W. Mansoor, S. Atalla, A. Benzaibak, C. Boudellal, Improving cnn-based person re-identification using score normalization, in: 2023 IEEE International Conference on Image Processing (ICIP), IEEE, 2023, pp. 2890–2894.
- [3] Y. Himeur, S. Al-Maadeed, N. Almaadeed, K. Abualsaud, A. Mohamed, T. Khattab, O. Elharrouss, Deep visual social distancing monitoring to combat covid-19: A comprehensive survey, *Sustainable cities and society* 85 (2022) 104064.
- [4] S. S. Sohail, F. Farhat, Y. Himeur, M. Nadeem, D. Ø. Madsen, Y. Singh, S. Atalla, W. Mansoor, Decoding chatgpt: A taxonomy of existing research, current challenges, and possible future directions, *Journal of King Saud University-Computer and Information Sciences* (2023) 101675.
- [5] Y. Himeur, M. Elnour, F. Fadli, N. Meskin, I. Petri, Y. Rezgui, F. Bensaali, A. Amira, Ai-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives, *Artificial Intelligence Review* 56 (6) (2023) 4929–5021.
- [6] F. M. Calisto, N. Nunes, J. C. Nascimento, Modeling adoption of intelligent agents in medical imaging, *International Journal of Human-Computer Studies* 168 (2022) 102922.
- [7] Y. E. Amine Becha and, R. Medjoudj, Y. Himeur, A. Amira, Harnessing transformers: A leap forward in lung cancer image detection, in: 2022 6th International Conference on Signal Processing and Information Security (ICSPIS), IEEE, 2023, pp. 1–6.
- [8] Y. Habchi, Y. Himeur, H. Kheddar, A. Boukabou, S. Atalla, A. Chouchane, A. Ouamane, W. Mansoor, Ai in thyroid cancer diagnosis: Techniques, trends, and future directions, *Systems* 11 (10) (2023) 519.
- [9] F. Dabbagh Moghaddam, F. Romana Bertani, Application of microfluidic platforms in cancer therapy, *Materials Chemistry Horizons* 1 (1) (2022) 69–88.
- [10] S. S. Arunachalam, A. P. Shetty, N. Panniyadi, C. Meena, J. Kumari, B. Rani, P. Das, S. Kumari, Study on knowledge of chemotherapy's adverse effects and their self-care ability to manage-the cancer survivors impact, *Clinical Epidemiology and Global Health* 11 (2021) 100765.
- [11] E. Atlıhan-Gundogdu, D. İlem-Ozdemir, M. Ekinci, E. Ozgenc, E. S. Demir, B. Sánchez-Dengra, I. González-Alvárez, Recent developments in cancer therapy and diagnosis, *Journal of pharmaceutical investigation* 50 (2020) 349–361.
- [12] H. S. Salem, Cancer status in the occupied palestinian territories: types; incidence; mortality; sex, age, and geography distribution; and possible causes, *Journal of Cancer Research and Clinical Oncology* 149 (8) (2023) 5139–5163.
- [13] Y. Deng, H. Li, M. Wang, N. Li, T. Tian, Y. Wu, P. Xu, S. Yang, Z. Zhai, L. Zhou, et al., Global burden of thyroid cancer from 1990 to 2017, *JAMA network open* 3 (6) (2020) e208759–e208759.
- [14] D. Hammouda, M. Aoun, K. Bouzerar, et al., *Registre des tumeurs d'algérie* (2006).
- [15] M. Castellana, A. Piccardo, C. Virili, L. Scappaticcio, G. Grani, C. Durante, L. Giovanella, P. Trimboli, Can ultrasound systems for risk stratification of thyroid nodules identify follicular carcinoma?, *Cancer cytopathology* 128 (4) (2020) 250–259.
- [16] L. Hitu, K. Gabora, E.-A. Bonci, A. Piciu, A.-C. Hitu, P.-A. Ştefan, D. Piciu, Microrna in papillary thyroid carcinoma: A systematic review from 2018 to june 2020, *Cancers* 12 (11) (2020) 3118.
- [17] L. Giovanella, G. Treaglia, I. Iakovou, J. Mihailovic, F. A. Verburg, M. Luster, Eanm practice guideline for pet/ct imaging in medullary thyroid carcinoma, *European journal of nuclear medicine and molecular imaging* 47 (1) (2020) 61–77.
- [18] S. M. Ferrari, G. Elia, F. Ragusa, I. Ruffilli, C. La Motta, S. R. Paparo, A. Patrizio, R. Vita, S. Benvenga, G. Materazzi, et al., Novel treatments for anaplastic thyroid carcinoma, *Gland surgery* 9 (Suppl 1) (2020) S28.
- [19] Z. Jin, Y. Zhu, S. Zhang, F. Xie, M. Zhang, Y. Zhang, X. Tian, J. Zhang, Y. Luo, J. Cao, Ultrasound computer-aided diagnosis (cad) based on the thyroid imaging reporting and data system (ti-rads) to distinguish benign from malignant thyroid nodules and the diagnostic performance of radiologists with different diagnostic experience, *Medical Science Monitor: International Medical Journal of Experimental and Clinical Research* 26 (2020) e918452–1.
- [20] M. Khammari, A. Chouchane, A. Ouamane, M. Bessaoudi, Y. Himeur, M. Hassaballah, et al., High-order knowledge-based discriminant features for kinship verification, *Pattern Recognition Letters* 175 (2023) 30–37.
- [21] A. Hamza, B. Lekouaghet, Y. Himeur, Hybrid whale-mud-ring optimization for precise color skin cancer image segmentation, in: 2022 6th International Conference on Signal Processing and Information Security (ICSPIS), IEEE, 2023, pp. 1–6.
- [22] F. N. Tessler, W. D. Middleton, E. G. Grant, J. K. Hoang, L. L. Berland, S. A. Teefey, J. J. Cronan, M. D. Beland, T. S. Desser, M. C. Frates, et al., Acr thyroid imaging, reporting and data system (ti-rads): white paper of the acr ti-rads committee, *Journal of the American college of radiology* 14 (5) (2017) 587–595.

- [23] F. N. Tessler, W. D. Middleton, E. G. Grant, Thyroid imaging reporting and data system (ti-rads): a user's guide, *Radiology* 287 (1) (2018) 29–36.
- [24] Genomic Data Commons Data Portal, Available online: <https://portal.gdc.cancer.gov/>, accessed: 2021-01-10.
- [25] H. Zhou, Y. Jin, L. Dai, M. Zhang, Y. Qiu, J. Tian, J. Zheng, et al., Differential diagnosis of benign and malignant thyroid nodules using deep learning radiomics of thyroid ultrasound images, *European Journal of Radiology* 127 (2020) 108992.
- [26] M. Schlumberger, M. Tahara, L. J. Wirth, B. Robinson, M. S. Brose, R. Elisei, M. A. Habra, K. Newbold, M. H. Shah, A. O. Hoff, et al., Lenvatinib versus placebo in radioiodine-refractory thyroid cancer, *New England Journal of Medicine* 372 (7) (2015) 621–630.
- [27] M. C. Wettasinghe, S. Rosairo, N. Ratnatunga, N. D. Wickramasinghe, Diagnostic accuracy of ultrasound characteristics in the identification of malignant thyroid nodules, *BMC research notes* 12 (1) (2019) 193.
- [28] R. Nayak, N. Nawar, J. Webb, M. Fatemi, A. Alizad, Impact of imaging cross-section on visualization of thyroid microvessels using ultrasound: Pilot study, *Scientific reports* 10 (1) (2020) 1–9.
- [29] N. Singh Ospina, S. Maraka, A. Espinosa DeYcaza, D. O'Keeffe, J. P. Brito, M. R. Gionfriddo, M. R. Castro, J. C. Morris, P. Erwin, V. M. Montori, Diagnostic accuracy of thyroid nodule growth to predict malignancy in thyroid nodules with benign cytology: systematic review and meta-analysis, *Clinical endocrinology* 85 (1) (2016) 122–131.
- [30] V. Kumar, J. Webb, A. Gregory, D. D. Meixner, J. M. Knudsen, M. Callstrom, M. Fatemi, A. Alizad, Automated segmentation of thyroid nodule, gland, and cystic components from ultrasound images using deep learning, *IEEE Access* 8 (2020) 63482–63496.
- [31] J. Ma, F. Wu, T. Jiang, Q. Zhao, D. Kong, Ultrasound image-based thyroid nodule automatic segmentation using convolutional neural networks, *International journal of computer assisted radiology and surgery* 12 (11) (2017) 1895–1910.
- [32] J. S. A. Song, R. D. Hart, Fine-needle aspiration biopsy of thyroid nodules: Determining when it is necessary, *Canadian Family Physician* 64 (2) (2018) 127.
- [33] S. Y. Hahn, J. H. Shin, Y. L. Oh, K. W. Park, Y. Lim, comparison between fine needle aspiration and core needle biopsy for the diagnosis of thyroid nodules: Effective indications according to us findings, *Scientific reports* 10 (1) (2020) 1–7.
- [34] H. Ullah, T. Saba, N. Islam, N. Abbas, A. Rehman, Z. Mehmood, A. Anjum, An ensemble classification of exudates in color fundus images using an evolutionary algorithm based optimal features selection, *Microscopy research and technique* 82 (4) (2019) 361–372.
- [35] T. Saba, S. T. F. Bokhari, M. Sharif, M. Yasmin, M. Raza, Fundus image classification methods for the detection of glaucoma: A review, *Microscopy research and technique* 81 (10) (2018) 1105–1121.
- [36] B. Mughal, N. Muhammad, M. Sharif, A. Rehman, T. Saba, Removal of pectoral muscle based on topographic map and shape-shifting silhouette, *BMC cancer* 18 (1) (2018) 1–14.
- [37] M. Morais, F. M. Calisto, C. Santiago, C. Aleluia, J. C. Nascimento, Classification of breast cancer in mri with multimodal fusion, in: 2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI), IEEE, 2023, pp. 1–4.
- [38] P. Diogo, M. Morais, F. M. Calisto, C. Santiago, C. Aleluia, J. C. Nascimento, Weakly-supervised diagnosis and detection of breast cancer using deep multiple instance learning, in: 2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI), IEEE, 2023, pp. 1–4.
- [39] X. Wang, J. Zhang, S. Yang, J. Xiang, F. Luo, M. Wang, J. Zhang, W. Yang, J. Huang, X. Han, A generalizable and robust deep learning algorithm for mitosis detection in multicenter breast histopathological images, *Medical Image Analysis* 84 (2023) 102703.
- [40] B. Mughal, M. Sharif, N. Muhammad, T. Saba, A novel classification scheme to decline the mortality rate among women due to breast tumor, *Microscopy research and technique* 81 (2) (2018) 171–180.
- [41] N. Abbas, T. Saba, Z. Mehmood, A. Rehman, N. Islam, K. T. Ahmed, An automated nuclei segmentation of leukocytes from microscopic digital images., *Pakistan journal of pharmaceutical sciences* 32 (5) (2019).
- [42] N. Abbas, T. Saba, A. Rehman, Z. Mehmood, N. Javaid, M. Tahir, N. U. Khan, K. T. Ahmed, R. Shah, Plasmodium species aware based quantification of malaria parasitemia in light microscopy thin blood smear, *Microscopy research and technique* 82 (7) (2019) 1198–1214.
- [43] Y. Wang, W. Yue, X. Li, S. Liu, L. Guo, H. Xu, H. Zhang, G. Yang, Comparison study of radiomics and deep learning-based methods for thyroid nodules classification using ultrasound images, *Ieee Access* 8 (2020) 52010–52017.
- [44] P. Qin, K. Wu, Y. Hu, J. Zeng, X. Chai, Diagnosis of benign and malignant thyroid nodules using combined conventional ultrasound and ultrasound elasticity imaging, *IEEE journal of biomedical and health informatics* 24 (4) (2019) 1028–1036.
- [45] H. Wu, Z. Deng, B. Zhang, Q. Liu, J. Chen, Classifier model based on machine learning algorithms: application to differential diagnosis of suspicious thyroid nodules via sonography, *American Journal of Roentgenology* 207 (4) (2016) 859–864.
- [46] B. Zhang, J. Tian, S. Pei, Y. Chen, X. He, Y. Dong, L. Zhang, X. Mo, W. Huang, S. Cong, et al., Machine learning–assisted system for thyroid nodule diagnosis, *Thyroid* 29 (6) (2019) 858–867.
- [47] M. Sollini, L. Cozzi, A. Chiti, M. Kirienko, Texture analysis and machine learning to characterize suspected thyroid nodules and differentiated thyroid cancer: Where do we stand?, *European journal of radiology* 99 (2018) 1–8.
- [48] C. Q. Yang, L. Gardiner, H. Wang, M. T. Hueman, D. Chen, Creating prognostic systems for well-differentiated thyroid cancer using machine learning, *Frontiers in endocrinology* 10 (2019) 288.
- [49] H. Abbad Ur Rehman, C.-Y. Lin, Z. Mushtaq, Effective k-nearest neighbor algorithms performance analysis of thyroid disease, *Journal of the Chinese Institute of Engineers* 44 (1) (2021) 77–87.
- [50] J. N. Taylor, K. Mochizuki, K. Hashimoto, Y. Kumamoto, Y. Harada, K. Fujita, T. Komatsuzaki, High-resolution raman microscopic detection of follicular thyroid cancer cells with unsupervised machine learning, *The Journal of Physical Chemistry B* 123 (20) (2019) 4358–4372.
- [51] J. A. Chandio, G. A. Mallah, N. A. Shaikh, Decision support system for classification medullary thyroid cancer, *IEEE Access* 8 (2020) 145216–145226.
- [52] J.-H. Lee, Y. J. Chai, A deep-learning model to assist thyroid nodule diagnosis and management, *The Lancet Digital Health* (2021).
- [53] M. Buda, B. Wildman-Tobriner, J. K. Hoang, D. Thayer, F. N. Tessler, W. D. Middleton, M. A. Mazurowski, Management of thyroid nodules seen on us images: deep learning may match performance of radiologists, *Radiology* 292 (3) (2019) 695–701.
- [54] Y. Liu, J. Liang, S. Peng, W. Wang, H. Xiao, A deep-learning model to assist thyroid nodule diagnosis and management–authors' reply, *The Lancet Digital Health* 3 (7) (2021) e411–e412.

- [55] A. Iesato, C. Nucera, Role of regulatory non-coding rnas in aggressive thyroid cancer: Prospective applications of neural network analysis, *Molecules* 26 (10) (2021) 3022.
- [56] Y. Sharifi, M. A. Bakhshali, T. Dehghani, M. DanaiAshgari, M. Sargolzaei, S. Eslami, Deep learning on ultrasound images of thyroid nodules, *Biocybernetics and Biomedical Engineering* 41 (2) (2021) 636–655.
- [57] Y.-J. Lin, T.-K. Chao, M.-A. Khalil, Y.-C. Lee, D.-Z. Hong, J.-J. Wu, C.-W. Wang, Deep learning fast screening approach on cytological whole slides for thyroid cancer diagnosis, *Cancers* 13 (15) (2021) 3891.
- [58] E. J. Ha, J. H. Baek, Applications of machine learning and deep learning to thyroid imaging: where do we stand?, *Ultrasonography* 40 (1) (2021) 23.
- [59] X. L. Wu, M. Li, X.-w. Cui, G. Xu, Deep multimodal learning for lymph node metastasis prediction of primary thyroid cancer, *Physics in Medicine & Biology* (2022).
- [60] S. Pavithra, G. Yamuna, R. Arunkumar, Deep learning method for classifying thyroid nodules using ultrasound images, in: 2022 International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN), IEEE, 2022, pp. 1–6.
- [61] R. Paul, A. Juliano, W. Faquin, A. W. Chan, An artificial intelligence ultrasound platform for screening and staging of thyroid cancer, *International Journal of Radiation Oncology, Biology, Physics* 112 (5) (2022) e8.
- [62] M. Ilyas, H. Malik, M. Adnan, U. Bashir, W. A. Bukhari, M. I. A. Khan, A. Ahmad, Deep learning based classification of thyroid cancer using different medical imaging modalities: A systematic review (2022).
- [63] M. Tarkov, E. Chiglintsev, Data space dimensionality reduction in the problem of diagnosing a thyroid disease, *Bulletin of the Novosibirsk Computing Center. Series: Computer Science* (2012) 79–84.
- [64] B. Shankarla, P. Sathya, Performance analysis of thyroid tumor detection and segmentation using pca-based random classification method, in: *Innovations in Electrical and Electronics Engineering*, Springer, 2020, pp. 833–841.
- [65] A. Soulaymani, H. Aschawa, Epidemiological study of thyroid carcinoma using principal component analysis, *Journal of Clinical Epigenetics* 4 (1) (2018) 9.
- [66] C. Liu, Y. Huang, J. A. Ozolek, M. G. Hanna, R. Singh, G. K. Rohde, Setsvm: an approach to set classification in nuclei-based cancer detection, *IEEE Journal of Biomedical and Health Informatics* 23 (1) (2018) 351–361.
- [67] S. Zhang, H. Du, Z. Jin, Y. Zhu, Y. Zhang, F. Xie, M. Zhang, Z. Jiao, X. Tian, J. Zhang, et al., Integrating clinical knowledge in a thyroid nodule classification model based on, in: 2019 IEEE International Ultrasonics Symposium (IUS), IEEE, 2019, pp. 2334–2336.
- [68] H. Zhang, C. Zhao, L. Guo, X. Li, Y. Luo, J. Lu, H. Xu, Diagnosis of thyroid nodules in ultrasound images using two combined classification modules, in: 2019 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), IEEE, 2019, pp. 1–5.
- [69] D. Chen, J. Zhang, W. Li, Thyroid nodule classification using two levels attention-based bi-directional lstm with ultrasound reports, in: 2018 9th International Conference on Information Technology in Medicine and Education (ITME), IEEE, 2018, pp. 309–312.
- [70] X. Ma, B. Sun, W. Liu, D. Sui, J. Chen, Z. Tian, Amseg: A novel adversarial architecture based multi-scale fusion framework for thyroid nodule segmentation, *IEEE Access* (2023).
- [71] N. Yadav, R. Dass, J. Virmani, Assessment of encoder-decoder-based segmentation models for thyroid ultrasound images, *Medical & Biological Engineering & Computing* (2023) 1–37.
- [72] M. Jajroodi, T. Baniasadi, L. Kamkar, F. Arbab, M. Sanei, M. Ahmadzade, Prediction of survival in thyroid cancer using data mining technique, *Technology in cancer research & treatment* 13 (4) (2014) 353–359.
- [73] V. Sajeev, A. H. Vyshnavi, P. K. Namboori, Thyroid cancer prediction using gene expression profile, pharmacogenomic variants and quantum image processing in deep learning platform-a theranostic approach, in: 2020 International Conference for Emerging Technology (INCET), IEEE, 2020, pp. 1–5.
- [74] N. Liu, A. Fenster, D. Tessier, S. Gou, J. Chong, Self-supervised learning enhanced ultrasound video thyroid nodule tracking, in: *Medical Imaging 2023: Image Processing*, Vol. 12464, SPIE, 2023, pp. 683–687.
- [75] Y. Hou, Q. Sang, Boosting ultrasonic image classification via self-supervised representation learning, in: 2023 3rd International Conference on Computer, Control and Robotics (ICCCR), IEEE, 2023, pp. 116–120.
- [76] K. Chandel, V. Kunwar, S. Sabitha, T. Choudhury, S. Mukherjee, A comparative study on thyroid disease detection using k-nearest neighbor and naive bayes classification techniques, *CSI transactions on ICT* 4 (2-4) (2016) 313–319.
- [77] D.-Y. Liu, H.-L. Chen, B. Yang, X.-E. Lv, L.-N. Li, J. Liu, Design of an enhanced fuzzy k-nearest neighbor classifier based computer aided diagnostic system for thyroid disease, *Journal of medical systems* 36 (5) (2012) 3243–3254.
- [78] K. Geetha, S. S. Baboo, An empirical model for thyroid disease classification using evolutionary multivariate bayesian prediction method, *Global Journal of Computer Science and Technology* (2016).
- [79] J. Ma, S. Luo, M. Dighe, D.-J. Lim, Y. Kim, Differential diagnosis of thyroid nodules with ultrasound elastography based on support vector machines, in: 2010 IEEE International Ultrasonics Symposium, IEEE, 2010, pp. 1372–1375.
- [80] C.-Y. Chang, S.-J. Chen, M.-F. Tsai, Application of support-vector-machine-based method for feature selection and classification of thyroid nodules in ultrasound images, *Pattern recognition* 43 (10) (2010) 3494–3506.
- [81] E. Dogantekin, A. Dogantekin, D. Avci, An expert system based on generalized discriminant analysis and wavelet support vector machine for diagnosis of thyroid diseases, *Expert Systems with Applications* 38 (1) (2011) 146–150.
- [82] D. C. Yadav, S. Pal, Prediction of thyroid disease using decision tree ensemble method, *Human-Intelligent Systems Integration* 2 (1) (2020) 89–95.
- [83] Y. Hao, W. Zuo, Z. Shi, L. Yue, S. Xue, F. He, Prognosis of thyroid disease using ms-apriori improved decision tree, in: *International Conference on Knowledge Science, Engineering and Management*, Springer, 2018, pp. 452–460.
- [84] K. Dharmarajan, K. Balasree, A. Arunachalam, K. Abirmai, Thyroid disease classification using decision tree and svm, *Executive editor* 11 (03) (2020) 3234.
- [85] D. C. Yadav, S. Pal, Decision tree ensemble techniques to predict thyroid disease, *Int. J. Recent Technol. Eng.* 8 (3) (2019) 8242–8246.

- [86] R.-N. Zhao, B. Zhang, X. Yang, Y.-X. Jiang, X.-J. Lai, X.-Y. Zhang, Logistic regression analysis of contrast-enhanced ultrasound and conventional ultrasound characteristics of sub-centimeter thyroid nodules, *Ultrasound in medicine & biology* 41 (12) (2015) 3102–3108.
- [87] J. Yazdani-Charati, O. Akha, F. Khosravi, Factors affecting thyroid cancer in patients with thyroid nodules using logistic regression in interval censored data, *International Journal of Cancer Management* 11 (3) (2018).
- [88] M. D. Kate, V. Kale, Check for updates the role of machine learning in thyroid cancer diagnosis, in: *Proceedings of the International Conference on Applications of Machine Intelligence and Data Analytics (ICAMIDA 2022)*, Vol. 105, Springer Nature, 2023, p. 276.
- [89] M. S. Nobile, G. Capitoli, V. Sowirono, F. Clerici, I. Piga, K. van Abeelen, F. Magni, F. Pagni, S. Galimberti, P. Cazzaniga, et al., Unsupervised neural networks as a support tool for pathology diagnosis in maldi-msi experiments: A case study on thyroid biopsies, *Expert Systems with Applications* 215 (2023) 119296.
- [90] G. Manogaran, V. Vijayakumar, R. Varatharajan, P. M. Kumar, R. Sundarasekar, C.-H. Hsu, Machine learning based big data processing framework for cancer diagnosis using hidden markov model and gm clustering, *Wireless personal communications* 102 (3) (2018) 2099–2116.
- [91] U. Agrawal, D. Soria, C. Wagner, J. Garibaldi, I. O. Ellis, J. M. Bartlett, D. Cameron, E. A. Rakha, A. R. Green, Combining clustering and classification ensembles: A novel pipeline to identify breast cancer profiles, *Artificial intelligence in medicine* 97 (2019) 27–37.
- [92] M. C. de Souto, I. G. Costa, D. S. de Araujo, T. B. Ludermir, A. Schliep, Clustering cancer gene expression data: a comparative study, *BMC bioinformatics* 9 (1) (2008) 1–14.
- [93] M. Anas, K. Gupta, S. Ahmad, Skin cancer classification using k-means clustering, *International Journal of Technical Research and Applications* 5 (1) (2017) 62–65.
- [94] A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, Z. Mehmood, Brain tumor segmentation using k-means clustering and deep learning with synthetic data augmentation for classification, *Microscopy Research and Technique* (2021).
- [95] X. Yu, G. Yu, J. Wang, Clustering cancer gene expression data by projective clustering ensemble, *PloS one* 12 (2) (2017) e0171429.
- [96] K. Chandel, V. Kunwar, A. S. Sabitha, A. Bansal, T. Choudhury, Analysing thyroid disease using density-based clustering technique, *International Journal of Business Intelligence and Data Mining* 17 (3) (2020) 273–297.
- [97] D. K. Katikireddy Srinivas, Performa analysis of clustering of thyroid drug data using fuzzy and m-clust, *Journal of Critical Reviews* 7 (11) (2020) 2128–2141.
- [98] B. Venkataramana, L. Padmasree, M. S. Rao, D. Latha, G. Ganeshan, Comparative study on performance of fuzzy clustering algorithms on liver and thyroid data, *Journal of Fuzzy Set Valued Analysis* 2018 (1) (2018) 1–9.
- [99] K. K. Mahurkar, D. Gaikwad, Normalization using improvised k-means applied in diagnosing thyroid disease with ann, in: *2017 International Conference on Trends in Electronics and Informatics (ICETI)*, IEEE, 2017, pp. 579–583.
- [100] Y. Yang, Y. Song, B. Cao, An information entropy-based method to detect microrna regulatory module, *IPSJ Transactions on Bioinformatics* 12 (2019) 1–8.
- [101] S. P. Canton, E. Dadashzadeh, L. Yip, R. Forsythe, R. Handzel, Automatic detection of thyroid and adrenal incidentals using radiology reports and deep learning, *Journal of Surgical Research* 266 (2021) 192–200.
- [102] S. Peng, Y. Liu, W. Lv, L. Liu, Q. Zhou, H. Yang, J. Ren, G. Liu, X. Wang, X. Zhang, et al., Deep learning-based artificial intelligence model to assist thyroid nodule diagnosis and management: a multicentre diagnostic study, *The Lancet Digital Health* 3 (4) (2021) e250–e259.
- [103] Q. Guan, Y. Wang, J. Du, Y. Qin, H. Lu, J. Xiang, F. Wang, Deep learning based classification of ultrasound images for thyroid nodules: a large scale of pilot study, *Annals of Translational Medicine* 7 (7) (2019).
- [104] L.-N. Li, J.-H. Ouyang, H.-L. Chen, D.-Y. Liu, A computer aided diagnosis system for thyroid disease using extreme learning machine, *Journal of medical systems* 36 (5) (2012) 3327–3337.
- [105] C. Ma, J. Guan, W. Zhao, C. Wang, An efficient diagnosis system for thyroid disease based on enhanced kernelized extreme learning machine approach, in: *International Conference on Cognitive Computing*, Springer, 2018, pp. 86–101.
- [106] J. Xia, H. Chen, Q. Li, M. Zhou, L. Chen, Z. Cai, Y. Fang, H. Zhou, Ultrasound-based differentiation of malignant and benign thyroid nodules: An extreme learning machine approach, *Computer methods and programs in biomedicine* 147 (2017) 37–49.
- [107] R. Pavithra, L. Parthiban, Optimal deep learning with kernel extreme learning machine based thyroid disease diagnosis and classification model, *Journal of Computational and Theoretical Nanoscience* 18 (3) (2021) 639–649.
- [108] B. N. Rao, D. L. S. Reddy, G. Bhaskar, Thyroid diagnosis using multilayer perceptron, in: *International Conference on E-Business and Telecommunications*, Springer, 2019, pp. 452–459.
- [109] M. Hosseinzadeh, O. H. Ahmed, M. Y. Ghafour, F. Safara, S. Ali, B. Vo, H.-S. Chiang, et al., A multiple multilayer perceptron neural network with an adaptive learning algorithm for thyroid disease diagnosis in the internet of medical things, *The Journal of Supercomputing* (2020) 1–22.
- [110] I. Isa, Z. Saad, S. Omar, M. Osman, K. Ahmad, H. M. Sakim, Suitable mlp network activation functions for breast cancer and thyroid disease detection, in: *2010 Second International Conference on Computational Intelligence, Modelling and Simulation*, IEEE, 2010, pp. 39–44.
- [111] M. Mourad, S. Moubayed, A. Dezube, Y. Mourad, K. Park, A. Torreblanca-Zanca, J. S. Torrecilla, J. C. Cancilla, J. Wang, Machine learning and feature selection applied to seer data to reliably assess thyroid cancer prognosis, *Scientific Reports* 10 (1) (2020) 1–11.
- [112] R. Erol, S. N. Oğulata, C. Şahin, Z. N. Alparslan, A radial basis function neural network (rbfnn) approach for structural classification of thyroid diseases, *Journal of medical systems* 32 (3) (2008) 215–220.
- [113] M. F. Ferreira, R. Camacho, L. F. Teixeira, Autoencoders as weight initialization of deep classification networks applied to papillary thyroid carcinoma, in: *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, IEEE, 2018, pp. 629–632.
- [114] V. Teixeira, R. Camacho, P. G. Ferreira, Learning influential genes on cancer gene expression data with stacked denoising autoencoders, in: *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, IEEE, 2017, pp. 1201–1205.
- [115] T. Liu, Q. Guo, C. Lian, X. Ren, S. Liang, J. Yu, L. Niu, W. Sun, D. Shen, Automated detection and classification of thyroid nodules in ultrasound images using clinical-knowledge-guided convolutional neural networks, *Medical image analysis* 58 (2019) 101555.

- [116] E. J. Ha, J. H. Baek, D. G. Na, Deep convolutional neural network models for the diagnosis of thyroid cancer, *The Lancet Oncology* 20 (3) (2019) e130.
- [117] T. Qiao, S. Liu, Z. Cui, X. Yu, H. Cai, H. Zhang, M. Sun, Z. Lv, D. Li, Deep learning for intelligent diagnosis in thyroid scintigraphy, *Journal of International Medical Research* 49 (1) (2021) 0300060520982842.
- [118] Q. ZHANG, J. HU, S. ZHOU, The detection of hyperthyroidism by the modified lenet-5 network, *Indian Journal of Pharmaceutical Sciences* (2020) 108–114.
- [119] H. Tekchandani, S. Verma, N. D. Londhe, R. R. Jain, A. Tiwari, Severity assessment of cervical lymph nodes using modified vgg-net, and squeeze and excitation concept, in: 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, 2021, pp. 0709–0714.
- [120] J. Chi, E. Walia, P. Babyn, J. Wang, G. Groot, M. Eramian, Thyroid nodule classification in ultrasound images by fine-tuning deep convolutional neural network, *Journal of digital imaging* 30 (4) (2017) 477–486.
- [121] L. Ke, Y. Deng, W. Xia, M. Qiang, X. Chen, K. Liu, B. Jing, C. He, C. Xie, X. Guo, et al., Development of a self-constrained 3d densenet model in automatic detection and segmentation of nasopharyngeal carcinoma using magnetic resonance images, *Oral Oncology* 110 (2020) 104862.
- [122] J. Cox, S. Rubin, J. Adams, C. Pereira, M. Dighe, A. Alessio, Hyperparameter selection for resnet classification of malignancy from thyroid ultrasound images, in: *Medical Imaging 2020: Computer-Aided Diagnosis*, Vol. 11314, International Society for Optics and Photonics, 2020, p. 1131447.
- [123] X. Li, S. Zhang, Q. Zhang, X. Wei, Y. Pan, J. Zhao, X. Xin, C. Qin, X. Wang, J. Li, et al., Diagnosis of thyroid cancer using deep convolutional neural network models applied to sonographic images: a retrospective, multicohort, diagnostic study, *The Lancet Oncology* 20 (2) (2019) 193–201.
- [124] S. Xie, J. Yu, T. Liu, Q. Chang, L. Niu, W. Sun, Thyroid nodule detection in ultrasound images with convolutional neural networks, in: 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA), IEEE, 2019, pp. 1442–1446.
- [125] J. Koh, E. Lee, K. Han, E.-K. Kim, E. J. Son, Y.-M. Sohn, M. Seo, M.-r. Kwon, J. H. Yoon, J. H. Lee, et al., Diagnosis of thyroid nodules on ultrasonography by a deep convolutional neural network, *Scientific reports* 10 (1) (2020) 1–9.
- [126] X. Liang, J. Yu, J. Liao, Z. Chen, Convolutional neural network for breast and thyroid nodules diagnosis in ultrasound imaging, *BioMed Research International* 2020 (2020).
- [127] D. Chen, C. Shi, M. Wang, Q. Pan, Thyroid nodule classification using hierarchical recurrent neural network with multiple ultrasound reports, in: *International Conference on Neural Information Processing*, Springer, 2017, pp. 765–773.
- [128] V. S. Vairale, S. Shukla, Physical fitness recommender framework for thyroid patients using restricted boltzmann machines.
- [129] W. Yang, J. Zhao, Y. Qiang, X. Yang, Y. Dong, Q. Du, G. Shi, M. B. Zia, Dscgans: Integrate domain knowledge in training dual-path semi-supervised conditional generative adversarial networks and s3vm for ultrasonography thyroid nodules classification, in: *International Conference on Medical Image Computing and Computer-Assisted Intervention*, Springer, 2019, pp. 558–566.
- [130] T. K. Yoo, J. Y. Choi, H. K. Kim, A generative adversarial network approach to predicting postoperative appearance after orbital decompression surgery for thyroid eye disease, *Computers in Biology and Medicine* 118 (2020) 103628.
- [131] Y. I. Liu, A. Kamaya, T. S. Desser, D. L. Rubin, A bayesian network for differentiating benign from malignant thyroid nodules using sonographic and demographic features, *American Journal of Roentgenology* 196 (5) (2011) W598–W605.
- [132] Y. I. Liu, A. Kamaya, T. S. Desser, D. L. Rubin, A controlled vocabulary to represent sonographic features of the thyroid and its application in a bayesian network to predict thyroid nodule malignancy, *Summit on Translational Bioinformatics* 2009 (2009) 68.
- [133] M. Ashraf, G. Chetty, D. Tran, D. Sharma, Hybrid approach for diagnosing thyroid, hepatitis, and breast cancer based on correlation based feature selection and naïve bayes, in: *International Conference on Neural Information Processing*, Springer, 2012, pp. 272–280.
- [134] V. Chandran, M. Sumithra, A. Karthick, T. George, M. Deivakani, B. Elakkya, U. Subramaniam, S. Manoharan, Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images, *BioMed Research International* 2021 (2021).
- [135] D. Chen, J. Hu, M. Zhu, N. Tang, Y. Yang, Y. Feng, Diagnosis of thyroid nodules for ultrasonographic characteristics indicative of malignancy using random forest, *BioData mining* 13 (1) (2020) 1–21.
- [136] Y. Himeur, K. Ghanem, A. Alsalemi, F. Bensaali, A. Amira, Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives, *Applied Energy* 287 (2021) 116601.
- [137] P. Mehta, M. Bukov, C.-H. Wang, A. G. Day, C. Richardson, C. K. Fisher, D. J. Schwab, A high-bias, low-variance introduction to machine learning for physicists, *Physics reports* 810 (2019) 1–124.
- [138] Q. Pan, Y. Zhang, M. Zuo, L. Xiang, D. Chen, Improved ensemble classification method of thyroid disease based on random forest, in: 2016 8th International Conference on Information Technology in Medicine and Education (ITME), IEEE, 2016, pp. 567–571.
- [139] T. Chen, C. Guestrin, Xgboost: A scalable tree boosting system, in: *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 785–794.
- [140] S. Lim, S. Chi, Xgboost application on bridge management systems for proactive damage estimation, *Advanced Engineering Informatics* 41 (2019) 100922.
- [141] C. Ji, X. Zou, Y. Hu, S. Liu, L. Lyu, X. Zheng, Xg-sf: An xgboost classifier based on shapelet features for time series classification, *Procedia computer science* 147 (2019) 24–28.
- [142] J. Guo, L. Yang, R. Bie, J. Yu, Y. Gao, Y. Shen, A. Kos, An xgboost-based physical fitness evaluation model using advanced feature selection and bayesian hyper-parameter optimization for wearable running monitoring, *Computer Networks* 151 (2019) 166–180.
- [143] Y. Xu, X. Yang, H. Huang, C. Peng, Y. Ge, H. Wu, J. Wang, G. Xiong, Y. Yi, Extreme gradient boosting model has a better performance in predicting the risk of 90-day readmissions in patients with ischaemic stroke, *Journal of Stroke and Cerebrovascular Diseases* 28 (12) (2019) 104441.
- [144] Y. Chen, D. Li, X. Zhang, J. Jin, Y. Shen, Computer aided diagnosis of thyroid nodules based on the devised small-datasets multi-view ensemble learning, *Medical Image Analysis* 67 (2020) 101819.

- [145] J. Thomas, T. Haertling, Aibx, artificial intelligence model to risk stratify thyroid nodules, *Thyroid* 30 (6) (2020) 878–884.
- [146] B. Kezlarian, O. Lin, Artificial intelligence in thyroid fine needle aspiration biopsies, *Acta Cytologica* (2020) 1–6.
- [147] P. Sanyal, T. Mukherjee, S. Barui, A. Das, P. Gangopadhyay, Artificial intelligence in cytopathology: a neural network to identify papillary carcinoma on thyroid fine-needle aspiration cytology smears, *Journal of pathology informatics* 9 (2018).
- [148] J. Yoon, E. Lee, J. S. Koo, J. H. Yoon, K.-H. Nam, J. Lee, Y. S. Jo, H. J. Moon, V. Y. Park, J. Y. Kwak, Artificial intelligence to predict the brafv600e mutation in patients with thyroid cancer, *PloS one* 15 (11) (2020) e0242806.
- [149] D. T. Nguyen, J. K. Kang, T. D. Pham, G. Batchuluun, K. R. Park, Ultrasound image-based diagnosis of malignant thyroid nodule using artificial intelligence, *Sensors* 20 (7) (2020) 1822.
- [150] T. Liu, S. Xie, J. Yu, L. Niu, W. Sun, Classification of thyroid nodules in ultrasound images using deep model based transfer learning and hybrid features, in: 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2017, pp. 919–923.
- [151] F. Abdolali, J. Kapur, J. L. Jaremko, M. Noga, A. R. Hareendranathan, K. Punithakumar, Automated thyroid nodule detection from ultrasound imaging using deep convolutional neural networks, *Computers in Biology and Medicine* 122 (2020) 103871.
- [152] X. Li, S. Wang, X. Wei, J. Zhu, R. Yu, M. Zhao, M. Yu, Z. Liu, S. Liu, Fully convolutional networks for ultrasound image segmentation of thyroid nodules, in: 2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), IEEE, 2018, pp. 886–890.
- [153] E. Kim, M. Corte-Real, Z. Baloch, A deep semantic mobile application for thyroid cytopathology, in: Medical Imaging 2016: PACS and Imaging Informatics: Next Generation and Innovations, Vol. 9789, International Society for Optics and Photonics, 2016, p. 97890A.
- [154] L. Ma, C. Ma, Y. Liu, X. Wang, Thyroid diagnosis from spect images using convolutional neural network with optimization, Computational intelligence and neuroscience 2019 (2019).
- [155] Y. Chai, J. Song, M. Shear, Artificial intelligence for thyroid nodule ultrasound image analysis, *Annals of Thyroid* 5 (2020).
- [156] J. Song, Y. J. Chai, H. Masuoka, S.-W. Park, S.-j. Kim, J. Y. Choi, H.-J. Kong, K. E. Lee, J. Lee, N. Kwak, et al., Ultrasound image analysis using deep learning algorithm for the diagnosis of thyroid nodules, *Medicine* 98 (15) (2019).
- [157] M. Barczyński, M. Stopa-Barczyńska, B. Wojtczak, A. Czarniecka, A. Konturek, Clinical validation of s-detecttm mode in semi-automated ultrasound classification of thyroid lesions in surgical office, *Gland surgery* 9 (Suppl 2) (2020) S77.
- [158] Y. J. Choi, J. H. Baek, H. S. Park, W. H. Shim, T. Y. Kim, Y. K. Shong, J. H. Lee, A computer-aided diagnosis system using artificial intelligence for the diagnosis and characterization of thyroid nodules on ultrasound: initial clinical assessment, *Thyroid* 27 (4) (2017) 546–552.
- [159] C. Fragopoulos, A. Pouliakis, C. Meristoudis, E. Mastorakis, N. Margari, N. Chroniaris, N. Koufopoulos, A. G. Delides, N. Machairas, V. Ntomi, et al., Radial basis function artificial neural network for the investigation of thyroid cytological lesions, *Journal of Thyroid Research* 2020 (2020).
- [160] R. Savala, P. Dey, N. Gupta, Artificial neural network model to distinguish follicular adenoma from follicular carcinoma on fine needle aspiration of thyroid, *Diagnostic cytopathology* 46 (3) (2018) 244–249.
- [161] L.-R. Li, B. Du, H.-Q. Liu, C. Chen, Artificial intelligence for personalized medicine in thyroid cancer: Current status and future perspectives, *Frontiers in Oncology* 10 (2021) 3360.
- [162] Y. Zhao, L. Zhao, T. Mao, L. Zhong, Assessment of risk based on variant pathways and establishment of an artificial neural network model of thyroid cancer, *BMC medical genetics* 20 (1) (2019) 1–10.
- [163] B. Wildman-Tobriner, M. Buda, J. K. Hoang, W. D. Middleton, D. Thayer, R. G. Short, F. N. Tessler, M. A. Mazurowski, Using artificial intelligence to revise acr ti-rads risk stratification of thyroid nodules: diagnostic accuracy and utility, *Radiology* 292 (1) (2019) 112–119.
- [164] L. Wang, S. Yang, S. Zhao, G. Tian, Y. Gao, Y. Chen, Y. Lu, Automatic thyroid nodule recognition and diagnosis in ultrasound imaging with the yolov2 neural network, *World journal of surgical oncology* 17 (1) (2019) 1–9.
- [165] J. A. Ozolek, A. B. Tosun, W. Wang, C. Chen, S. Kolouri, S. Basu, H. Huang, G. K. Rohde, Accurate diagnosis of thyroid follicular lesions from nuclear morphology using supervised learning, *Medical image analysis* 18 (5) (2014) 772–780.
- [166] W. Wang, J. A. Ozolek, G. K. Rohde, Detection and classification of thyroid follicular lesions based on nuclear structure from histopathology images, *Cytometry Part A: The Journal of the International Society for Advancement of Cytometry* 77 (5) (2010) 485–494.
- [167] Y. Zhu, Q. Sang, S. Jia, Y. Wang, T. Deyer, Deep neural networks could differentiate bethesda class iii versus class iv/vi, *Annals of translational medicine* 7 (11) (2019).
- [168] S. Bhalla, H. Kaur, R. Kaur, S. Sharma, G. P. Raghava, Expression based biomarkers and models to classify early and late-stage samples of papillary thyroid carcinoma, *PLoS One* 15 (4) (2020) e0231629.
- [169] J. M. Dolezal, A. Trzcinska, C.-Y. Liao, S. Kochanny, E. Blair, N. Agrawal, X. M. Keutgen, P. Angelos, N. A. Cipriani, A. T. Pearson, Deep learning prediction of braf-ras gene expression signature identifies noninvasive follicular thyroid neoplasms with papillary-like nuclear features, *Modern Pathology* (2020) 1–13.
- [170] K. Daniels, S. Gummadi, Z. Zhu, S. Wang, J. Patel, B. Swendseid, A. Lyshchik, J. Curry, E. Cottrill, J. Eisenbrey, Machine learning by ultrasonography for genetic risk stratification of thyroid nodules, *JAMA Otolaryngology–Head & Neck Surgery* 146 (1) (2020) 36–41.
- [171] H. Kheddar, M. Hemis, Y. Himeur, D. Megias, A. Amira, Deep learning for diverse data types steganalysis: A review, *arXiv preprint arXiv:2308.04522* (2023).
- [172] M. Lasseck, Audio-based bird species identification with deep convolutional neural networks., in: CLEF (Working Notes), 2018.
- [173] D. M. Chandler, S. S. Hemami, Vsnr: A wavelet-based visual signal-to-noise ratio for natural images, *IEEE transactions on image processing* 16 (9) (2007) 2284–2298.
- [174] W. Zhou, Z. Wang, W. Xie, Weighted signal-to-noise ratio robust design for a new double sampling npx chart, *Computers & Industrial Engineering* 139 (2020) 106124.
- [175] The ThyroidOmics Consortium, Available online: <https://transfer.syspepi.medizin.uni-greifswald.de/thyroidomics/>, accessed: 2021-03-01.

- [176] Thyroid Disease Data Set, Available online: <https://archive.ics.uci.edu/ml/datasets/thyroid+disease>, accessed: 2021-03-01.
- [177] Knowledge Extraction based on Evolutionary Learning, Available online: <https://sci2s.ugr.es/keel/dataset.php?cod=67>, accessed: 2021-03-01.
- [178] Gene Expression Omnibus, Available online: <https://www.ncbi.nlm.nih.gov/geo/>, accessed: 2021-03-01.
- [179] The digital database of Thyroid Ultrasound Images, Available online: <http://cimalab.intec.co/?lang=en&mod=project&id=31>, accessed: 2021-03-01.
- [180] The National Cancer Registration and Analysis Service, Available online: http://www.ncin.org.uk/about_ncin/, accessed: 2021-03-01.
- [181] The Prostate, Lung, Colorectal and Ovarian (PLCO) Cancer Screening Trial , Available online: <https://prevention.cancer.gov/major-programs/prostate-lung-colorectal-and-ovarian-cancer-screening-trial>, accessed: 2021-03-01.
- [182] Z. Li, K. Yang, L. Zhang, C. Wei, P. Yang, W. Xu, Classification of thyroid nodules with stacked denoising sparse autoencoder, International Journal of Endocrinology 2020 (2020).
- [183] S. Y. Ko, J. H. Lee, J. H. Yoon, H. Na, E. Hong, K. Han, I. Jung, E.-K. Kim, H. J. Moon, V. Y. Park, et al., Deep convolutional neural network for the diagnosis of thyroid nodules on ultrasound, Head & neck 41 (4) (2019) 885–891.
- [184] C. Lee, Y. Kim, Y. S. Kim, J. Jang, Automatic disease annotation from radiology reports using artificial intelligence implemented by a recurrent neural network, American Journal of Roentgenology 212 (4) (2019) 734–740.
- [185] A. Sharifi, K. Alizadeh, Comparison of the particle swarm optimization with the genetic algorithms as a training for multilayer perceptron technique to diagnose thyroid functional disease, Shiraz E-Medical Journal 22 (1) (2021).
- [186] V. S. Vairale, S. Shukla, Recommendation of food items for thyroid patients using content-based knn method, in: Data Science and Security, Springer, 2021, pp. 71–77.
- [187] Y. Shen, Y. Lai, D. Xu, L. Xu, L. Song, J. Zhou, C. Song, J. Wang, Diagnosis of thyroid neoplasm using support vector machine algorithms based on platelet rna-seq, Endocrine (2020) 1–26.
- [188] Y. Wu, K. Rao, J. Liu, C. Han, L. Gong, Y. Chong, Z. Liu, X. Xu, Machine learning algorithms for the prediction of central lymph node metastasis in patients with papillary thyroid cancer, Frontiers in endocrinology 11 (2020) 816.
- [189] S. Borzouei, H. Mahjub, N. A. Sajadi, M. Farhadian, Diagnosing thyroid disorders: Comparison of logistic regression and neural network models, Journal of family medicine and primary care 9 (3) (2020) 1470–1476.
- [190] D. Li, D. Yang, J. Zhang, Arb: Knowledge discovery and disease diagnosis on thyroid disease diagnosis integrating association rule with bagging algorithm., Engineering Letters 28 (2) (2020).
- [191] L. Cui, L. Ge, H. Gan, X. Liu, Y. Zhang, Ovarian cancer identification based on feature weighting for high-throughput mass spectrometry data, Journal of Systems Biology 1 (1) (2018) 1.
- [192] M. Ashraf, G. Chetty, D. Tran, Feature selection techniques on thyroid, hepatitis, and breast cancer datasets, International Journal on Data Mining and Intelligent Information Technology Applications 3 (1) (2013) 1.
- [193] M. Al-Batah, B. Zaqaibeh, S. A. Alomari, M. S. Alzboon, Gene microarray cancer classification using correlation based feature selection algorithm and rules classifiers., International Journal of Online & Biomedical Engineering 15 (8) (2019).
- [194] I. Jain, V. K. Jain, R. Jain, Correlation feature selection based improved-binary particle swarm optimization for gene selection and cancer classification, Applied Soft Computing 62 (2018) 203–215.
- [195] Z. Rustam, N. Maghfirah, Correlated based svm-rfe as feature selection for cancer classification using microarray databases, in: AIP Conference Proceedings, Vol. 2023, AIP Publishing LLC, 2018, p. 020235.
- [196] D. O'Dea, M. Bongiovanni, G. P. Sykiotis, P. G. Ziros, A. D. Meade, F. M. Lyng, A. Malkin, Raman spectroscopy for the preoperative diagnosis of thyroid cancer and its subtypes: An in vitro proof-of-concept study, Cytopathology 30 (1) (2019) 51–60.
- [197] F. M. Selaru, J. Yin, A. Olaru, Y. Mori, Y. Xu, S. H. Epstein, F. Sato, E. Deacu, S. Wang, A. Sterian, et al., An unsupervised approach to identify molecular phenotypic components influencing breast cancer features, Cancer research 64 (5) (2004) 1584–1588.
- [198] V. K. Sudarshan, M. R. K. Mookiah, U. R. Acharya, V. Chandran, F. Molinari, H. Fujita, K. H. Ng, Application of wavelet techniques for cancer diagnosis using ultrasound images: a review, Computers in biology and medicine 69 (2016) 97–111.
- [199] S. O. Haji, R. Z. Yousif, A novel run-length based wavelet features for screening thyroid nodule malignancy, Brazilian Archives of Biology and Technology 62 (2019).
- [200] B. Yu, Z. Wang, R. Zhu, X. Feng, M. Qi, J. Li, R. Zhao, L. Huang, R. Xin, F. Li, et al., The transverse ultrasonogram of thyroid papillary carcinoma has a better prediction accuracy than the longitudinal one, IEEE Access 7 (2019) 100763–100770.
- [201] D. T. Nguyen, T. D. Pham, G. Batchuluun, H. S. Yoon, K. R. Park, Artificial intelligence-based thyroid nodule classification using information from spatial and frequency domains, Journal of clinical medicine 8 (11) (2019) 1976.
- [202] P. Poudel, A. Illanes, C. Arens, C. Hansen, M. Friebel, Active contours extension and similarity indicators for improved 3d segmentation of thyroid ultrasound images, in: Medical Imaging 2017: Imaging Informatics for Healthcare, Research, and Applications, Vol. 10138, International Society for Optics and Photonics, 2017, p. 1013803.
- [203] P. Poudel, C. Hansen, J. Sprung, M. Friebel, 3d segmentation of thyroid ultrasound images using active contours, Current Directions in Biomedical Engineering 2 (1) (2016) 467–470.
- [204] H. A. Nugroho, A. Nugroho, L. Choridah, Thyroid nodule segmentation using active contour bilateral filtering on ultrasound images, in: 2015 International Conference on Quality in Research (QIR), IEEE, 2015, pp. 43–46.
- [205] J. Xie, L. Guo, C. Zhao, X. Li, Y. Luo, L. Jianwei, A hybrid deep learning and handcrafted features based approach for thyroid nodule classification in ultrasound images, in: Journal of Physics: Conference Series, Vol. 1693, IOP Publishing, 2020, p. 012160.
- [206] X. Mei, X. Dong, T. Deyer, J. Zeng, T. Trafalis, Y. Fang, Thyroid nodule benignity prediction by deep feature extraction, in: 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE), IEEE, 2017, pp. 241–245.

- [207] G. Song, F. Xue, C. Zhang, A model using texture features to differentiate the nature of thyroid nodules on sonography, *Journal of Ultrasound in Medicine* 34 (10) (2015) 1753–1760.
- [208] M. Dinčić, J. Todorović, J. N. Ostojić, S. Kovačević, D. Dunderović, S. Lopičić, S. Spasić, S. Radojević-Škodrić, D. Stanisavljević, A. Ž. Ilić, The fractal and glcm textural parameters of chromatin may be potential biomarkers of papillary thyroid carcinoma in hashimoto's thyroiditis specimens, *Microscopy and Microanalysis* 26 (4) (2020) 717–730.
- [209] I. Kalaimani, Analysis for the prediction of thyroid disease by using ica and optimal kernel svm approach, *International Journal of Emerging Technology and Innovative Engineering* 5 (3) (2019).
- [210] W. Ahmad, L. Huang, A. Ahmad, F. Shah, A. Iqbal, A. Saeed, Thyroid diseases forecasting using a hybrid decision support system based on anfis, k-nn and information gain method, *J Appl Environ Biol Sci* 7 (10) (2017) 78–85.
- [211] H. A. Nugroho, A. Nugroho, E. L. Frannita, I. Ardiyanto, et al., Classification of thyroid ultrasound images based on shape features analysis, in: 2017 10th Biomedical Engineering International Conference (BMEiCON), IEEE, 2017, pp. 1–5.
- [212] H. Song, C. Dong, X. Zhang, W. Wu, C. Chen, B. Ma, F. Chen, C. Chen, X. Lv, Rapid identification of papillary thyroid carcinoma and papillary microcarcinoma based on serum raman spectroscopy combined with machine learning models, *Photodiagnosis and Photodynamic Therapy* 37 (2022) 102647.
- [213] U. R. Acharya, O. Faust, S. V. Sree, F. Molinari, J. S. Suri, Thyroscreen system: high resolution ultrasound thyroid image characterization into benign and malignant classes using novel combination of texture and discrete wavelet transform, *Computer methods and programs in biomedicine* 107 (2) (2012) 233–241.
- [214] H. A. Nugroho, E. L. Frannita, I. Ardiyanto, L. Choridah, et al., Computer aided diagnosis for thyroid cancer system based on internal and external characteristics, *Journal of King Saud University-Computer and Information Sciences* 33 (3) (2021) 329–339.
- [215] C. Sun, Y. Zhang, Q. Chang, T. Liu, S. Zhang, X. Wang, Q. Guo, J. Yao, W. Sun, L. Niu, Evaluation of a deep learning-based computer-aided diagnosis system for distinguishing benign from malignant thyroid nodules in ultrasound images, *Medical Physics* 47 (9) (2020) 3952–3960.
- [216] C. Liu, S. Chen, Y. Yang, D. Shao, W. Peng, Y. Wang, Y. Chen, Y. Wang, The value of the computer-aided diagnosis system for thyroid lesions based on computed tomography images, *Quantitative imaging in medicine and surgery* 9 (4) (2019) 642.
- [217] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, *Advances in neural information processing systems* 30 (2017).
- [218] M. H. Tran, O. Gomez, B. Fei, A video transformer network for thyroid cancer detection on hyperspectral histologic images, in: *Medical Imaging 2023: Digital and Computational Pathology*, Vol. 12471, SPIE, 2023, pp. 32–41.
- [219] J. Chi, Z. Li, Z. Sun, X. Yu, H. Wang, Hybrid transformer unet for thyroid segmentation from ultrasound scans, *Computers in Biology and Medicine* 153 (2023) 106453.
- [220] R. Sharma, G. K. Mahanti, G. Panda, A. Rath, S. Dash, S. Mallik, R. Hu, A framework for detecting thyroid cancer from ultrasound and histopathological images using deep learning, meta-heuristics, and mcdm algorithms, *Journal of Imaging* 9 (9) (2023) 173.
- [221] A. Pathak, Z. Yu, D. Paredes, E. P. Monsour, A. O. Rocha, J. P. Brito, N. S. Ospina, Y. Wu, Extracting thyroid nodules characteristics from ultrasound reports using transformer-based natural language processing methods, *arXiv preprint arXiv:2304.00115* (2023).
- [222] H. Bi, C. Cai, J. Sun, Y. Jiang, G. Lu, H. Shu, X. Ni, Bpat-unet: Boundary preserving assembled transformer unet for ultrasound thyroid nodule segmentation, *Computer Methods and Programs in Biomedicine* 238 (2023) 107614.
- [223] F. Chen, H. Han, P. Wan, H. Liao, C. Liu, D. Zhang, Joint segmentation and differential diagnosis of thyroid nodule in contrast-enhanced ultrasound images, *IEEE Transactions on Biomedical Engineering* (2023).
- [224] D. Dov, S. Assaad, S. Si, R. Wang, H. Xu, S. Z. Kovalsky, J. Bell, D. E. Range, J. Cohen, R. Henao, et al., Affinitention nets: kernel perspective on attention architectures for set classification with applications to medical text and images, in: *Proceedings of the Conference on Health, Inference, and Learning*, 2021, pp. 14–24.
- [225] F. JERBI, N. ABOUDI, N. KHLIFA, Automatic classification of ultrasound thyroids images using vision transformers and generative adversarial networks, *Scientific African* 20 (2023) e01679.
- [226] T. Jiang, W. Xing, M. Yu, D. Ta, A hybrid enhanced attention transformer network for medical ultrasound image segmentation, *Biomedical Signal Processing and Control* 86 (2023) 105329.
- [227] G. Li, R. Chen, J. Zhang, K. Liu, C. Geng, L. Lyu, Fusing enhanced transformer and large kernel cnn for malignant thyroid nodule segmentation, *Biomedical Signal Processing and Control* 83 (2023) 104636.
- [228] Q. Liu, F. Ding, J. Li, S. Ji, K. Liu, C. Geng, L. Lyu, Dca-net: Dual-branch contextual-aware network for auxiliary localization and segmentation of parathyroid glands, *Biomedical Signal Processing and Control* 84 (2023) 104856.
- [229] J. Nam, J.-W. Choi, Y.-G. Shin, S. Park, A bert-based artificial intelligence to analyze free-text clinical notes for binary classification in papillary thyroid carcinoma recurrence, in: *2023 IEEE International Conference on Consumer Electronics (ICCE)*, IEEE, 2023, pp. 1–2.
- [230] J. Sun, B. Wu, T. Zhao, L. Gao, K. Xie, T. Lin, J. Sui, X. Li, X. Wu, X. Ni, Classification for thyroid nodule using vit with contrastive learning in ultrasound images, *Computers in Biology and Medicine* 152 (2023) 106444.
- [231] I. E. Tampu, A. Eklund, K. Johansson, O. Gimm, N. Haj-Hosseini, Diseased thyroid tissue classification in oct images using deep learning: Towards surgical decision support, *Journal of Biophotonics* 16 (2) (2023) e202200227.
- [232] Z. Tao, H. Dang, Y. Shi, W. Wang, X. Wang, S. Ren, Local and context-attention adaptive lca-net for thyroid nodule segmentation in ultrasound images, *Sensors* 22 (16) (2022) 5984.
- [233] Z. Wang, L. Yu, X. Ding, X. Liao, L. Wang, Shared-specific feature learning with bottleneck fusion transformer for multi-modal whole slide image analysis, *IEEE Transactions on Medical Imaging* (2023).
- [234] Z. Wang, L. Yu, X. Ding, X. Liao, L. Wang, Lymph node metastasis prediction from whole slide images with transformer-guided multiinstance learning and knowledge transfer, *IEEE Transactions on Medical Imaging* 41 (10) (2022) 2777–2787.
- [235] N. Xiao, Z. Li, S. Chen, L. Zhao, Y. Yang, H. Xie, Y. Liu, Y. Quan, J. Duan, Contrast-enhanced ct image synthesis of thyroid based on transformer and texture branching, in: *2022 5th International Conference on Artificial Intelligence and Big Data (ICAIBD)*, IEEE, 2022, pp. 94–100.

- [236] P. Yin, B. Yu, C. Jiang, H. Chen, Pyramid tokens-to-token vision transformer for thyroid pathology image classification, in: 2022 Eleventh International Conference on Image Processing Theory, Tools and Applications (IPTA), IEEE, 2022, pp. 1–6.
- [237] B. Yu, P. Yin, H. Chen, Y. Wang, Y. Zhao, X. Cong, J. Dijkstra, L. Cong, Pyramid multi-loss vision transformer for thyroid cancer classification using cytological smear, *Knowledge-Based Systems* (2023) 110721.
- [238] P. M. Murphy, Uci repository of machine learning databases, <ftp://pub/machine-learning-databaseonics. uci. edu> (1994).
- [239] N. T. Duc, Y.-M. Lee, J. H. Park, B. Lee, An ensemble deep learning for automatic prediction of papillary thyroid carcinoma using fine needle aspiration cytology, *Expert Systems with Applications* 188 (2022) 115927.
- [240] F.-s. Ouyang, B.-l. Guo, L.-z. Ouyang, Z.-w. Liu, S.-j. Lin, W. Meng, X.-y. Huang, H.-x. Chen, H. Qiu-Gen, S.-m. Yang, Comparison between linear and nonlinear machine-learning algorithms for the classification of thyroid nodules, *European journal of radiology* 113 (2019) 251–257.
- [241] I. Shin, Y. J. Kim, K. Han, E. Lee, H. J. Kim, J. H. Shin, H. J. Moon, J. H. Youk, K. G. Kim, J. Y. Kwak, Application of machine learning to ultrasound images to differentiate follicular neoplasms of the thyroid gland, *Ultrasonography* 39 (3) (2020) 257.
- [242] C.-K. Zhao, T.-T. Ren, Y.-F. Yin, H. Shi, H.-X. Wang, B.-Y. Zhou, X.-R. Wang, X. Li, Y.-F. Zhang, C. Liu, et al., A comparative analysis of two machine learning-based diagnostic patterns with thyroid imaging reporting and data system for thyroid nodules: diagnostic performance and unnecessary biopsy rate, *Thyroid* 31 (3) (2021) 470–481.
- [243] V. V. Vadhiraj, A. Simpkin, J. O'Connell, N. Singh Ospina, S. Maraka, D. T. O'Keeffe, Ultrasound image classification of thyroid nodules using machine learning techniques, *Medicina* 57 (6) (2021) 527.
- [244] M. L. Gild, M. Chan, J. Gajera, B. Lurie, Z. Gandomkar, R. J. Clifton-Bligh, Risk stratification of indeterminate thyroid nodules using ultrasound and machine learning algorithms, *Clinical Endocrinology* 96 (4) (2022) 646–652.
- [245] J. Ma, F. Wu, J. Zhu, D. Xu, D. Kong, A pre-trained convolutional neural network based method for thyroid nodule diagnosis, *Ultrasonics* 73 (2017) 221–230.
- [246] Y. Zhu, Z. Fu, J. Fei, An image augmentation method using convolutional network for thyroid nodule classification by transfer learning, in: 2017 3rd IEEE international conference on computer and communications (ICCC), IEEE, 2017, pp. 1819–1823.
- [247] L. Gao, R. Liu, Y. Jiang, W. Song, Y. Wang, J. Liu, J. Wang, D. Wu, S. Li, A. Hao, et al., Computer-aided system for diagnosing thyroid nodules on ultrasound: A comparison with radiologist-based clinical assessments, *Head & neck* 40 (4) (2018) 778–783.
- [248] D. Zuo, L. Han, K. Chen, C. Li, Z. Hua, J. Lin, Extraction of calcification in ultrasonic images based on convolution neural network, *Sheng wu yi xue Gong Cheng xue za zhi= Journal of Biomedical Engineering= Shengwu Yixue Gongchengxue Zazhi* 35 (5) (2018) 679–687.
- [249] J. Zhu, S. Zhang, R. Yu, Z. Liu, H. Gao, B. Yue, X. Liu, X. Zheng, M. Gao, X. Wei, An efficient deep convolutional neural network model for visual localization and automatic diagnosis of thyroid nodules on ultrasound images, *Quantitative Imaging in Medicine and Surgery* 11 (4) (2021) 1368.
- [250] Y.-J. Kim, Y. Choi, S.-J. Hur, K.-S. Park, H.-J. Kim, M. Seo, M. K. Lee, S.-L. Jung, C. K. Jung, Deep convolutional neural network for classification of thyroid nodules on ultrasound: Comparison of the diagnostic performance with that of radiologists, *European Journal of Radiology* 152 (2022) 110335.
- [251] J. H. Lee, E. J. Ha, J. H. Kim, Application of deep learning to the diagnosis of cervical lymph node metastasis from thyroid cancer with ct, *European radiology* 29 (2019) 5452–5457.
- [252] P. Tsou, C.-J. Wu, Mapping driver mutations to histopathological subtypes in papillary thyroid carcinoma: applying a deep convolutional neural network, *Journal of clinical medicine* 8 (10) (2019) 1675.
- [253] G. Kim, E. Lee, H. Kim, J. Yoon, V. Park, J. Kwak, Convolutional neural network to stratify the malignancy risk of thyroid nodules: diagnostic performance compared with the american college of radiology thyroid imaging reporting and data system implemented by experienced radiologists, *American Journal of Neuroradiology* 42 (8) (2021) 1513–1519.
- [254] G.-G. Wu, W.-Z. Lv, R. Yin, J.-W. Xu, Y.-J. Yan, R.-X. Chen, J.-Y. Wang, B. Zhang, X.-W. Cui, C. F. Dietrich, Deep learning based on acr ti-rads can improve the differential diagnosis of thyroid nodules, *Frontiers in Oncology* 11 (2021) 575166.
- [255] R. Wei, H. Wang, L. Wang, W. Hu, X. Sun, Z. Dai, J. Zhu, H. Li, Y. Ge, B. Song, Radiomics based on multiparametric mri for extrathyroidal extension feature prediction in papillary thyroid cancer, *BMC Medical Imaging* 21 (2021) 1–8.
- [256] J. Gu, J. Zhu, Q. Qiu, Y. Wang, T. Bai, Y. Yin, Prediction of immunohistochemistry of suspected thyroid nodules by use of machine learning-based radiomics, *American Journal of Roentgenology* 213 (6) (2019) 1348–1357.
- [257] V. Y. Park, K. Han, E. Lee, E.-K. Kim, H. J. Moon, J. H. Yoon, J. Y. Kwak, Association between radiomics signature and disease-free survival in conventional papillary thyroid carcinoma, *Scientific reports* 9 (1) (2019) 4501.
- [258] Y. Himeur, I. Varlamis, H. Kheddar, A. Amira, S. Atalla, Y. Singh, F. Bensaali, W. Mansoor, Federated learning for computer vision, arXiv preprint arXiv:2308.13558 (2023).
- [259] A. A. Shah, H. A. M. Malik, A. Muhammad, A. Alourani, Z. A. Butt, Deep learning ensemble 2d cnn approach towards the detection of lung cancer, *Scientific Reports* 13 (1) (2023) 2987.
- [260] J. Salazar-Vega, E. Ortiz-Prado, P. Solis-Pazmino, L. Gómez-Barreno, K. Simbaña-Rivera, A. R. Henriquez-Trujillo, J. P. Brito, T. Toukeridis, M. Coral-Almeida, Thyroid cancer in ecuador, a 16 years population-based analysis (2001–2016), *BMC cancer* 19 (2019) 1–8.
- [261] L. W. Elmore, S. F. Greer, E. C. Daniels, C. C. Saxe, M. H. Melner, G. M. Krawiec, W. G. Cance, W. C. Phelps, Blueprint for cancer research: Critical gaps and opportunities, *CA: A Cancer Journal for Clinicians* 71 (2) (2021) 107–139.
- [262] S. H. Park, J. Choi, J.-S. Byeon, Key principles of clinical validation, device approval, and insurance coverage decisions of artificial intelligence, *Korean journal of radiology* 22 (3) (2021) 442.
- [263] Y.-C. Zhu, A. AlZoubi, S. Jassim, Q. Jiang, Y. Zhang, Y.-B. Wang, X.-D. Ye, D. Hongbo, A generic deep learning framework to classify thyroid and breast lesions in ultrasound images, *Ultrasonics* 110 (2021) 106300.
- [264] C.-W. Wang, K.-Y. Lin, Y.-J. Lin, M.-A. Khalil, K.-L. Chu, T.-K. Chao, A soft label deep learning to assist breast cancer target therapy and thyroid cancer diagnosis, *Cancers* 14 (21) (2022) 5312.
- [265] Z. Al-Qurayshi, G. W. Randolph, E. Kandil, Cost-effectiveness of computed tomography nodal scan in patients with papillary thyroid carcinoma, *Oral oncology* 118 (2021) 105326.

- [266] J. Yao, Z. Lei, W. Yue, B. Feng, W. Li, D. Ou, N. Feng, Y. Lu, J. Xu, W. Chen, et al., Deepthy-net: A multimodal deep learning method for predicting cervical lymph node metastasis in papillary thyroid cancer, *Advanced Intelligent Systems* 4 (10) (2022) 2200100.
- [267] A. N. Sayed, Y. Himeur, F. Bensaali, From time-series to 2d images for building occupancy prediction using deep transfer learning, *Engineering Applications of Artificial Intelligence* 119 (2023) 105786.
- [268] A. Karsa, S. Punwani, K. Shmueli, An optimized and highly repeatable mri acquisition and processing pipeline for quantitative susceptibility mapping in the head-and-neck region, *Magnetic Resonance in Medicine* 84 (6) (2020) 3206–3222.
- [269] S. Kim, J.-I. Bang, D. Boo, B. Kim, I. Y. Choi, S. Ko, I. R. Yoo, K. Kim, J. Kim, Y. Joo, et al., Second primary malignancy risk in thyroid cancer and matched patients with and without radioiodine therapy analysis from the observational health data sciences and informatics, *European Journal of Nuclear Medicine and Molecular Imaging* 49 (10) (2022) 3547–3556.
- [270] C. Sardianos, I. Varlamis, C. Chronis, G. Dimitrakopoulos, A. Alsailemi, Y. Himeur, F. Bensaali, A. Amira, The emergence of explainability of intelligent systems: Delivering explainable and personalized recommendations for energy efficiency, *International Journal of Intelligent Systems* 36 (2) (2021) 656–680.
- [271] T. Masuda, T. Nakaura, Y. Funama, K. Sugino, T. Sato, T. Yoshiura, Y. Baba, K. Awai, Machine learning to identify lymph node metastasis from thyroid cancer in patients undergoing contrast-enhanced ct studies, *Radiography* 27 (3) (2021) 920–926.
- [272] D. Dov, S. Kovalsky, J. Cohen, D. Range, R. Henao, L. Carin, Thyroid cancer malignancy prediction from whole slide cytopathology images, *arXiv preprint arXiv:1904.00839* (2019).
- [273] D. Dov, S. Z. Kovalsky, J. Cohen, D. E. Range, R. Henao, L. Carin, Ai-assisted thyroid malignancy prediction from whole-slide images.
- [274] M. Halicek, M. Shahedi, J. V. Little, A. Y. Chen, L. L. Myers, B. D. Sumer, B. Fei, Head and neck cancer detection in digitized whole-slide histology using convolutional neural networks, *Scientific reports* 9 (1) (2019) 1–11.
- [275] J.-B. Lamy, B. Sekar, G. Guezennec, J. Bouaud, B. Séroussi, Explainable artificial intelligence for breast cancer: A visual case-based reasoning approach, *Artificial intelligence in medicine* 94 (2019) 42–53.
- [276] K. Kobylinska, T. Mikolajczyk, M. Adamek, T. Orłowski, P. Biecek, Explainable machine learning for modeling of early postoperative mortality in lung cancer, in: *Artificial Intelligence in Medicine: Knowledge Representation and Transparent and Explainable Systems*, Springer, 2019, pp. 161–174.
- [277] E. Pintelas, M. Liaskos, I. E. Livieris, S. Kotsiantis, P. Pintelas, Explainable machine learning framework for image classification problems: Case study on glioma cancer prediction, *Journal of Imaging* 6 (6) (2020) 37.
- [278] J.-B. Lamy, B. D. Sekar, G. Guezennec, J. Bouaud, B. Séroussi, Intelligence artificielle explicable pour le cancer du sein: Une approche visuelle de raisonnement à partir de cas., in: *EGC*, 2020, pp. 457–466.
- [279] M. Poceviciute, G. Eilertsen, C. Lundström, Survey of xai in digital pathology, *Artificial Intelligence and Machine Learning for Digital Pathology: State-of-the-Art and Future Challenges* 12090 (2020) 56.
- [280] A. N. Sayed, F. Bensaali, Y. Himeur, M. Houchati, Edge-based real-time occupancy detection system through a non-intrusive sensing system, *Energies* 16 (5) (2023) 2388.
- [281] A. Alsailemi, Y. Himeur, F. Bensaali, A. Amira, An innovative edge-based internet of energy solution for promoting energy saving in buildings, *Sustainable Cities and Society* 78 (2022) 103571.
- [282] A. Sayed, Y. Himeur, A. Alsailemi, F. Bensaali, A. Amira, Intelligent edge-based recommender system for internet of energy applications, *IEEE Systems Journal* 16 (3) (2021) 5001–5010.
- [283] E. Charteros, I. Koutsopoulos, Edge computing for having an edge on cancer treatment: A mobile app for breast image analysis, in: *2020 IEEE International Conference on Communications Workshops (ICC Workshops)*, IEEE, 2020, pp. 1–6.
- [284] A. Sufian, A. Ghosh, A. S. Sadiq, F. Smarandache, A survey on deep transfer learning to edge computing for mitigating the covid-19 pandemic, *Journal of Systems Architecture* 108 (2020) 101830.
- [285] J. Chen, K. Li, H. Rong, K. Bilal, N. Yang, K. Li, A disease diagnosis and treatment recommendation system based on big data mining and cloud computing, *Information Sciences* 435 (2018) 124–149.
- [286] X. Chai, Diagnosis method of thyroid disease combining knowledge graph and deep learning, *IEEE Access* 8 (2020) 149787–149795.
- [287] P. Jagtap, P. Jagdale, S. Gawade, P. Javalkar, Online healthcare system using the concept of cloud computing, *International Journal of Scientific Research in Science, Engineering and Technology (ijrsset. com)*, IJRSRSET 2 (2) (2016).
- [288] M. Anuradha, T. Jayasankar, N. Prakash, M. Y. Sikkandar, G. Hemalakshmi, C. Bharatiraja, A. S. F. Britto, IoT enabled cancer prediction system to enhance the authentication and security using cloud computing, *Microprocessors and Microsystems* 80 (2021) 103301.
- [289] D. Kečo, A. Subasi, J. Kevric, Cloud computing-based parallel genetic algorithm for gene selection in cancer classification, *Neural Computing and Applications* 30 (5) (2018) 1601–1610.
- [290] J. P. Rajan, S. E. Rajan, R. J. Martis, B. K. Panigrahi, Fog computing employed computer aided cancer classification system using deep neural network in internet of things based healthcare system, *Journal of medical systems* 44 (2) (2020) 1–10.
- [291] A. A. Mutlag, M. K. Abd Ghani, N. a. Arunkumar, M. A. Mohammed, O. Mohd, Enabling technologies for fog computing in healthcare iot systems, *Future Generation Computer Systems* 90 (2019) 62–78.
- [292] M. Hartmann, U. S. Hashmi, A. Imran, Edge computing in smart health care systems: Review, challenges, and research directions, *Transactions on Emerging Telecommunications Technologies* (2019) e3710.
- [293] J. M. Corchado Rodríguez, et al., Ai, blockchain and edge computing for industrial predictive maintenance (2019).
- [294] A. Gueriani, H. Kheddar, A. C. Mazari, Deep reinforcement learning for intrusion detection in iot: A survey, in: *2023 2nd International Conference on Electronics, Energy and Measurement (IC2EM)*, Vol. 1, IEEE, 2023, pp. 1–7.
- [295] P. Balaprakash, R. Egele, M. Salim, S. Wild, V. Vishwanath, F. Xia, T. Brettin, R. Stevens, Scalable reinforcement-learning-based neural architecture search for cancer deep learning research, in: *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, 2019, pp. 1–33.
- [296] Z. Li, Y. Xia, Deep reinforcement learning for weakly-supervised lymph node segmentation in ct images, *IEEE Journal of Biomedical and Health Informatics* (2020).

- [297] O. Kerdjidj, Y. Himeur, S. S. Sohail, A. Amira, F. Fadli, S. Atalla, W. Mansoor, A. Copiaco, M. Daradkeh, A. Gawanmeh, et al., Uncovering the potential of indoor localization: Role of deep and transfer learning (2023).
- [298] H. Kheddar, Y. Himeur, A. I. Awad, Deep transfer learning for intrusion detection in industrial control networks: A comprehensive review, *Journal of Network and Computer Applications* 220 (2023) 103760.
- [299] Y. Himeur, S. Al-Maadeed, H. Kheddar, N. Al-Maadeed, K. Abualsaad, A. Mohamed, T. Khattab, Video surveillance using deep transfer learning and deep domain adaptation: Towards better generalization, *Engineering Applications of Artificial Intelligence* 119 (2023) 105698.
- [300] H. Kheddar, Y. Himeur, S. Al-Maadeed, A. Amira, F. Bensaali, Deep transfer learning for automatic speech recognition: Towards better generalization, *Knowledge-Based Systems* 277 (2023) 110851.
- [301] V. Narayan, P. K. Mall, A. Alkhayyat, K. Abhishek, S. Kumar, P. Pandey, et al., Enhance-net: An approach to boost the performance of deep learning model based on real-time medical images, *Journal of Sensors* 2023 (2023).
- [302] J. Yu, Y. Deng, T. Liu, J. Zhou, X. Jia, T. Xiao, S. Zhou, J. Li, Y. Guo, Y. Wang, et al., Lymph node metastasis prediction of papillary thyroid carcinoma based on transfer learning radiomics, *Nature communications* 11 (1) (2020) 1–10.
- [303] S. W. Kwon, I. J. Choi, J. Y. Kang, W. I. Jang, G.-H. Lee, M.-C. Lee, Ultrasonographic thyroid nodule classification using a deep convolutional neural network with surgical pathology, *Journal of digital imaging* 33 (2020) 1202–1208.
- [304] Y. Wang, Q. Guan, I. Lao, L. Wang, Y. Wu, D. Li, Q. Ji, Y. Wang, Y. Zhu, H. Lu, et al., Using deep convolutional neural networks for multi-classification of thyroid tumor by histopathology: a large-scale pilot study, *Annals of Translational Medicine* 7 (18) (2019).
- [305] K. S. Sundar, S. S. S. Sai, Exploring transfer learning, fine-tuning of thyroid ultrasound images (2018).
- [306] D. Liu, D. Zhang, Y. Song, C. Zhang, F. Zhang, L. O'Donnell, W. Cai, Nuclei segmentation via a deep panoptic model with semantic feature fusion., in: *IJCAI*, 2019, pp. 861–868.
- [307] O. Elharrouss, S. Al-Maadeed, N. Subramanian, N. Ottakath, N. Almaadeed, Y. Himeur, Panoptic segmentation: A review, *arXiv preprint arXiv:2111.10250* (2021).
- [308] X. Yu, B. Lou, D. Zhang, D. Winkel, N. Arrahmane, M. Diallo, T. Meng, H. von Busch, R. Grimm, B. Kiefer, et al., Deep attentive panoptic model for prostate cancer detection using biparametric mri scans, in: *International Conference on Medical Image Computing and Computer-Assisted Intervention*, Springer, 2020, pp. 594–604.
- [309] W. Cai, Z. Xiong, X. Sun, P. L. Rosin, L. Jin, X. Peng, Panoptic segmentation-based attention for image captioning, *Applied Sciences* 10 (1) (2020) 391.
- [310] D. Ivanova, Artificial intelligence in internet of medical imaging things: The power of thyroid cancer detection, in: *2018 International Conference on Information Technologies (InfoTech)*, IEEE, 2018, pp. 1–4.
- [311] P. Borovska, D. Ivanova, I. Draganov, Internet of medical imaging things and analytics in support of precision medicine for the case study of thyroid cancer early diagnostics, *Serdica Journal of Computing*, Bulgarian Academy of Sciences, Institute of Mathematics and Informatics, accepted paper (2018).
- [312] D. Ivanova, Internet of medical imaging things and the application of information technologies for early detection of thyroid cancer, *Silico Intellect* 1 (2017) 20–25.
- [313] P. Seifert, S.-L. Ullrich, C. Kühnel, F. Gühne, R. Drescher, T. Winkens, M. Freesmeyer, Optimization of thyroid volume determination by stitched 3d-ultrasound data sets in patients with structural thyroid disease, *Biomedicines* 11 (2) (2023) 381.
- [314] W.-B. Li, B. Zhang, Q.-L. Zhu, Y.-X. Jiang, J. Sun, M. Yang, J.-C. Li, Comparison between thin-slice 3-d volumetric ultrasound and conventional ultrasound in the differentiation of benign and malignant thyroid lesions, *Ultrasound in medicine & biology* 41 (12) (2015) 3096–3101.
- [315] A. Lyschik, V. Drozd, C. Reiners, Accuracy of three-dimensional ultrasound for thyroid volume measurement in children and adolescents, *Thyroid* 14 (2) (2004) 113–120.
- [316] M. Ying, D. M. Yung, K. K. Ho, Two-dimensional ultrasound measurement of thyroid gland volume: a new equation with higher correlation with 3-d ultrasound measurement, *Ultrasound in medicine & biology* 34 (1) (2008) 56–63.
- [317] N. Pakkasjärvi, T. Luthra, S. Anand, Artificial intelligence in surgical learning, *Surgeries* 4 (1) (2023) 86–97.
- [318] S. Bodenstedt, M. Wagner, B. P. Müller-Stich, J. Weitz, S. Speidel, Artificial intelligence-assisted surgery: potential and challenges, *Visceral Medicine* 36 (6) (2020) 450–455.
- [319] X.-Y. Zhou, Y. Guo, M. Shen, G.-Z. Yang, Artificial intelligence in surgery, *arXiv preprint arXiv:2001.00627* (2019).
- [320] X.-Y. Zhou, Y. Guo, M. Shen, G.-Z. Yang, Application of artificial intelligence in surgery, *Frontiers of Medicine* (2020) 1–14.
- [321] G. B. Berikol, G. Berikol, D. Bozdereli, Artificial intelligence in neuro, head, and neck surgery, in: *Artificial Intelligence in Precision Health*, Elsevier, 2020, pp. 393–404.
- [322] L. Tan, D. Tivey, H. Kopunic, W. Babidge, S. Langley, G. Maddern, Part 1: Artificial intelligence technology in surgery, *ANZ Journal of Surgery* 90 (12) (2020) 2409–2414.
- [323] M. B. Habal, Brave new surgical innovations: The impact of bioprinting, machine learning, and artificial intelligence in craniofacial surgery (2020).
- [324] D. Lee, H. W. Yu, H. Kwon, H.-J. Kong, K. E. Lee, H. C. Kim, Evaluation of surgical skills during robotic surgery by deep learning-based multiple surgical instrument tracking in training and actual operations, *Journal of clinical medicine* 9 (6) (2020) 1964.
- [325] S. Voglis, C. H. van Niftrik, V. E. Staartjes, G. Brandi, O. Tschopp, L. Regli, C. Serra, Feasibility of machine learning based predictive modelling of postoperative hyponatremia after pituitary surgery, *Pituitary* 23 (2020) 543–551.
- [326] A. J. Navarrete-Welton, D. A. Hashimoto, Current applications of artificial intelligence for intraoperative decision support in surgery, *Frontiers of Medicine* (2020) 1–13.
- [327] Y. Himeur, A. Alsalemi, A. Al-Kababji, F. Bensaali, A. Amira, C. Sardianos, G. Dimitrakopoulos, I. Varlamis, A survey of recommender systems for energy efficiency in buildings: Principles, challenges and prospects, *Information Fusion* 72 (2021) 1–21.
- [328] Q. M. Areeb, M. Nadeem, S. S. Sohail, R. Imam, F. Doctor, Y. Himeur, A. Hussain, A. Amira, Filter bubbles in recommender systems: Fact or fallacy—a systematic review, *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* (2023) e1512.

- [329] I. Varlamis, C. Sardianos, C. Chronis, G. Dimitrakopoulos, Y. Himeur, A. Alsalemi, F. Bensaali, A. Amira, Smart fusion of sensor data and human feedback for personalized energy-saving recommendations, *Applied Energy* 305 (2022) 117775.
- [330] S. Atalla, M. Daradkeh, A. Gawanmeh, H. Khalil, W. Mansoor, S. Miniaoui, Y. Himeur, An intelligent recommendation system for automating academic advising based on curriculum analysis and performance modeling, *Mathematics* 11 (5) (2023) 1098.
- [331] R. S. Antunes, C. André da Costa, A. Küderle, I. A. Yari, B. Eskofier, Federated learning for healthcare: Systematic review and architecture proposal, *ACM Transactions on Intelligent Systems and Technology (TIST)* 13 (4) (2022) 1–23.
- [332] H. Lee, Y. J. Chai, H. Joo, K. Lee, J. Y. Hwang, S.-M. Kim, K. Kim, I.-C. Nam, J. Y. Choi, H. W. Yu, et al., Federated learning for thyroid ultrasound image analysis to protect personal information: Validation study in a real health care environment, *JMIR medical informatics* 9 (5) (2021) e25869.
- [333] S. S. Sohail, D. Ø. Madsen, Y. Himeur, M. Ashraf, Using chatgpt to navigate ambivalent and contradictory research findings on artificial intelligence, *Frontiers in Artificial Intelligence* 6 (2023) 1195797. [doi:10.3389/frai.2023.1195797](https://doi.org/10.3389/frai.2023.1195797).
- [334] F. Farhat, E. S. Silva, H. Hassani, D. Ø. Madsen, S. S. Sohail, Y. Himeur, M. A. Alam, A. Zafar, Analyzing the scholarly footprint of chatgpt: mapping the progress and identifying future trends (2023).
- [335] S. S. Sohail, F. Farhat, Y. Himeur, M. Nadeem, D. Ø. Madsen, Y. Singh, S. Atalla, W. Mansoor, The future of gpt: A taxonomy of existing chatgpt research, current challenges, and possible future directions, *Current Challenges, and Possible Future Directions* (April 8, 2023) (2023).
- [336] H. L. Haver, E. B. Ambinder, M. Bahl, E. T. Oluyemi, J. Jeudy, P. H. Yi, Appropriateness of breast cancer prevention and screening recommendations provided by chatgpt, *Radiology* 307 (4) (2023) e230424.
- [337] J. J. Cao, D. H. Kwon, T. T. Ghaziani, P. Kwo, G. Tse, A. Kesselman, A. Kamaya, J. R. Tse, Accuracy of information provided by chatgpt regarding liver cancer surveillance and diagnosis, *American Journal of Roentgenology* (2023).
- [338] V. Sorin, E. Klang, M. Sklair-Levy, I. Cohen, D. B. Zippel, N. Balint Lahat, E. Konen, Y. Barash, Large language model (chatgpt) as a support tool for breast tumor board, *NPJ Breast Cancer* 9 (1) (2023) 44.