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# Review of the application of artificial intelligence technology in the field of thyroid medical imaging

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**Abstract.** In recent years, there has been a noticeable increase in the incidence of thyroid diseases, posing severe challenges to the traditional diagnosis and treatment methods. As a result, artificial intelligence technology has emerged as a valuable tool in the field of thyroid medical imaging, offering substantial support for auxiliary diagnosis and treatment in the future. In this paper, the application of artificial intelligence in the field of thyroid medical imaging is divided into three parts: image segmentation and texture analysis, benign and malignant diagnosis of thyroid gland, and postoperative analysis and prediction of thyroid conditions. Through an examination of recent research datasets and an analysis of the medical imaging process, this paper investigates the application of various algorithm models in these three areas and provides a comprehensive overview of the latest research trends. Furthermore, some certain directions for future research are also provided in this work.

**Keywords:** Artificial Intelligence, Thyroid Gland, Medical Imaging, Image Features.

## 1. Introduction

With the development of computer information technology, artificial intelligence (AI) has found widespread applications in various fields of image processing [1]. Multiple studies have indicated that [2-5], in recent years, the global incidence of thyroid disease has been on the rise, with abnormal thyroid function becoming the second most common endocrine disorder. Thyroid diseases, including thyroid cancer, exhibit a complex pathogenesis, highly diverse clinical manifestations, hidden symptoms, and a high rate of clinical misdiagnosis and missed diagnosis, thereby posing significant threats to the physical and mental health of residents. The diagnosis and treatment of thyroid-related diseases primarily rely on image analysis. AI, due to its ability to operate without external interference and maintain efficient and continuous performance, offers an effective solution to the inefficiency and potential oversight of traditional manual subjective analysis. This can greatly improve the efficiency and quality of imaging doctors' reading [6]. Therefore, since the 1960s, some computer scientists have been exploring the application of computer analysis in medical image processing [7]. In recent years, the rapid advancement of various technologies and algorithm models has allowed AI to establish a comprehensive application framework in the field of thyroid medical imaging, with promising prospects for further development.

In light of the recent research on the application of AI in thyroid-related medical imaging, this paper aims to summarize and analyze the application process from three aspects: image segmentation and texture analysis, benign and malignant thyroid diagnosis, and postoperative analysis and predictive

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efficacy of thyroid treatments. Additionally, this paper compiles the datasets used in the referenced studies and incorporates a dataset perspective to further analyze the diagnostic efficiency of algorithm models in each stage.

## 2. Overview

Over the years, the accumulation of thyroid medical images and the establishment and standardization of the database have provided a rich source of datasets for thyroid AI models. The diagnosis of thyroid diseases, especially thyroid cancer, currently mainly relies on ultrasound, CT, nuclear medicine, and other imaging examinations, as well as pathological examination [5]. In recent years, it has been observed that the selection of different image datasets has some influence on the accuracy and generalization ability of the algorithm models in different stages.

Image segmentation and texture analysis serve as the initial step in the application of AI in the thyroid medicine. By employing model algorithms to accurately extract the area of thyroid lesions and highlight their features, this approach can effectively reduce the time required for diagnostic testing, and provide a reference for subsequent manual analysis [8]. The field of image segmentation and texture analysis encompasses a wide range of research and applications, mainly focusing on improving its recognition accuracy, speed, and the generalization ability of the model. It plays a fundamental role in the application of related medical imaging [9].

Accurately distinguishing between benign and malignant thyroid cases is crucial for subsequent diagnosis and treatment. Traditional diagnostic methods mainly rely on the experience and judgment of doctors. However, given the complex and variable nature of thyroid cases and the low proportion of malignant lesions in the general population, overdiagnosis or misdiagnosis is prone to occur [10,11]. In contrast, AI models can build classifiers by leveraging a large number of cases and training algorithms to learn the relationship between case features and benign/malignant labels. This enables quick and accurate determination of benign and malignant thyroid tumors and reduces the influence of human experience.

Postoperative analysis and efficacy prediction can provide valuable insights for the diagnosis and treatment process of thyroid diseases. Some thyroid diseases, represented by thyroid cancer, have the risk of metastasis in the process of diagnosis and treatment, making traditional manual prediction difficult and time-consuming [11,12]. AI-based prediction models can swiftly identify influencing factors and conduct comprehensive analysis using multi-party data. This assists doctors in making more accurate diagnosis and treatment decision, mitigating risks, and optimizing the allocation of medical resources.

The analysis flow of this paper is shown in Figure 1.

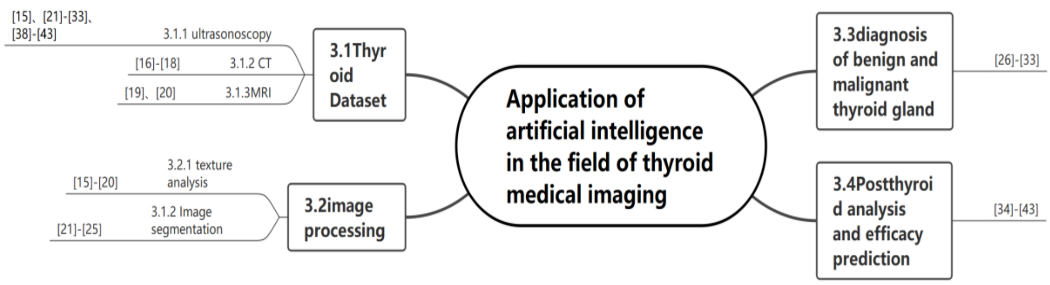


**Figure 1.** The structure of this work

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## 3. Research Work of AI Aided Diagnosis in Thyroid Medical Imaging

### *3.1. Thyroid Dataset*

*3.1.1. Ultrasonography.* Ultrasound images are generated by sending and receiving ultrasound waves to the target area, and they are the preferred method for screening and examining thyroid nodules [14]. Compared to CT and MRI, ultrasonic images have several advantages, including their affordability, lack of radiation, non-invasiveness, and ease of use. As a result, ultrasound images have the largest dataset. However, ultrasound has limitations in terms of poor penetration, low signal-to-noise ratio, and differences in image accuracy compared to CT and MRI. Therefore, it is more suitable for the initial routine diagnosis of thyroid disease, and has great advantages in obvious lesion division and scanning of shallow tissue. Another advantage of ultrasound images is their high temporal resolution, which allows for long-term scanning of the target area, formation of dynamic images, and measurement of functional parameters such as blood flow rate. Various application models, including deep learning models like convolutional neural network (CNN) [21-30], generative adversarial network (GAN), and artificial neural network (ANN) [15], can often be used to extract more complex features and patterns. Machine learning algorithms, such as random Forest (RF) [39,40] and extreme gradient lifting [41,42,43], have also been widely studied in studies based on ultrasound datasets. The combination of ultrasound images and artificial intelligence has been applied in various aspects of the field of thyroid medicine.

*3.1.2. CT Image.* CT images use X-rays to illuminate the target area, obtain sectional images of all levels inside the organization, and then synthesize a 3D target model through computer processing. CT images have high resolution and contrast, allowing for the observation of small structures and lesions within the target area. They are highly prioritized for the early detection and diagnosis of thyroid nodule tumors and cancers, as well as scenarios requiring high precision. CT imaging technology has various types, and energy spectral CT technology is widely used in the field of thyroid diagnosis and treatment. Energy spectrum imaging has been applied and rapidly developed since the 21st century, but its widespread application still faces challenges such as long imaging time and high cost. Efforts are being made to shorten the imaging time and reduce radiation hazards as much as possible. CT images have high accuracy and a relatively large dataset, making them suitable for deep learning algorithm to improve the accuracy of the generated model. At the same time, machine learning, transfer learning, and linear regression models are also widely used. The application of artificial intelligence based on CT image datasets is relatively well-established and has been applied in all stages of the field of thyroid medical treatment. Some works that utilize CT images as datasets include [16], [17], and [18].

*3.1.3. MRI Image.* MRI images, like CT images, can be generated by the reconstruction of digital signals, and they have high image resolution and contrast. The advantage of MRI over CT is that it does not use X-rays andtherefore does not pose radiation hazards to the human body. In addition, MRI is more flexible, and can generate different types of images (such as structural images, functional images, etc.) by designing different sequences. For complex situations, combining multiple images can generate more detailed and reliable conclusions. However, it is important to note that that MRI has a long imaging time, high cost, and limited scope of application. Due to the small dataset size and high difficulty in obtaining MRI images, there are relatively fewer AI applications based on MRI images. To address the limited dataset size, traditional machine learning models such as support vector machine (SVM) or random forest (RF) are often chosen to avoid overfitting problems, or transfer learning can be used to supplement the dataset gap. However, due to the high resolution and contrast of MRI images and the good imaging effect, its application models are commonly used in risk stratification and prognostic analysis stages that require high accuracy or tackle difficult situations. Further technical improvements and cost reductions are still needed for the wider application of MRI images. Some works that utilize MRI images as datasets include [19] and [20].

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In addition to the differences in dataset sources, there are also some differences in the collection and pre-treatment of datasets. Different datasets may have different annotations and annotation methods. For datasets with detailed annotations such as thyroid nodule location and size, supervised models can be selected for training and prediction. For datasets with only dichotomous criteria, unsupervised or semi-supervised learning models can be used for training and prediction. In general, the selection of the thyroid AI training model should fully consider the image type, data quantity, data quality, and annotation factors of the dataset. Moreover, regional differences in patient groups and diseases may also have an impact on the generalization ability of the model algorithms.

### *3.2. Image Processing*

*3.2.1. Texture Analysis.* Texture analysis is a method used in digital image processing to reveal the surface details and texture features in images by conducting statistical analysis, feature extraction, and classification of image texture. By enhancing the potential features in the image, the easily overlooked details in the routine examination imaging can be highlighted [14].

Chen et al. [15] used two-dimensional ultrasound images as the dataset for their study. They selected the Fisher coefficient, classification error probability combined average correlation coefficient (POE + ACC), interaction information (MI), and the combination (Fisher + POE + ACC + MI) as the parameters for analysis. They then constructed the artificial neural network model (ANN) to compare the differences of thyroid cancer texture characteristics between the metastatic and non-metastatic groups. The results showed no obvious difference between the combination method and the sonographer's assessment, which further proved the predictive value of texture analysis for lymph node metastasis in thyroid cancer. Ma et al. [16] used CT images as their dataset and employed the MaZda software to extract the CT texture features of lymph nodes. They analyzed the differences between groups and used a dimension reduction algorithm and difference test to identify texture feature parameters with significant statistical differences. The results indicated that CT texture analysis has a good diagnostic value in differentiating PTC lymph node metastasis. Texture analysis needs to consider various texture parameters, and the selection of different texture parameters holds research value in improving the effectiveness of tumor diagnosis. For the study of texture parameters, He et al. [17] took positron emission tomography and X-ray tomography (PET / CT) images as the dataset. They selected six texture parameters, such as entropy, kurtosis, and energy, for analysis. Their findings suggested that only entropy indicators exhibited statistically significant differences in the detection of thyroid diseases. In contrast, Zhang et al. [18] used PET / CT images as the dataset to study non-small cell lung cancer. Their results showed that, besides entropy, the differences between texture parameters such as kurtosis and energy were also statistically significant between lymph node metastasis and non-metastasis groups. In another study, Zhang et al. [19] used MRI T2WI images as dataset. They employed independent sample t-tests and Mann-Whitney U tests to compare the differences between two groups, taking into account sample variance and normal distribution to minimize unnecessary influence between different samples. They used ROC curves to evaluate the prediction efficacy of different texture parameters, and found that entropy, standard deviation, correlation and angular second moment were significantly different among PTC patients with cervical lymph node metastasis. Among these parameters, entropy exhibited the best prediction efficacy, which aligns with the results of some previous studies [17,18]. However, there are some differences in the statistical differences observed for skewness and kurtosis compared to other studies [20]. Based on the discussion provided in each study, it can be concluded that the different sources of the dataset have minimal influence on the statistical significance of the difference in texture parameters. The results may be affected by the composition of the scan sequence and patient samples.

*3.2.2. Image Segmentation.* By dividing the image into multiple areas with specific semantics, the volume data, such as three-dimensional ultrasound, is decomposed into multiple two-dimensional sections for observation and analysis. This technique allows for the extraction and segmentation of the

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thyroid nodule area, which is of great value in assisting doctors to further determine the range of lesions and assess the risk level.

Deep learning techniques are widely used in the image segmentation field. In 2015, Ronneberger et al. [21] has proposed the UNet model based on the improvement of the full convolutional neural network (FCN). It consists of an encoder part gradually reduces the spatial resolution of the image and extracts abstract features, and a decoder part that recovers the resolution of the image through upsampling and convolution operations. The UNet model also incorporates a jump connection mechanism, which connects the feature maps at different levels of the encoder directly to the corresponding level of the decoder, thus realizing multi-scale feature fusion. The innovation of this mechanism enables the UNet model to fully utilize the feature information at different scales and retain details and boundary information during the segmentation process. Despite its widespread use, it is important to note that the UNet model requires a large number of parameters, has specific requirements for input and training image sizes, and carries a risk of overfitting. To address the limitations of the UNet model and better adapt to the specific requirements of thyroid image segmentation, many improved model networks based on UNet and FCN have emerged in recent years.

For example, Ying et al. [22] argue that FCN algorithm has some defects in terms of segmentation accuracy, particularly in the fine segmentation of edges. They suggest that future research should prioritize improving the accuracy of edge segmentation to improve the accuracy of nodule segmentation results and identify complex edge details. Based on ultrasound images, they proposed a thyroid nodule segmentation model in the form of a cascade convolutional neural network on the basis of UNet and FCN . The Dice coefficient of their model reached 0.9304. Similarly, based on the unclear edge of image nodules, which led to misdiagnosis and missed diagnosis during manual diagnosis and screening, Zhou et al. [23] proposed an ultrasound segmentation method called MSA-UNet (multi-scale attention UNet) that incorporates multi-scale attention mechanisms. The Dice coefficient achieved by this algorithm is 84.6%. In order to improve the accuracy of ultrasonic thyroid nodule segmentation, enhance the generalization performance, and reduce the number of parameters, Yu et al. [24] proposed an "h" shape network for ultrasound image segmentation. This algorithm utilizes a double decoder fusion approach, with a decoder that includes an enhanced sampling module and a fusion convolution pooling pyramid module. These improvements contribute to nodule segmentation accuracy, feature extraction at different scales, and a reduction in the required number of parameters. The Dice coefficient achieved by this algorithm is 0.8721. It demonstrates high robustness and improved generalization. However, the number of memory and parameters required by the algorithm is still large, and the accuracy could be further enhanced to meet practical application standards. Another improved UNet architecture, called DSR UNet, which incorporates ResNeSt blocks, ASPP and DC v3 for the segmentation of thyroid and nodules, was proposed by Zheng et al. [25]. According to the experimental results, DSR UNet can not only effectively analyze shallow features to better segment edges and small nodules, but also analyze depth information at multiple scales to improve the segmentation effect of glands and very large nodules. Its average Dice value and the nodule Dice value achieved by DSR UNet are 92.5% and 94.1%, respectively. Compared to the traditional UNet networks, DSR UNet demonstrates enhanced segmentation performance for large nodules and other special cases, which is relatively rare in other improved types. In recent years, improvements based on UNet have focused on reducing the number of parameters and improving the accuracy of complex edge details, yielding promising results in practical applications. However, it is worth noting that ultrasonic images are mostly used in datasets, and different models have strict restrictions on images and target size. Furthermore, different models may exhibit variations in the application effectiveness when tested with different datasets. Consequently, there is still ample room for improvement regarding the portability and segmentation accuracy of algorithm models.

### *3.3. Diagnosis of Benign and Malignant Thyroid Gland*

Early algorithms for diagnosing benign and malignant thyroid gland using artificial neural network (ANN), support vector machine (SVM), random forest (RF) and other traditional algorithms have achieved some results. However, they suffer from manual feature extraction, poor generalization ability, and weak anti-interference ability. In recent years, with the rise of deep learning algorithms, its end-to-end learning ability and multi-layer neuron design have made great progress in handling complex relationships such as benign and malignant thyroid diagnosis. Among them, the CNN nodule classification model has been the most successful [26].

Commonly used CNN classification networks include AlexNet, VGG, ResNet, GoogLeNet, etc. When it comes to the specific task of benign and malignant thyroid diagnosis, researchers can choose to use a single CNN or multiple CNN cascade for diagnosis. The latter approach can take full advantage of the variability of multiple CNN models, resulting in improved performance, accuracy and robustness. However, it may also involve more complex and time-consuming model design and training.

Early classification detection mainly relies on a single CNN model. Song et al. [27] suggested that sensitivity and NPV are the two most meaningful parameters for evaluating the diagnostic performance of a deep feature learning algorithm (DLA). They used the ultrasound images as a dataset and input them into the Inception-V3 network model to pre-train using the ImageNet database. For the external test set, the final sensitivity reached 95.2%, and the negative predictive value (NPV) reached 90.3%. However, the specificity was only 56.0%, which varied greatly from the sensitivity. The diagnostic ability for benign nodules was weak, potentially leading to unnecessary misdiagnosis. Chi et al. [28] used ultrasound images as a dataset to achieve precise transfer learning by normalizing and removing artifacts on the basis of existing GoogLeNet image preprocessing operations. They also innovatively sliced different regions from images containing thyroid nodules and surrounding tissues in the data enhancement step to enhance thyroid samples, successfully fine-tuning the original model. The experimental results showed that the image classification accuracy in the open access database reached 98.29%, with a sensitivity of 99.10% and a specificity of 93.90%. These values were much higher than the image classification accuracy in the local health area database.

In order to adapt to more complex situations and grasp more features, the cascade and integrated CNN algorithm design model has been developed in recent years. Liu et al. [29] proposed a joint convolutional neural network (IF-JCNN) that incorporates information fusion. This approach utilizes two branch CNNs for deep feature extraction: one for thyroid images from the United States and the other for RF signals. By innovatively incorporating the RF signal as an input, the IF-JCNN achieved improved accuracy, sensitivity and specificity indicators of 0.896, 0.885, 0.910, respectively, compared to using US image alone as input. To solve the problems of a small number of training image samples and neglect of multi-scale structure and texture information, an ultrasonic image recognition method of thyroid nodules based on the integration of multi-scale fine-tuned convolutional neural network was proposed by Liang et al [30]. By transforming images into three different scales of information and performing fusion training using ResNet-50, AlexNet, and VGG-16, they obtained nine submodels. The final integrated model, obtained by using the model output category, achieved high accuracy, sensitivity, and specificity of 96.0%, 94.1%, and 97.7%, respectively. However, this algorithm relies on the manually annotated training data, making the process of formulating the training dataset more complex. Based on the above research, it can be found that the structure of a single CNN model is relatively simple and requires a small amount of training data. However, by cascading and ensembling CNN models, richer features can be extracted, resulting in improved classification accuracy and generalization ability. Nonetheless, preprocessing the original dataset to meet the requirements of different models, as well as formulating the training dataset, can be challenging. Furthermore, finding the optimal algorithm that integrates multiple CNN networks and other inputs more efficiently remains a key factor in enhancing the performance of multi-CNN models.

In addition, to further standardize the criteria for risk stratification in diagnosing benign and malignant thyroid diseases, the American Society of Radiology (ACR) proposed the ACR version of the Thyroid Image Reporting and Data System (ACR TI-RADS). It provides guidance on managing the thyroid nodules based on ultrasound imaging, using an objective scoring system [31]. With its worldwide popularity, some researchers have tried to explore the AI risk monitoring models based on this standard. Yang et al. [32] retrospectively analyzed the TR3~5 classification of ACR TI-RADS and verified that the best diagnostic malignant cut-off value for suspicious thyroid nodules was TR5.

However, the medical situation and standards vary across different regions. Tian et al. [33] established a ROC diagnostic assessment model based on local datasets to compare the diagnostic effectiveness of currently commonly used Kwak TIRADS, ACR TI-RADS, ATA risk stratification, and C-TIRADS classification for papillary thyroid carcinoma. The results found that C-TIRADS had better diagnostic efficacy and higher sensitivity and specificity. This is quite different from the results of the studies based on the US dataset. Most of the current studies are based on local datasets. Considering how to improve the diagnostic performance of models based on specific risk stratification standards, there is a lack of research on cross-regional datasets or how to establish buffer zones between different standards. The generalization ability of artificial intelligence risk monitoring models based on specific standards is relatively low.

### *3.4. Postthyroid Analysis and Efficacy Prediction*

There are many algorithms applied in the field of thyroid postoperative analysis and efficacy prediction, including Logistic regression analysis, support vector machine (SVM), random forest (RF), decision tree (DT), and some algorithms based on deep learning neural network.

Among them, Logistic regression has been widely used in the field of thyroid efficacy and metastasis risk prediction. It can be directly applied to build a regression prediction model. However, its accuracy and AUC (Area Under the Curve) value are not very outstanding. For instance, Yang et al. [34] built a Logistic regression model to predict the risk of postoperative infection of thyroid cancer, but the AUC value was only 0.793. According to multiple studies [34-37], Logistic regression analysis is often used to analyze the influencing factors of the prediction model. However, other algorithms such as nomogram or machine learning are considered for model development.

By combining histogram and histogram together, the nomogram can show the size and trend of data points in multiple dimensions, strengthening the comparative relationship between data, and making it easier to understand and interpret. Ye et al. [36] used Logistic regression analysis to determine the risk factors for cancer fatigue (Cancer-related fatigue, CRF) after thyroid cancer. They built a nomogram prediction model with an AUC value of 0.761. The Hosmer-Lemeshow test was $\chi$ 2 (chi square) =7.296, P=0.505, which has a high accuracy in this field. Tong et al. [38] retrospectively evaluated the demographic and clinicopathological variables of patients from the SEER thyroid cancer (TC) database from 2010 to 2015. They used Logistic regression analysis and chi-square analysis to identify independent risk factors and developed a new nomogram prediction model to assess the risk of bone metastasis in thyroid cancer. This study used a large population-based sample size (14772 patients' data selected), and the final AUC values reached 0.925 and 0.842 in the training and validation sets, respectively. The calibration curve and decision curve analysis (DCA) also demonstrated the reliability and accuracy of the clinical prediction model.

In the field of metastasis prediction of thyroid cancer, the application of machine learning algorithms has also achieved good results. Similarly for the prediction of bone metastasis in thyroid cancer, Liu et al. [39] retrospectively analyzed the demographic and clinical pathology variables of patients with thyroid cancer (TC) in the SEER database from 2010 to 2016, on which a random forest algorithm model was developed to predict bone metastasis in thyroid cancer. By determining the best ntree value (ntree = 7) through model iteration, they reduced the impact of redundant characteristics on the model. Finally, the algorithm model AUC reached 0.917 and the accuracy reached 0.904. At the same time, classifiers such as AdaBoost, decision tree (DT), naive Bayes classifier (NBC), and support vector machine were introduced for comparison. The experimental results showed that the random forest model had good predictive ability. Moreover, liu et al identified grade, T stage, histology, race, gender, age, and N stage as important predictive characteristics of bone metastasis (BM), which is consistent with the studies by Tong et al [38] and Liu et al [40].

In order to address the various issues faced by machine learning algorithms when it comes to predicting thyroid cancer metastasis, it is crucial to assess and compare the diagnostic effectiveness of specific algorithms in different scenarios. Liu et al. [40] extracted data from demographic and clinicopathological characteristics of 212 thyroid cancer patients in the NIH database between 2010 and

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2015, and comprehensively compared six machine learning algorithms for predicting thyroid cancer lung metastasis. These algorithms included support vector machine (SVM), logistic regression (LR), extreme gradient boost (XGBoost), decision tree (DT), random forest (RF) and k nearest neighbor (KNN). It is also concluded that the random forest model has the best predictive ability (AUC =0.99, accuracy = 0.99) . Through analysis and comparison of multiple studies [36-38], the predictive characteristics of metastasis in different sites of thyroid cancer are highly similar or related to the same database used in the three studies. Li et al. [41] conducted a retrospective study of 274 patients with thyroid nodules who underwent fine needle aspiration (FNA) cytology or surgery at Xianyang Central Hospital from October 2018 to 2020. They built thyroid malignant prediction models using six machine learning algorithms, including decision tree (DT), extreme gradient boost (XGBoost), gradient hoist (GBM), Naive Bayes classifier (NBC), random forest (RF) and logistic regression (LR). Internal validation was conducted using a 10-fold cross-validation. However, the experimental results showed that the ML-ed model based on XGBoost is significantly better than the other models (AUC = 0.829), which was different from the previous two studies. Furthermore, they suggested using the probability of 51% as the threshold to determine the risk stratification of malignant nodules, achieving a high detection rate based on the experimental dataset. Chen et al. [42] also believed that the XGBoost model predicts better. Chen et al established a XGBoost-based prediction model for CT lymph node metastasis in thyroid cancer and trained the test model with a 5-fold cross-validation method, achieving an accuracy of 87.41%. This was better than the SVM algorithm model used as a control group. Zhang et al. [43] compared the prediction effect of thyroid cancer metastasis using three improvement models (CatBoost, XGBoost and LightGBM) of gradient lifting tree (Gradient Boosting Tree). They concluded that the CatBoost model had the best effect, which was somewhat different from the previous conclusion.

Considering the above studies, it can be found that the model based on machine learning related algorithms is better than the model based on nomogram division. The types of data set sources (ultrasound, CT images, etc.) have little impact on the selection of the optimal machine learning algorithm. Additionally, the selection of predictive features is roughly the same for different studies. However, the regional sample selection of data sets has a key impact on the selection of the optimal model. Therefore, it can be inferred that the prediction algorithm model has a large regional limitation and a low generalization ability. How to effectively unify and standardize the pretreatment process of data sets and samples, and reduce the characteristics of patient samples in different regions may be the key to build a cross-regional thyroid efficacy and risk prediction model.

## 4. Conclusion

This paper aims to explore the datasets of recent studies and analyze the application of artificial intelligence in thyroid medical imaging. The focus is on three main areas: image segmentation and texture analysis, benign and malignant thyroid diagnosis, and postoperative analysis of thyroid and efficacy prediction. Among them, the application of therapeutic image segmentation and texture analysis is most completed and widely used. At present, the research on benign and malignant diagnosis, postoperative analysis, and efficacy prediction is still in the experimental stage of model construction. While the accuracy of these models meets the preliminary requirements, they have certain limitations and have not yet reached practical standards. The limitations of artificial intelligence in the diagnosis of benign and malignant thyroid gland mainly come from the lack of unified evaluation criteria, inadequate number of data sets, and regional influences. The application of postoperative analysis and efficacy prediction is also challenging due to the influence of various predictors and the lack of effective and efficient design and search methods. Furthermore, the limited generalization ability of prediction models due to regional influences and diverse disease pathology and patient groups restrict their practical application. As medical and health awareness continues to improve, along with advancements in technology and the expansion of data sets, the feasibility and research interest in benign and malignant diagnosis, postoperative analysis, and efficacy prediction are likely to become future hotspots of research and garner more extensive attention.

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