Enhanced deep learning based on Fusion data to diagnosis malignancy Thyroid tumour

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Abstract. The predominant type of cancer within the endocrine system is Thyroid Cancer (TC), with the majority falling under the category of low-risk tumour. However, the over-diagnosis and over-treatment of such conditions serve as primary factors contributing to a patient's deteriorating state, heightening the risk of recurrence and potentially complicating future interventions. Consequently, these practices elevate mortality rates and hinder complete recovery. Our paper focuses on developing a robust neural network model that integrates ultrasound radiomics with clinical data to accurately diagnose malignant thyroid tumours, aiming to mitigate issues associated with misdiagnosis and over-diagnosis. Based on independent cohort testing, the model demonstrates outstanding performance metrics with values of 0.97, 0.99, 0.97, and 0.98 for accuracy, AUC, precision, and recall, respectively.

Keywords: Deep learning· Feature selection· Thyroid cancer diagnosis· Ultrasound radiomics features· Data Fusion.

1 Introduction

Cancer poses an increasing health problem for our world [25]. The World Health Organization (WHO) has declared TC has the ninth-highest cancer incidence worldwide and has been rising for the past 40 years [7]. The WHO estimated the new case number of TC to be around 586,202 cases in 2020. The vast majority of the affected cases are women, accounting for 448,915 cases, which is 76.5% of all instances of TC. In Algeria among women, TC has the third-highest incidence, accounting for 9.3 new cases per 100,000 women [6]. The thyroid gland, situated in the lower neck region, is an endocrine system component. This gland controls

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numerous bodily functions, including metabolism, growth, and development, by secreting hormones like thyroxine and triiodothyronine. Generally, cancer is a non-typical cell, that has been genetically mutated and earned the capability to multiply and grow murderously and spread to other tissues, constructing nodules which could be malignant or benign. TC has four sub-types, i.e. papillary, follicular, medullary and anaplastic. These sub-types differ from most common, well prognosis, low rate aggressive and progression to little common, poor prognosis, high rate aggressive and progression, orderly [4] [15] [23].

One of the reasons that have a high impact on the increasing incidence of TC is the improvement of diagnostic tools, which now leads to the over-diagnosis of patients, enabling the detection of small and low-risk tumours [22]. These contribute to the problem of over-treatment and worsen the condition of the patients. The ultrasound instrument is a pivotal diagnostic tool for screening nodules in the thyroid gland. Renowned healthcare organizations have recommended it as the primary imaging modality for assessing suspected thyroid tissue [16] [10].

Ultrasound-based risk stratification systems are guidelines based on sonographic features extracted from ultrasound images, to classify nodules into high-suspicious malignant thyroid nodules that warrant biopsy test, or non-threatening benign thyroid nodules that warrant ultrasonography follow-up [26]. The Thyroid Imaging Reporting and Data Systems (TI-RADS), designed with the American College of Radiology, is a highly esteemed and widely recognized system for staging thyroid nodules. This system relies on sonographic features (e.g., anechoic, spongiform, etc.) pre-assigned based on risk levels and categorized according to the five characteristic keys (shape, margin, composition, echogenic foci, echogenicity). After inspection and collecting sonographic features, all the scores associated with sonographic features aggregate together to calculate the ti-rads level, which extends across TR1 non-threatening benign nodules to TR5 highly threatening malignant nodules [26]. However, extracting sonographic features heavily relies on the radiologist's experience and the diagnostic instruments' capabilities. Consequently, this can make the diagnosis subjective, leading to potential misdiagnosis and thereby contributing to over-treatment [30] [8].

Ultrasound radiomics is a method of analysing ultrasound images and extracting numerical data, named sonographic features, to diagnose the malignancy of thyroid nodules, perform prognostic analysis, or even predict the presence of genetic mutations [17] [1]. The radiomics method is considered a noninvasive, cost-effective, time-saving, and repeatable method. Moreover, radiomics is highly effective in addressing tumour heterogeneity and serves as an intermediate step between imaging and biopsy tests, facilitating a deeper understanding of tumours and thereby enhancing treatment planning for the lesion [19] [28] [20]. Radiomics typically involves a five-step process: data collection, region of interest (ROI) delineation, feature extraction, feature selection, and modelling, with traditional machine learning models being commonly utilized [24].

This paper aims to enhance TC diagnostic accuracy and reduce problems associated with over-diagnosis and unnecessary treatment. To achieve this, we utilized an ultrasound-based radiomics approach and integrated the One-dimensional CNN (1D-CNN) model into our methodology. We used deep learning due to the capability of deep learning compared with traditional machine learning that is usually used in the radiomics method, showing great performance in a load of fields [5] [11] [13] [21]. Fig 1 shows the full proposed approach, which consists of three layers. The first layer involves extracting ultrasound images and their segmentation, then passing them through the PyRadiomics library to obtain sonographic features for ROI in the images. The second layer concatenates sonographic features with metadata attached to the image (i.e., demographic data, size and location information, and acr ti-rads descriptors) by nodule id. Subsequently, it selects the most pertinent features to assess the tumour's condition, utilizing feature selection techniques. Finally, on the thread layer, we build and perform cross-validation to test the model's robustness and validate its performance. The model's code is accessible at `https://github.com/Daizwpa/One-Dimension-CNN-for-thyroid-cancer-diangosis.git`.

The structure of the paper is as follows: Section 2 presents a review of the literature and related works. Section 3 outlines the adopted approach, including detailed methodology and implementation. Section 4 shows the effectiveness and capabilities of the developed model. Finally, section 5 critically examines and discusses the overarching approach, providing insights and reflections on its strengths and limitations.

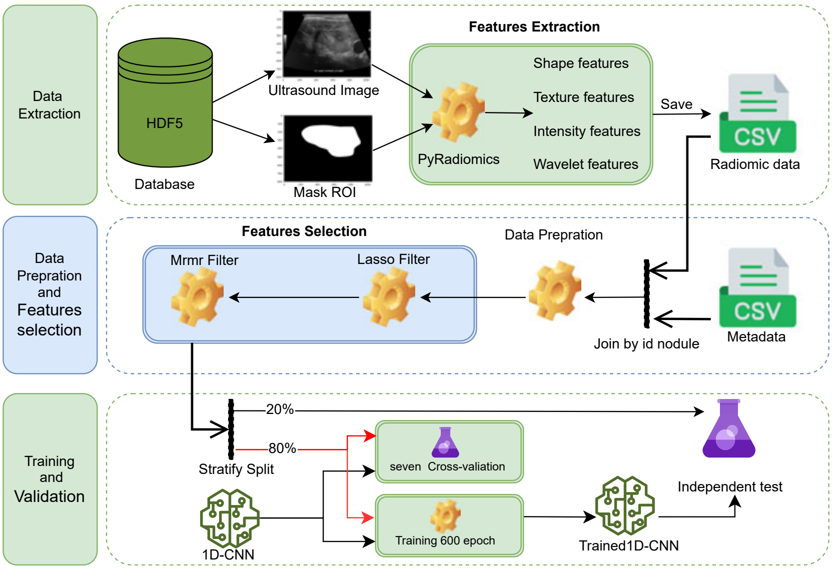

Fig. 1. Full proposed approach.

2 Related work

In this section, exhibiting some applications of machine learning to improve the accuracy of diagnosing malignant thyroid tumours, showcasing the comparison between the capabilities of machine learning and radiologists, along with investigation methods for integration into clinical settings. Table 1 summarises the section.

Pre-operative assessment of thyroid nodules is a crucial task, while 30% of all biopsy tests are categorized as indeterminate cytology type [18], and this one affected the management of surgery and complicated intervention. Zhang et al. compared the performance of the Back Propagation Neural Network (BPNN) with the multivariate logistic regression model. model for the pre-operative assessment of Papillary Thyroid Carcinoma (PTC) malignancy, particularly for tumours categorized as Bethesda III and IV, which are considered indeterminate type tumours. The dataset comprised 2090 TC patients (571 benign, 1519 malignant), incorporating serological, demographic, sonographic, and biopsy features. Statistical analyses such as the Chi-square test, T-test, and multivariate and univariate analyses were adopted to select highly relevant features for PTC malignancy. Multivariate logistic regression and BPNN were trained on the selected features. Both models satisfactorily differentiated PTC from benign cases, with AUCs of 94.8% and 92.4%, respectively. Only the BPNN outperformed the logistic model in specificity, achieving 88.3% and 73.9%, respectively. Their findings underscore the potential and feasibility of utilizing Bethesda categories, ti-rads, nodule size, and serum levels of high-density lipoprotein cholesterol in assessing PTC malignancy, providing valuable insights for clinical decision-making [29].

The inherent subjectivity in decision-making is an inevitable aspect of diagnostics, stemming from variations in instrument settings and expertise levels. Zhou et al. developed a systematic and objective deep learning model called Deep Learning Radiomics of Thyroid (DLRT), which is a pre-trained CNN model from their prior work. The model was transformed to distinguish between malignant and benign thyroid nodules using ultrasound images. DLRT comprises four layers, with the initial three layers representing the transfer model, seamlessly integrated with a fully connected dense layer tailored to address the specific problem. To elucidate the model's insights, they implemented class activation maps to generate heat maps on images. Remarkably, the model achieved impressive AUC scores of 0.96, 0.97 and 0.95 in the train, external and internal cohorts, respectively. Also, they Evaluated the model against two radiologists—one with over 12 years of thyroid diagnosis experience and the other with three years—on both internal and external validation cohorts, which demonstrated the model's superior sensitivity and specificity. The radiologists were completely blinded to the results during this comparison [30].

Affectivity ultrasound-extracted features for malignancy assessment is a controversial task. Arabi et al. highlighted the importance of these features as efficient, cost-effective, and non-invasive biomarkers for thyroid nodule evaluation. The study involved 210 patients (172 benign, 38 malignant) whose images were captured using two different ultrasound machines at two separate centres. Using

LifeX software, they extracted 64 radiomics features from ultrasound images and developed two models: Random Forest (RF) and XGBoost, incorporating them with two selection methods, Lasso and Mrmr. The model shows outstanding performance in differentiating benign and malignant thyroid nodules [2].

Tian et al. developed a pioneering multiscale-level CNN model, named Effective-CNN (E-CNN), tailored for tumour classification, training five versions using breast and thyroid cancer ultrasound image datasets. These versions encompassed E-CNN trained on breast cancer data, thyroid cancer data, a combination of both, and fine-tuned models for cross-application. They introduced a novel cropping algorithm for ROI, customized cross-entropy for imbalanced datasets, and utilized Grad-Cam for heatmap generation. Their models exhibited remarkable performance, showcasing superior learning abilities compared to other CNN architectures in tumour classification tasks [27].

Chen et al. explored the potential of the Light Gradient Boosting Machine by training three versions using radiomics features data, clinical data, and a combination of both, known as radiomics-clinical. To predict papillary microcarcinoma in thyroid nodules categorised as TR3. The radiomics features set, comprising 1477 features extracted by the PyRadiomics library, was narrowed down to 50 through Lasso selection. Clinical data included parameters like age, sex, tumour diameter, echogenicity, and echotexture. They highlighted a superior model trained on radiomics-clinical data, achieving an AUC of 0.898, emphasizing the effectiveness of ultrasound-based radiomics in predicting TR3 microcarcinoma tumors [9].

The literature demonstrates the effort to enhance the diagnosis performance of TC, and the ability of AI to reduce the subjective diagnosis and work as a computer-aided diagnosis system to assist in making the decision and the planning of treatment. Ultrasound-based radiomics combined with other source types of data, proves the strong ability to diagnose micro-carcinoma nodules and even indeterminate cytology nodules. The fusion technique could improve the accuracy and shift the gear to a more precise diagnosis.

Table 1. Summarise table for related work.

Year	Ref	Model	Features selection	Transform learning	Content dataset	Accuracy	AUC	Precision	Recall
2022	[29]	BPNN	No	No	demographic, serological, ultrasound, and biopsy data	NA	0.94	0.88	0.93
2020	[30]	DLRT	No	Yes	ultrasound images	NA	0.97	0.84	0.89
2023	[2]	RF and XGBoost	Mrmr, Lasso	No	ultrasound images	0.89	0.94	NA	NA
2023	[27]	Multiscale-level CNN	No	Yes	ultrasound images	0.94	0.95	0.88	0.95
2024	[9]	LightGBM	Lasso	No	ultrasound images, clinical data	NA	0.89	0.84	0.90

Note: values in the table represent measurements obtained from the test cohort.

3 Material and approach

In this section, we delve deeper into our proposed approach, covering key aspects such as data preparation, model architecture, and dataset description. As previously outlined, our approach comprises three distinct layers. Illustrated in Figure 1, the overarching approach begins with the first layer focused on feature extraction, followed by the second layer dedicated to data preparation and feature selection. Finally, the third layer involves constructing the model and assessing its performance.

3.1 Data preparation

Data preparation is a crucial part of machine learning development, which involves procedures to deal with missed values, splitting datasets into train and test sets, normalization into similar scales, and balancing class to avert bias problems [3]. We divided the dataset into 80% and 20% for training and testing, respectively. The dataset includes only one missed value in size_z column, we patched it with size_x column of the same row. To normalize the dataset, this study divides the features into three types (i.e. categorical, numerical and acr ti-rads description data except ti-rads level). For categorical types e.g. sex and location, we implement one hot coding, while acr ti-rads have a scoring nature, we implement ordinal coding with a min-max scaler. All the rest of the features (e.g. age, size, ti-rads level, and all extracted radiomics features) were processed with a standard scaler. To deal with the imbalanced dataset, we use the oversampling technique on train and test sets separately. The technique duplicates the instance in the set to balance the class in a set.

3.2 Features extraction and Selection

We obtained 487 radiomics features within ROI in an ultrasound image using a PyRadiomics Python library [12]. The features include shape, first order, neighbouring grey tone difference matrix (NGTDM), and grey level matrices (GLCM, GLRLM, GLSZM, GLDM), generated using both original and wavelet filters. To effectively identify features closely linked to the target variable, we employ a combination of Lasso and Mrmr. Initially, Lasso regression was utilized to constrain the feature set to just 190, retaining those with non-zero coefficients. These selected features then underwent further refinement through the Mrmr algorithm, resulting in a final subset of 30 features. Despite attempting the Boruta algorithm, no features were excluded through its application. Fig 2 exhibits the selected features and Pearson correlation coefficient (PCC) for selected features with the result of histopathology diagnosis.

features	PCC
size_x	-0.213760
wavelet-LH_gldm_DependenceEntropy	-0.209130
size_y	-0.184830
wavelet-HL_glszm_HighGrayLevelZoneEmphasis	-0.158281
age	-0.155812
wavelet-HL_glszm_LargeAreaHighGrayLevelEmphasis	-0.154272
wavelet-LH_glszm_LargeAreaHighGrayLevelEmphasis	-0.149555
wavelet-HL_firstorder_Energy	-0.148087
wavelet-HH_glszm_LargeAreaHighGrayLevelEmphasis	-0.143657
original_firstorder_InterquartileRange	-0.139565
size_z	-0.138829
wavelet-HH_glrlm_RunLengthNonUniformity	-0.135904
wavelet-LL_glcm_MCC	-0.115000
wavelet-HH_firstorder_Variance	-0.098976
original_shape2D_Sphericity	-0.079879
original_ngtdm_Coarseness	-0.050857
wavelet-LL_glszm_LargeAreaLowGrayLevelEmphasis	-0.037759
wavelet-LH_glcm_SumEntropy	-0.036344
original_glszm_LargeAreaLowGrayLevelEmphasis	-0.035525
wavelet-HH_glcm_MaximumProbability	-0.003235
wavelet-HH_glrlm_RunLengthNonUniformityNormalized	0.074071
wavelet-HL_firstorder_Median	0.154911
wavelet-HL_glrlm_ShortRunLowGrayLevelEmphasis	0.163737
original_firstorder_Skewness	0.208346
original_firstorder_Kurtosis	0.221436

Fig. 2. List of selected features along with their respective PCC correlated with the histopathology diagnosis results.

3.3 Model and train

In this paper, we prefer to use the radiomics method, regarding its effectivity in the diagnosis state of tumours and Acceptance in clinical practices. Radiomics offers a promising approach to tumour diagnosis that integrates imaging data with advanced computational methods to provide valuable insights into tumour biology, patient management, and treatment outcomes [17] [1]. Typically, the radiomics method employs classical machine learning models. However, integrating CNN into the workflow could potentially augment the method's performance. CNN is widely used in classification problems, especially in images, due to its capability to capture non-linear complex problems and automatic Feature Extraction. This motivates us to implement a one-dimensional version of CNN. Fig 3 shows the full architecture of our 1D-CNN model. In our architecture, we've standardized the kernel size for all convolution and pooling layers at 6. The model utilizes 30 input features, chosen by Lasso and Mrmr algorithms. We performed model training for a total of 600 epochs. The batch size and learning rate were 32, 0.01 respectively. Furthermore, we incorporated scheduler and shuffling techniques to optimize the model training for improved performance and efficiency.

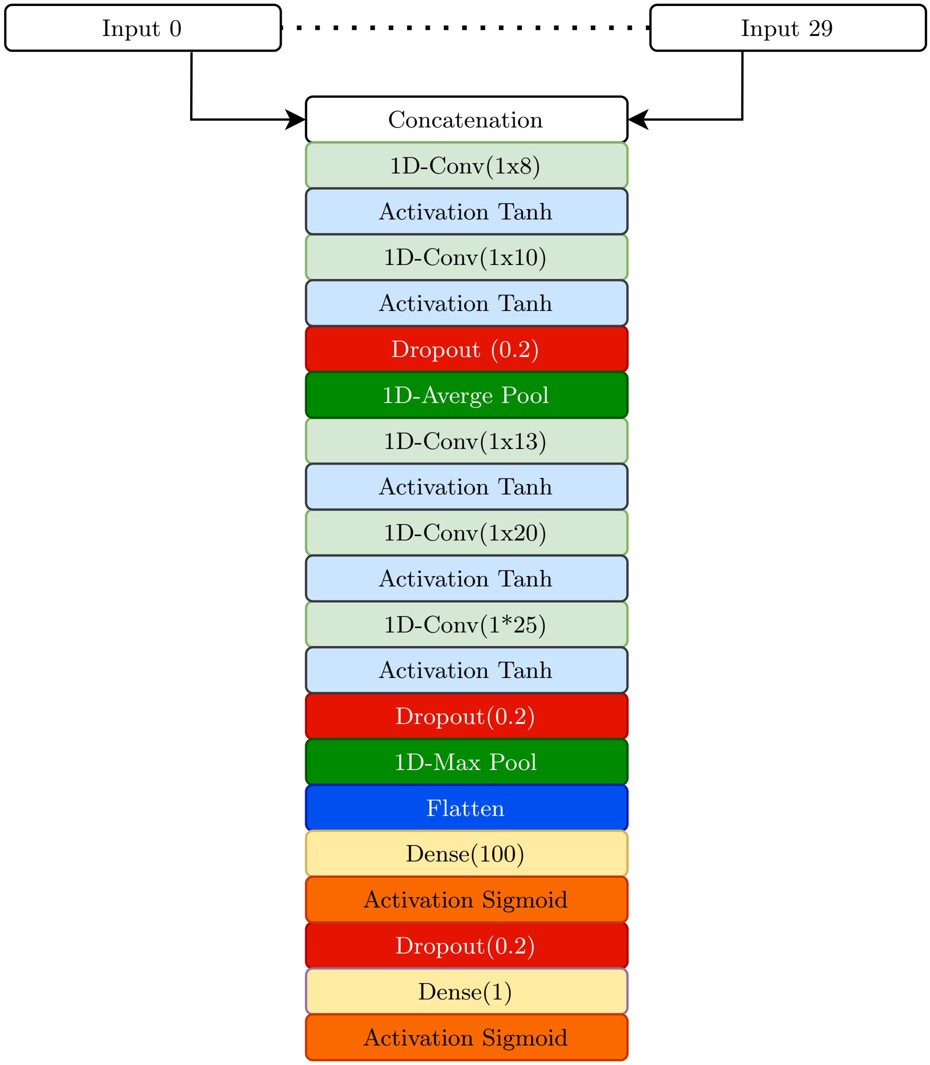

Fig. 3. Full architecture of 1D-CNN model.

3.4 Data description

This study used a Thyroid Ultrasound Cine-clip dataset from Stanford AIMI Shared Datasets, including 17412 ultrasound images of 192 thyroid nodules from

167 patients, which were confirmed by biopsy tests, radiologist-annotated segmentations for ROI, patient demographics (e.g. age and sex), lesion size and location, acr ti-rads descriptors and level, and histopathological diagnosis. The dataset was collected at the Stanford University Medical Center. In this dataset, each image is considered an independent case for analysis.

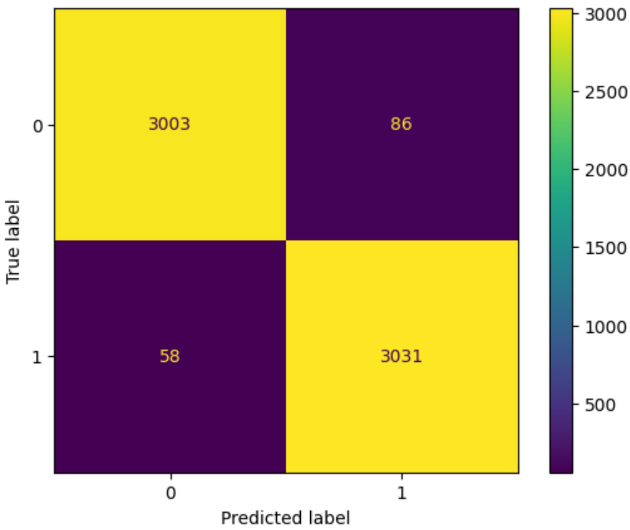

Fig. 4. The confusion matrix generated by the model on the test cohort.

4 Result and experiment

Our model exhibits astonishing performance in validation and independent test sets. Fig 5 and 6 are the standard deviation and the average for the loss function and ROC curves in seven cross-validations. Those curves showcase the capability of the model to learn from the train set and generalize on the validation set and a low rate error on the test set. In the validation set, the model achieved scores of 0.9840, 0.9709, and 0.9980 for accuracy, precision, and recall, respectively. In the test cohort, it achieved scores of 0.9767, 0.9724, and 0.9812 for accuracy, precision, and recall, respectively. Table 2 summarizes the model performance. Fig 4 displays the confusion matrix of the model for the test set. Our training and experimentation were conducted on an Intel I5 12500H machine with 16GB RAM.

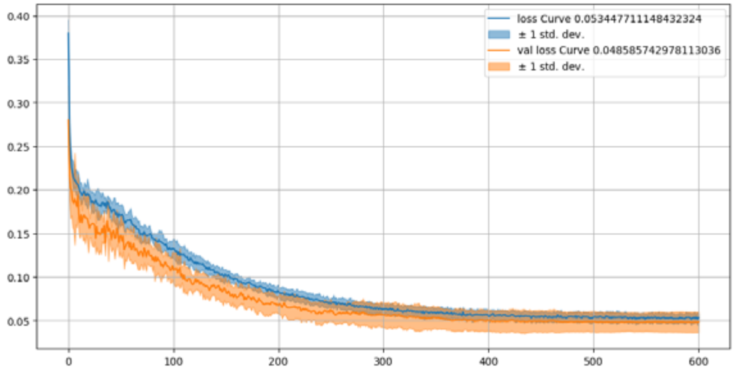

Fig. 5. Average loss function curve and standard deviation through cross-validation in training and validation set.

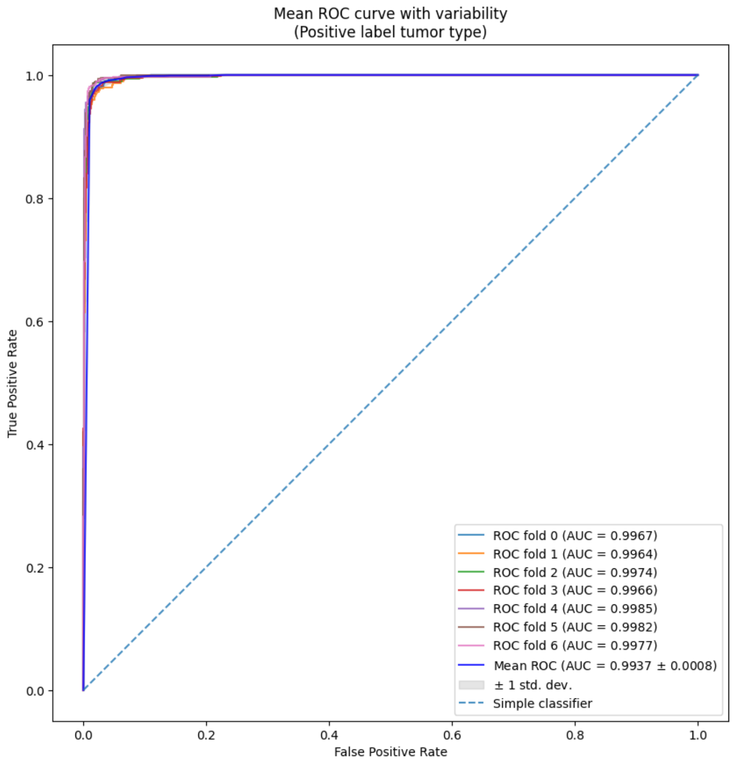

Fig. 6. Average and standard deviation for ROC Curve and AUC through cross-validation in the test set.

5 Discussion

This paper introduces a 1D-CNN model aimed at distinguishing malignant thyroid nodules by leveraging extracted radiomics values, encompassing parameters such as shape, density, texture, and wavelet features, alongside clinical data including age, sex, acr ti-rads descriptors, tumour location, and size. The radiomics features, obtained from the ROI in ultrasound images, are combined with clinical data and subjected to feature selection using Lasso and Mrmr techniques. Despite attempts to reduce dimensionality using the Boruta algorithm with random forest classification, all features selected by Lasso and Mrmr were retained. Before training, we preprocessed the dataset using scalers and encoders, and balanced target classes via oversampling techniques.

Our 1D-CNN model architecture includes five layers of convolution, two layers of pooling, and fully connected dense layers. To evaluate its ability to differentiate malignant nodules, we employed seven cross-validations, yielding average classification accuracy and AUC of 0.9854 and 0.9946, respectively. Furthermore, assessment on an independent test set demonstrated compelling performance, with an accuracy of 0.9766, precision of 0.9724, and recall of 0.9812. Notably, the integration of radiomics with clinical data yields remarkable diagnostic performance, underscoring the robustness and potential of our approach. These findings contribute to the existing literature and affirm the viability of our diagnostic methodology.

The model showcases remarkable performance improvements regarding the mentioned model in the related work section. Table 2 and 1 depicted our model's and other models' performances in related work.

Table 2. Preformance table of our model.

Performance metrics	Validation cohort	Test cohort
AUC	0.99	0.99
Accuracy	0.98	0.97
Recall	0.99	0.98
Precision	0.97	0.97

6 Conclusion

1D-CNN model based on fusion radiomics features with clinical data showed good performance. Also, we emphasize about information fusion technique, and the ability of the 1D-CNN model to solve no-linear problems. However, our study faces some limitations. The first one is the explainability problem, which is a crucial problem that prevents the adoption of those systems in daily clinical practices. Our approach does not involve any explanation method. Most of the research in the radiomics method that involves feature extraction uses classical machine learning due to the interpretability nature of those models. For this one, we plan to incorporate the explainability concept into our further searches. The second limitation is a lack of multi-centre validation test sets, incorporating multi-centre and different ultrasound instruments could help the model to well generalize [14], so further research should direct to construct such a benchmark dataset.

References

1. Agyekum, E.A., guo Wang, Y., Xu, F.J., Akortia, D., zhen Ren, Y., Chambers, K.H., Wang, X., Taupa, J.O., qin Qian, X.: Predicting brafv600e mutations in papillary thyroid carcinoma using six machine learning algorithms based on ultrasound elastography. Scientific Reports **13**, 12604 (8 2023). https://doi.org/10.1038/s41598-023-39747-6, `https://www.nature.com/articles/s41598-023-39747-6`
2. arabi, M., Nazari, M., Salahshour, A., Jenabi, E., Hajianfar, G., Khateri, M., Shayesteh, S.P.: A machine learning-based sonomics for prediction of thyroid nodule malignancies. Endocrine **82**, 326–334 (11 2023). https://doi.org/10.1007/s12020-023-03407-6
3. Belaala, A., Terrissa, L.S., Masry, Z.A., Bourezane, Y., Maouche, I., Remadna, I., Zroug, S., Zerhouni, N.: Enhancing dermoscopy-based skin lesions diagnosis: A fusion of convolutional neural networks and self-training. pp. 192–197. Institute of Electrical and Electronics Engineers Inc. (2023). https://doi.org/10.1109/DASA59624.2023.10286688
4. Bhattacharya, S., Mahato, R.K., Singh, S., Bhatti, G.K., Mastana, S.S., Bhatti, J.S.: Advances and challenges in thyroid cancer: The interplay of genetic modulators, targeted therapies, and ai-driven approaches. Life Sciences p. 122110 (11 2023). https://doi.org/10.1016/j.lfs.2023.122110
5. Boulesnane, A., Saidi, Y., Kamel, O., Bouhamed, M.M., Mennour, R.: Dzchatbot: A medical assistant chatbot in the algerian arabic dialect using seq2seq model (Oct 2022). https://doi.org/https://doi.org/10.1109/pais56586.2022.9946867
6. Bounedjar, A., Melzi, M.A., Idir, H., Heba, N.: General Oncology Care in Algeria, pp. 15–30. Springer Singapore, Singapore (2022). https://doi.org/10.1007/978-981-16-7945-2_2
7. Chen, D.W., Lang, B.H., McLeod, D.S., Newbold, K., Haymart, M.R.: Thyroid cancer (5 2023). https://doi.org/10.1016/S0140-6736(23)00020-X
8. Chen, Y., Gao, Z., He, Y., Mai, W., Li, J., Zhou, M., Li, S., Yi, W., Wu, S., Bai, T., Zhang, N., Zeng, W., Lu, Y., Liu, H.: An artificial intelligence model based on acr ti-rads characteristics for us diagnosis of thyroid nodules. Radiology **303**, 613–619 (6 2022). https://doi.org/10.1148/radiol.211455
9. Chen, Z., Zhan, W., Wu, Z., He, H., Wang, S., Huang, X., Xu, Z., Yang, Y.: The ultrasound-based radiomics-clinical machine learning model to predict papillary thyroid microcarcinoma in ti-rads 3 nodules. Translational Cancer Research **13**, 278–289 (2024). https://doi.org/10.21037/tcr-23-1375
10. Cleere, E.F., Davey, M.G., O'neill, S., Corbett, M., O'donnell, J.P., Hacking, S., Keogh, I.J., Lowery, A.J., Kerin, M.J.: Radiomic detection of malignancy within thyroid nodules using ultrasonography—a systematic review and meta-analysis (4 2022). https://doi.org/10.3390/diagnostics12040794

11. Elbachir, Y.M., Makhlouf, D., Mohamed, G., Bouhamed, M.M., Abdellah, K.: Federated learning for multi-institutional on 3d brain tumor segmentation (Apr 2024). https://doi.org/https://doi.org/10.1109/pais62114.2024.10541292
12. van Griethuysen, J.J.M., Fedorov, A., Parmar, C., Hosny, A., Aucoin, N., Narayan, V., Beets-Tan, R.G.H., Fillion-Robin, J.C., Pieper, S., Aerts, H.J.W.L.: Computational radiomics system to decode the radiographic phenotype. Cancer Res. **77**(21), e104–e107 (Nov 2017)
13. Guia, S.S., Laouid, A., Chait, K.: Categorization of digital pathology image using deep learning model (Dec 2023). https://doi.org/https://doi.org/10.1145/3644713.3644769
14. Guzzo, A., Fortino, G., Greco, G., Maggiolini, M.: Data and model aggregation for radiomics applications: Emerging trend and open challenges (12 2023). https://doi.org/10.1016/j.inffus.2023.101923
15. Habchi, Y., Himeur, Y., Kheddar, H., Boukabou, A., Atalla, S., Chouchane, A., Ouamane, A., Mansoor, W.: Ai in thyroid cancer diagnosis: Techniques, trends, and future directions. Systems **11**, 519 (10 2023). https://doi.org/10.3390/systems11100519, `https://www.mdpi.com/2079-8954/11/10/519`
16. Haugen, B.R., Alexander, E.K., Bible, K.C., Doherty, G.M., Mandel, S.J., Nikiforov, Y.E., Pacini, F., Randolph, G.W., Sawka, A.M., Schlumberger, M., Schuff, K.G., Sherman, S.I., Sosa, J.A., Steward, D.L., Tuttle, R.M., Wartofsky, L.: 2015 american thyroid association management guidelines for adult patients with thyroid nodules and differentiated thyroid cancer: The american thyroid association guidelines task force on thyroid nodules and differentiated thyroid cancer. Thyroid **26**, 1–133 (1 2016). https://doi.org/10.1089/thy.2015.0020
17. Huang, E.P., O'Connor, J.P., McShane, L.M., Giger, M.L., Lambin, P., Kinahan, P.E., Siegel, E.L., Shankar, L.K.: Criteria for the translation of radiomics into clinically useful tests (2 2023). https://doi.org/10.1038/s41571-022-00707-0
18. Kobaly, K., Kim, C.S., Mandel, S.J.: Annual review of medicine contemporary management of thyroid nodules (2021). https://doi.org/10.1146/annurev-med-042220, `https://doi.org/10.1146/annurev-med-042220-`
19. Ling, X., Alexander, G.S., Molitoris, J., Choi, J., Schumaker, L., Mehra, R., Gaykalova, D.A., Ren, L.: Identification of ct-based non-invasive radiomic biomarkers for overall survival prediction in oral cavity squamous cell carcinoma. Scientific Reports **13** (12 2023). https://doi.org/10.1038/s41598-023-48048-x
20. Lu, W.W., Zhang, D., Ni, X.J.: A review of the role of ultrasound radiomics and its application and limitations in the investigation of thyroid disease (2022). https://doi.org/10.12659/MSM.937738
21. Maalem, S., Bouhamed, M.M., Gasmi, M.: A deep-based compound model for lung cancer detection (Oct 2022). https://doi.org/https://doi.org/10.1109/pais56586.2022.9946875
22. Nabhan, F., Dedhia, P.H., Ringel, M.D.: Thyroid cancer, recent advances in diagnosis and therapy (9 2021). https://doi.org/10.1002/ijc.33690
23. Salgado, S.A., Kaye, E.R., Sargi, Z., Chung, C.H., Papaleontiou, M.: Management of advanced thyroid cancer: Overview, advances, and opportunities. American Society of Clinical Oncology Educational Book (5 2023). https://doi.org/10.1200/EDBK_389708
24. Scapicchio, C., Gabelloni, M., Barucci, A., Cioni, D., Saba, L., Neri, E.: A deep look into radiomics. La radiologia medica **126**, 1296–1311 (10 2021). https://doi.org/10.1007/s11547-021-01389-x, `https://link.springer.com/10.1007/s11547-021-01389-x`

25. Siegel, R.L., Miller, K.D., Wagle, N.S., Jemal, A.: Cancer statistics, 2023. CA: A Cancer Journal for Clinicians **73**, 17–48 (1 2023). https://doi.org/10.3322/caac.21763, this talked about cancer in US
26. Tessler, F.N., Middleton, W.D., Grant, E.G., Hoang, J.K., Berland, L.L., Teefey, S.A., Cronan, J.J., Beland, M.D., Desser, T.S., Frates, M.C., Hammers, L.W., Hamper, U.M., Langer, J.E., Reading, C.C., Scoutt, L.M., Stavros, A.T.: 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**, 587–595 (5 2017). https://doi.org/10.1016/j.jacr.2017.01.046
27. Tian, R., Yu, M., Liao, L., Zhang, C., Zhao, J., Sang, L., Qian, W., Wang, Z., Huang, L., Ma, H.: An effective convolutional neural network for classification of benign and malignant breast and thyroid tumors from ultrasound images. Physical and Engineering Sciences in Medicine (9 2023). https://doi.org/10.1007/s13246-023-01262-3
28. Xie, C.Y., Pang, C.L., Chan, B., Wong, E.Y.Y., Dou, Q., Vardhanabhuti, V.: Machine learning and radiomics applications in esophageal cancers using non-invasive imaging methods—a critical review of literature (5 2021). https://doi.org/10.3390/cancers13102469
29. Zhang, X., Ze, Y., Sang, J., Shi, X., Bi, Y., Shen, S., Zhang, X., Zhu, D.: Risk factors and diagnostic prediction models for papillary thyroid carcinoma. Frontiers in Endocrinology **13** (9 2022). https://doi.org/10.3389/fendo.2022.938008
30. Zhou, H., Jin, Y., Dai, L., Zhang, M., Qiu, Y., wang, K., Tian, J., Zheng, J.: Differential diagnosis of benign and malignant thyroid nodules using deep learning radiomics of thyroid ultrasound images. European Journal of Radiology **127** (6 2020). https://doi.org/10.1016/j.ejrad.2020.108992