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ThyroNet A Hybrid Deep Learning Model for Early Prediction of Recurrence in Thyroid Cancer Patients

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Abstract

Thyroid cancer is the most prevalent endocrine malignancy worldwide, and although the majority of patients have a good prognosis, a significant number suffer from disease recurrences. Thus, early detection of patients with high-risk of recurrence is crucial to guide clinical management, individualized treatment, and long-term surveillance. With the increased access to clinical health data, AI and DL have become promising tools for predictive models in medical diagnosis and prognosis. In this work, we introduce ThyroNet, a sophisticated hybrid deep learning model, to predict the recurrence of thyroid cancer with better accuracy by utilizing clinical and pathological features. The proposed ThyroNet model comprises CNN, BiLSTM and DNN layers to model hidden nonlinear correlations and high-level feature interactions among patients' data. The model is trained on a collected thyroid cancer dataset which consists of 383 patient records with 13 clinical attributes such as demographic information, tumor staging details, pathological findings, and treatment information. Before modelling, the categorical features were one-hot encoded, the data were scaled to 0-1 range, and the class imbalance was dealt with using Synthetic Minority Oversampling Technique (SMOTE). Feature patterns of clinical sections were extracted by the CNN layers, while contextual bidirectional dependency of these clinical features were revealed by the BiLSTM layer. Finally, binary classification for recurrence prediction was performed using dense neural layers. Experimental result shows

that the proposed model is good prediction. ThyroNet achieved 99.77% of training accuracy and 94.81% of testing accuracy, indicating its powerful learning and generalization capabilities. Results for the classification on the test data were Precision = Recall = F1 = 0.96 for the non-recurrent class and for the recurrent class Precision = Recall = F1 = 0.91, with an overall weighted F1-score of 0.95. These confirm that the hybrid deep learning architecture is more powerful to capture representative features for predicting recurrence risk in patients with thyroid cancer. With our approach, the developed model may serve as a smart clinical decision support tool to assist early recurrence risk prediction and personalized treatment planning for medical expert. By leveraging hybrid deep learning ThyroNet demonstrates that machine learning has the potential to transform predictive analytics and change the way patients with thyroid cancer are treated.

Keywords: Cancer, Recurrence Prediction, Deep Learning, HNN, CNN, BiLSTM, Clinical Data Analysis, AI in Healthcare

1 Introduction

Thyroid cancer (TC) [1] is one of the most common endocrine malignancies which has experienced a rapidly increasing incidence worldwide during the past several decades. The increase in detection rate was due to the introduction of medical imaging, diagnostic techniques and screening programs; Nevertheless, the survival is generally favorable, many patients relapsed after treatment. Thyroid cancer recurrence may cause complications, further treatments, more medical expenses, and a worse quality of life for patients. Therefore, early detection of patients who are more likely to develop recurrence is valuable for clinicians to tailor the treatments, to offer suitable follow-up, and possibly to improve long-term outcome of patients. Traditional clinical approaches to assessing prognosis are eventually based on the clinical expertise and a small number of prognostic indicators, which might not reflect all of the complex relationships between clinical and pathological variables [2]. As a result, the demand for intelligent predictive models that can assist clinicians in predicting recurrence risk more accurately utilizing the data of existing patients is gradually growing. In the past few years, Artificial Intelligence (AI) [3] and machine learning (ML) [4] techniques have shown great promise in the field of medicine, especially for disease prediction, diagnosis and prognosis evaluation. Some common traditional ML models including logistic regression, decision trees, random forests, support vector machines have also been successfully applied to medical data for prediction. These approaches possess the ability to yield good solutions for many problems; however, their performance may degrade when applied to complex nonlinear relationship with high-dimensional clinical data. Deep learning methods [5], which have the ability to learn hierarchical feature representations directly from the original raw data, have also demonstrated superiority as an alternative tool for predictive modeling in medical applications. Convolutional Neural Network (CNN) can detect meaningful patterns or shapes or local relationships among features, and Recurrent Neural Network (RNN), in particular LSTM, can learn

high-order nonlinear dependencies among sequential or correlated features. The integrated design of the two networks in the hybrid model can also significantly enhance the predictive performance based on merits of the two models [6]. Motivated by these advances, we introduce ThyroNet, a hybrid deep learning predictor for thyroid cancer recurrence using clinical and pathological features in this work. The method is based on CNN and BiLSTM layers as well as a DNN classifier to capture local and contextual relationships between clinical features. The CNN layers learn discriminative feature patterns from the encoded patient features and the BiLSTM layer enables learning of bidirectional feature dependencies, which has been shown to assist models in learning complex interactions among clinical features [7] such as tumor age, pathology type, treatment history and response outcomes. Then, the high-level features transformation and classification are accomplished by the fully connected layers for the prediction of the risk of recurrence. This hybrid structure allows the model to efficiently learn from the heterogeneous clinical data for clinical outcome prediction with high accuracy [8]. The important thing about this study is that it could help the doctors in early prediction of possibility of recurrence and individualized treatment of patients with thyroid cancer. Reliable predictive models may thus help to reduce the burden of unnecessary interventions for the low-risk patients while facilitating closer monitoring/aggressive management of the high-risk patients. Exploiting the power of end-to-end deep learning, our approach enables discovery of complex relationships among clinical attributes that cannot be spotted by traditional statistics. Moreover, predictive schemes such as ThyroNet can potentially trigger development of novel intelligent clinical decision-support systems directly contributing in increasing the effectiveness/reliability of healthcare services [9]. Furthermore, this study advances the state-of-the-art AI solutions for cancer by addressing a hypothyroid cancer recurrence prediction that is an extremely vital but difficult real-world problem. In contrast to classical methods which use one type of machine learning method, the proposed integrated framework combines spatial feature patterns and sequential dependence information in clinical data using convolutional and recurrent neural network models. The study also includes critical preprocessing such as encoding categorical variables, feature scaling, and balancing the classes using SMOTE (Synthetic Minority Oversampling Technique), for tackling class imbalance problems that is prevalent in healthcare datasets. The Performance metrics, e.g., Accuracy, Precision, Recall and F1-score of the proposed model are encouraging in clinical prediction application and the feasibility of application is also testified by case study in the real-world. The novelty of this study is in the development and implementation of a hybrid CNN–BiLSTM deep learning strategy for predicting recurrence based on structured clinical data instead of the conventional imaging-based data. Although numerous prior works are largely based on radiological or genomic information, in this paper, we have shown that significant predictive knowledge can also be obtained from clinical features, including tumor staging information, path type, risk classification and treat response parameters. Leveraging convolutional and bidirectional recurrent neural network-based elements in a single architecture, ThyroNet thus models feature interactions and context dependencies of patient features, leading to higher predictive performance and better generalization.

Our work demonstrates the applicability of hybrid deep learning techniques in healthcare analytics, and paves the way for future work on AI-based clinical decision support systems for cancer prognosis and prediction of recurrence.

The objectives of this research are as follows,

1. To present a hybrid deep learning model (ThyroNet) for the purpose of predicting the recurrence of the thyroid cancer.
2. Preprocessing and conversion of thyroid clinical data for model training.
3. To investigate the influence of clinical and pathologic characteristics on recurrence of thyroid cancer.
4. The assessment of the proposed model is done in terms of the accuracy, and other performance parameters.
5. To offer a predictive instrument, operational in supporting an early detection of recurrence, and useful for clinicians in the decisional process.

2 LITERATURE SURVEY

Penner et al. (2025) [10] studied the implications of the machine learning algorithms to differentiated thyroid cancer patients for recurrence prediction. Their work was dedicated to investigating the clinical and also the pathological features that affect the risk of recurrence and they applied several ML models to pinpoint key predictive factors. The findings indicated that ML algorithms could achieve promising results for the prediction of recurrence by effectively modeling the complex correlations between clinical variables (including tumor stage, treatment response, and patient demographics). The authors emphasized that ML-based predictive models have the potential to help clinicians in the risk stratification and long-term surveillance of thyroid cancer patients. Ahmad and Haddad (2024) [11] study brought a new perspective by focusing on the need for interpretability in clinical decision-making through deep learning models enhanced with explainability methods. The study demonstrated explainable AI techniques that achieve both a high level of accuracy and identify which causes are potentially responsible for the recurrence. This promotes confidence and openness between AI-medical system and medical staff to better understand the process of prediction development and the contribution of the important clinical features purpose of prediction of recurrence. Clark et al.(2024) [12] study employed various classification algorithms on clinical data to evaluate MLs ability to predict recurrence risk. The results indicated that ML-based approaches can provide high predictive accuracy by learning complex nonlinear relationships between patient features and disease outcomes. The authors noted that predictive analytics might be extremely effective for assisting clinicians in detecting patients at risk for early recurrence and, as such, the potential for improved patient management.” Aida et. al (2024) [13] performed a comparative analysis between two algorithms which are ELM and also the HMM for the purpose of predicting recurrence on differentiated thyroid cancer patients. In order to solve the class imbalance problem, which is commonly seen in medical data, was employed to the data. Their experimental results are indicative that the HMM method yields higher predictive accuracy than ELM, i.e., 86.96significance of this – when to make the datasets balanced and not; and which algorithm to choose from

in order to improve prediction accuracy in the best manner on healthcare solutions. Park et al. (2021) [14] built a prediction model for thyroid cancer recurrence using clinicopathological factors based on machine learning. The relevant features were the top 19 features evaluated by the algorithm from the multi-dimension feature space for prediction of recurrence, among different ML models. Their results showed that ML models can reach over 90% accuracy in predictions indicating that the ML based approach is a potential way to derive knowledge from clinical data, as well as to predict prognosis of patients with thyroid cancer. As per above research paper, make a summary of all Research Paper Study as shown in Table 1 indicates the different ML models provide significantly enhancement in prediction performance and clinical decision support. Techniques such as SMOTE have improved performance in the presence of class imbalance, with reported accuracy of 87% and more than 90%. Explainable AI has also improved the interpretability, and thus the trust, of prediction models. Nevertheless, challenges such as few dataset diversities, model interpretability, and need for external validation still remain. Subsequent research is warranted in larger multi-center datasets with more robust AI models, potentially increasing the clinical value of thyroid cancer recurrence prediction system.

3 RESEARCH METHODOLOGY

The adopted research approach is that a comprehensive intelligent DL based prediction model is devised to predict the recurrence of the thyroid cancer patients using the patient clinical and pathological information. The method is designed in stages as follows: data collection, data preprocessing, feature encoding, class balancing, model development, model training, model evaluation [15]. In order to avoid this, each stage of our proposed approach has been carefully crafted so that the final model can accurately capture patterns concealed in clinical data and provide reliable predictions for patients risk of recurrence. We collect and prepare the dataset as the first step of the method. We have a filtered Go dataset for thyroid cancer, which contains 383 patient records and 13 clinical attributes. The important demographic and clinical variables, including age, sex, etc., are covered in this data set [16]. These features are clinically relevant and are regularly used by endocrinologists in evaluating the prognosis of thyroid cancers. The target variable of the dataset is the recurrence status of the patient and it is denoted as “Yes” or “No”. Prior to preprocessing, the dataset was loaded and examined to gain familiarity with its structure, to identify anomalies, and to verify the integrity of the data. Then, data preprocessing and feature engineering [17] is performed to make the dataset ready for deep learning model training. Due to the existence of categorical variables in the dataset (e.g. gender, pathology type, tumor stage), these fields were encoded as numerical values using one-hot encoding. This transformation converts categorical values to binary vectors which effectively enables the deep learning model to process them. Also, the target variable for recurrence was transformed into binary values (1 for recurrence and 0 for no recurrence). Next, Feature scaling has been performed on data using StandardScaler method to normalize the feature values and also to give equal contribution to all the variables during learning. Normalization

Table 1 Different ML Models

Author Name (Year)	Technique	Findings	Limitations
Penner et al. (2025)	Machine Learning algorithms for recurrence prediction using clinical and pathological data demography.	ML models accurately predicted TSR by integrating complicated interactions of tumor stage, response to treatment, and patient demography. Our study demonstrated that ML may help clinicians in risk stratification and long-term follow up of patients with thyroid cancer.	The study relied mainly on available clinical variables and may require larger and more diverse datasets for improved generalization. Interpretability of some ML models may also remain limited.
Ahmad and Haddad (2024)	Explainable Artificial Intelligence (XAI) integrated with Deep Learning	The proposed XAI model achieved high prediction accuracy while providing explanations for the factors influencing recurrence. The study improved transparency and trust in AI-based medical decision systems by highlighting significant clinical features affecting recurrence.	Requirement of large datasets. The explainability techniques may still be complex for non-technical clinicians to fully interpret.
Clark et al. (2024)	Multiple Machine Learning Classification Algorithms for predictive analytics	The study demonstrated that ML algorithms can effectively capture nonlinear relationships between clinical features and disease outcomes, resulting in strong predictive performance for thyroid cancer recurrence risk.	Performance may vary depending on dataset quality and feature selection. The study did not focus deeply on model interpretability or clinical deployment challenges.
Aida et al. (2024)	(ELM) and (HMM) with SMOTE for class imbalance	The study showed that HMM achieved better prediction accuracy (86.96%) compared to ELM. The use of SMOTE improved dataset balance and enhanced model performance in recurrence prediction.	The comparison was limited to two algorithms. SMOTE may introduce synthetic samples that do not perfectly represent real clinical cases.
Park et al. (2021)	Different ML Models	The models used 19 clinicopathological features and achieved over 90% prediction accuracy for thyroid cancer recurrence. The study demonstrated the effectiveness of ML in extracting knowledge from clinical datasets for prognosis prediction.	The model may depend heavily on selected features and dataset characteristics. External validation across different populations was limited.

is needed especially for deep learning models to smoothen gradient updates and speed up convergence during training [18].

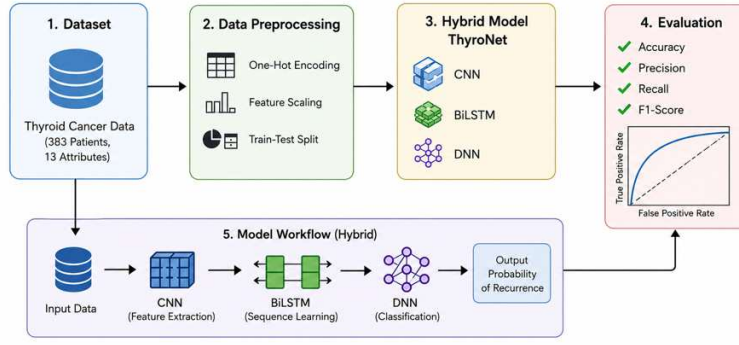


Fig. 1 Research Flow Diagram

The data processing includes dealing with missing values, encoding categorical features, normalizing numerical features and balancing classes by SMOTE [19]. Subsequently the data were divided into 80% for training and 20% for testing [20]. The proposed ThyroNet is a hybrid model that utilizes CNN to extract local information from the input and BiLSTM [21] to capture bidirectional relationships between clinical features. Binary classification is performed using a sigmoid activated dense layer with dropout. The model was trained on with the Adam optimizer and binary cross-entropy loss [22] and tested based on accuracy, precision, recall, F1-score, confusion matrix, ROC curve, Precision Recall curve and training/validation learning curves, which verify its efficiency for thyroid cancer recurrence prediction. Sample body text. Sample body text. Sample body text. Sample body text. Sample body text. Sample body text. Sample body text. Sample body text.

3.1 Convolutional Neural Network (CNN)

CNN [23] is a deep learning-based technique primarily required for the purpose of extraction of the features from the structured or spatial data. CNN uses convolutional layers that convolve the input to extract essential features and to detect patterns and statistical relationships among features. These masks allow the model to learn useful representations for free, without any feature engineering.

3.2 Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTM [24] is an expansion of LSTM to take advantage of the information from both directions of the sequence. Unlike normal LSTM-based model that only goes through the sequence in one direction, Bi-LSTM can have both backward and forward contexts. For the model to learn more richer contextual relations between the features. Here, we use the Bi-LSTM layer to capture the complex interactions among clinical factors such as tumor stage, pathology, treatment response, and recurrence prediction accuracy in our application.

3.3 Deep Neural Network (DNN)

A Deep Neural Network [25] consists of a number of fully connected layers that transform the extracted input features into high level representations in classification or regression tasks. The DNN layers are nonlinear transformations of its input layers, which let the model learn complex associations between the input features and a dependent variable. In our proposed model, DNN layers follow the CNN and Bi-LSTM layers to integrate the captured feature representations and classify(predict) the recurrence of thyroid cancer. This hierarchical design brings more accuracy in prediction and informed decision making.

3.4 Algorithm: Proposed Work

D. Algorithm: Proposed CNN-BiLSTM Framework for Thyroid Cancer Recurrence Prediction

Input: Clinical dataset $D = \{(x_i, y_i)\}_{i=1}^N$, where x_i represents feature vectors and $y_i \in \{0, 1\}$ denotes the recurrence label.

Output: Predicted recurrence probability $\hat{y}$.

Step 1: Data Preprocessing

Convert categorical attributes into numerical representation using one-hot encoding.

Normalize the dataset using standardization:

$$X' = \frac{X - \mu}{\sigma} \quad (1)$$

Balance the dataset using SMOTE to address class imbalance.

Split the dataset into training set D_{train} and testing set D_{test} .

Step 2: CNN Feature Extraction

Apply convolution operation:

$$h_{cnn} = f(W_{cnn} * X' + b_{cnn}) \quad (2)$$

where W_{cnn} denotes convolution weights.

Apply max pooling:

$$p = \max(h_{cnn}) \quad (3)$$

Step 3: Bidirectional LSTM Layer

Forward propagation:

$$\vec{h}_t = LSTM(x_t, \vec{h}_{t-1}) \quad (4)$$

Backward propagation:

$$\overleftarrow{h}_t = LSTM(x_t, \overleftarrow{h}_{t+1}) \quad (5)$$

Combine forward and backward states:

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad (6)$$

Step 4: Dense Neural Network

Generate dense representation:

$$z = f(W_d h_t + b_d) \quad (7)$$

Step 5: Output Layer

Predict recurrence probability using sigmoid activation:

$$\hat{y} = \sigma(W_o z + b_o) \quad (8)$$

where

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

Step 6: Loss Function

Compute Binary Cross-Entropy loss:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (10)$$

Step 7: Model Optimization

Update model parameters using gradient descent:

$$\theta_{t+1} = \theta_t - \alpha \nabla_{\theta} L \quad (11)$$

Return predicted recurrence probability $\hat{y}$.

4 RESEARCH METHODOLOGY

4.1 Dataset

The dataset which we used in our experiments is a curated thyroid cancer clinical dataset based on real-world data to facilitate prediction of thyroid cancer recurrence by employing deep learning methods. It includes 383 patient records with 13 clinical features, which are key demographic information, pathological information and treatment information of patients with thyroid cancer. The age, sex, history of radiotherapy and adenopathy, pathology type, focality etc.. are also included in the dataset. These features are commonly used in clinical practice to predict prognosis and risk of recurrence in thyroid cancer patients. The data are composed of numerical and categorical features, which were properly encoded and preprocessed for model training. The label ‘‘Recurred’’ identifies if the patient had a re-occurrence of cancer post treatment or not and is a binary class (Yes/No). This dataset has a significant clinical information which enables – the proposed ThyroNet hybrid deep model to capture the patterns of recurrence risk to help in early prediction and clinical decision-making for thyroid cancer treatment.

Table 2 Description of Dataset Attributes

Attribute	Description
Age	Age of the patient at the time of diagnosis.
Gender	Gender of the patient (Male/Female).
Hx Radiotherapy	Indicates whether the patient previously received radiotherapy.
Adenopathy	Presence of lymph node enlargement related to thyroid cancer.
Pathology	Histological type of thyroid cancer.
Focality	Indicates whether the tumour is unifocal or multifocal.
Risk	Risk classification of the patient based on clinical assessment.
T	Tumour size and extent according to the TNM classification.
N	Lymph node involvement according to the TNM staging system.
M	Presence or absence of distant metastasis.
Stage	Overall stage of thyroid cancer based on the TNM classification.
Response	Patient response to treatment.
Recurred	Target variable indicating recurrence of thyroid cancer (Yes/No).

The above table II displays the list of clinical features used in the thyroid cancer dataset with their descriptions. These were demographic, pathological, tumour staging, and treatment-related factors that influence risk of recurrence. These features provide full details about the patient’s condition and disease. With these features, our proposed ThyroNet deep model can effectively learn the clinical variable-recurrence association for predicting the recurrence of thyroid cancer.

4.2 Performance Analysis

The confusion matrix for the proposed ThyroNet on the testing set is shown in figure 2. The matrix contains information about the number of correct and wrong predicted samples for recurrence class and non-recurrence class. Of the 53 non-recurrence and 20 recurrence cases were correctly classified by the model, with 2 misclassifications in each class, which indicated a strong predictive power and a balanced classification ability.

The Figure 3 is the training and validation accuracy of the ThyroNet model for 150 training epochs. From the figure, we can see that the training and validation accuracies rise slowly and tend to level off at 100 percent, which indicates that the model learns the patterns well from the dataset, and achieves a good generalization performance.

In Figure 4, shows the training vs validation loss graphs to understand the model performance.

The ROC curve in Figure 5 is is ROC curve for TPR Vs FPR and shows AUC of .97 Training results in Table 3 of ThyroNet show that it is an excellent learner with 100% accuracy and precision, recall, and F1-score are 1.00 in both recurrence and non-recurrence classes. The SMOTE-constructed balanced dataset made the model learn

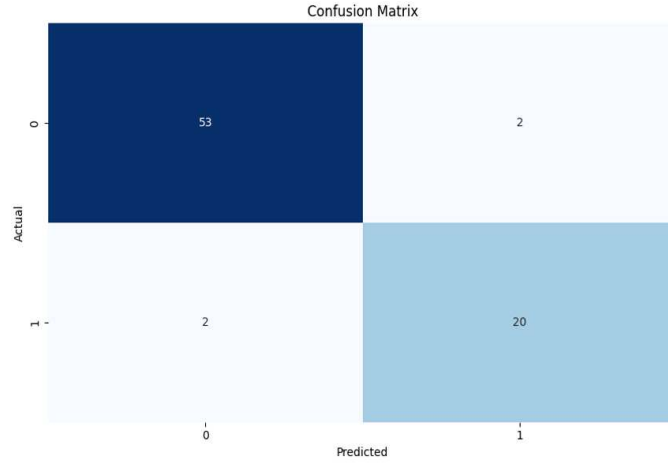


Fig. 2 Confusion Matrix [Implementation]

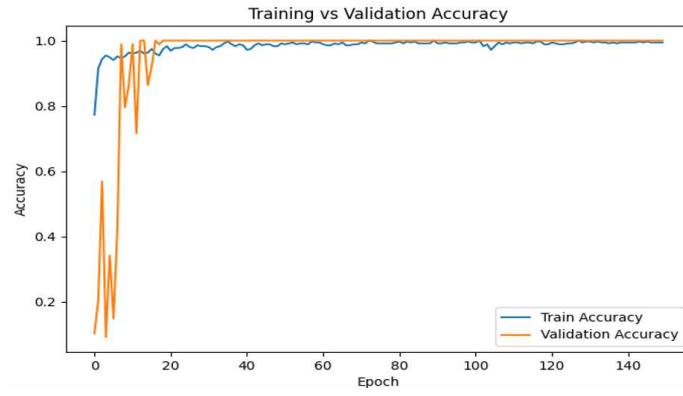


Fig. 3 Training vs Validation Accuracy curve over the epochs

Table 3 Performance Evaluation of ThyroNet on Training Dataset

Class	Precision	Recall	F1-Score	Support
Non-Recurred (0)	1.00	1.00	1.00	220
Recurred (1)	1.00	1.00	1.00	220
Accuracy	—		1.00	440
Macro Avg	1.00	1.00	1.00	440
Weighted Avg	1.00	1.00	1.00	440

both classes in a balanced manner. These results show that the hybrid CNN-BiLSTM

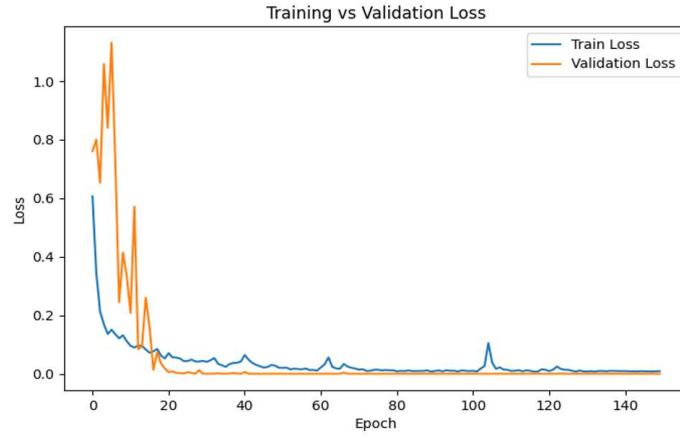


Fig. 4 Training Vs Validation Loss

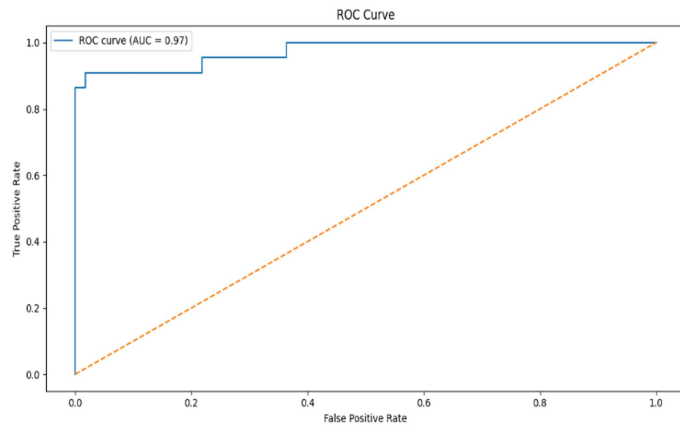


Fig. 5 Receiver Operating Characteristic (ROC) Curve

framework enables modeling complex clinical feature relationships. Although the training performance is perfect, the model needs to be evaluated on unseen test data to verify its generalization ability and to prevent overfitting.

Table 4 Performance Evaluation of ThyroNet on Testing Dataset

Class	Precision	Recall	F1-Score	Support
Non-Recurred (0)	0.96	0.96	0.96	55
Recurred (1)	0.91	0.91	0.91	22
Accuracy			0.95	77
Macro Avg	0.94	0.94	0.94	77
Weighted Avg	0.95	0.95	0.95	77

The testing results in Table 4 indicate that our proposed ThyroNet method has a good generalization towards unseen patient and the accuracy is overall 94.81%. The results were 96% precision, recall and F1 for the nonrecurrence class and 91% precision, recall and F1 for the recurrence class, which implies reasonably reliable prediction performance in both classes. The macro F1-score (0.94) and weighted F1-score (0.95) indicate balanced classification also. In summary, these findings demonstrate that the hybrid CNN–BiLSTM–DNN model can serve as a powerful tool for predicting thyroid cancer recurrence, suggesting that it has considerable capability to assist clinicians with early recurrence risk prediction and treatment planning.

Table 5 Comparison with Previous Research

Study	Method Used	Dataset Type	Key Contribution	Accuracy
Park et al. (2021)	Random Forest, SVM, Neural Network	Clinicopathological thyroid dataset	Developed an ML-based prediction model for thyroid cancer recurrence using clinical features.	90%
Aida et al. (2024)	ELM, HMM with SMOTE	Differentiated thyroid cancer dataset	Compared probabilistic and neural algorithms for recurrence prediction.	86.96%
Clark et al. (2024)	Multiple Machine Learning Algorithms	Clinical dataset	Applied predictive analytics for thyroid cancer recurrence risk prediction.	91–92%
Ahmad & Haddad (2024)	Explainable AI Deep Learning Model	Clinical dataset	Introduced an explainable AI model to improve interpretability of recurrence prediction.	96%
Penner et al. (2025)	Machine Learning with Feature Selection	Differentiated thyroid cancer dataset	Identified key predictive clinical features influencing recurrence risk.	95%
Proposed Study (ThyroNet)	Hybrid CNN + BiLSTM + DNN	Thyroid clinical dataset (383 patients)	Hybrid deep learning architecture capturing feature interactions and contextual dependencies for thyroid cancer recurrence prediction.	94.81%

The above table 5 presents a comparison of the ThyroNet hybrid deep learning model with other state-of-the-art approaches for prediction of thyroid cancer recurrence. The comparative overview of the methods include the applied methodologies, data utilized, and the reporting predictive performances. Early work such as that of Park et al. (2021) Traditional machine learning algorithms, such as RF, SVM and neural network classifiers, were used in most of the early studies (Park et al. 2021). They found that machine learning models can be used to accurately analyze clinicopathological features for prediction of recurrence with an accuracy 90%. While all of these models showed great potential, they were not powerful enough to account for complex nonlinear associations among clinical variables. On the other hand, recently, there have been investigations that aimed at increasing the predictive performance by means of more sophisticated algorithms and/or advanced data preprocessing techniques. For instance, Aida et al. (2024) assessed the ELM and HMM methods for the purpose of predicting recurrence in the case of differentiated thyroid cancer patients.

With their investigations, Schlaf et al, (2009) obtained the prediction accuracy of 86.96 %, where SMOTE was also employed to balance the data set. This solution can provide a balanced data set and more reliable classification results, but the constructed model is shallow and may not be capable of extracting extremely hidden clinical knowledge. Also, Clark et al. (2024) investigated predictive analytics with various machine learning approaches in risk prediction of thyroid cancer recurrence.

Their results indicated that the ML techniques were able to reach 91-92% prediction accuracy, demonstrating that the data-driven approach might be an effective method to predict recurrence risk. However, this approach is heavily centered on traditional ML techniques and does not incorporate DL architectures for learning hierarchical features representations. On the a separate note, scarcely 96% accuracy was obtained in an interpretable deep learning model introduced by Ahmad and Haddad(2024) focusing on sidewalk trafficability. Their results emphasized the need to create a clinically interpretable AI system that would enable clinicians to understand the foundations of the predictions. In the same way, Penner et al. (2025) also show that models can predict risk of recurrence with as much as with 95% accuracy while using feature selection methods. Proposed model approaches are better compared with the preceding aforementioned techniques. The CNN layer is responsible for learning informative feature patterns from the encoded patient information, the BiLSTM layer captures bidirectional dependencies between clinical factors like tumor stage, pathology type, treatment response, etc. The dense neural layers then execute high-level feature transformation and classification. This model reached 94.81% testing accuracy, which is comparable with those state-of-the-art methods in the literature. Unlike conventional machine learning models, ThyroNet directly learns feature representations from data, so that the manual effort in designing features can be avoided. In addition, the combination of CNN and BiLSTM layers enables the model to represent high-level nonlinear interactions among clinical variables. In summary, the comparison study demonstrates that our developed hybrid deep learning framework offers a powerful and promising solution for prediction of recurrence of transition papillary thyroid cancer and can help saving patients in clinical decisions.

Figure 6 illustrates the comparison of prediction accuracy among various models of thyroid cancer recurrence in the literature. Traditional machine learning based methods reported accuracy ranging from 86.96% to 92%, while more sophisticated deep learning and explainable AI models achieved accuracy of 95–96%. The proposed ThyroNet model attains a testing accuracy of 94.81% which is better than most of the traditional machine learning techniques and comparable to recent state-of-the-art technique. The findings conclude that the proposed hybrid CNN–BiLSTM–DNN model well captures the complicated clinical temporal dynamics and is trustworthy to predict thyroid cancer recurrence.

5 CONCLUSION

In this study, we introduced ThyroNet, a deep learning network based on CNN, BiLSTM and DNN for prediction of thyroid cancer recurrence with clinical + pathological

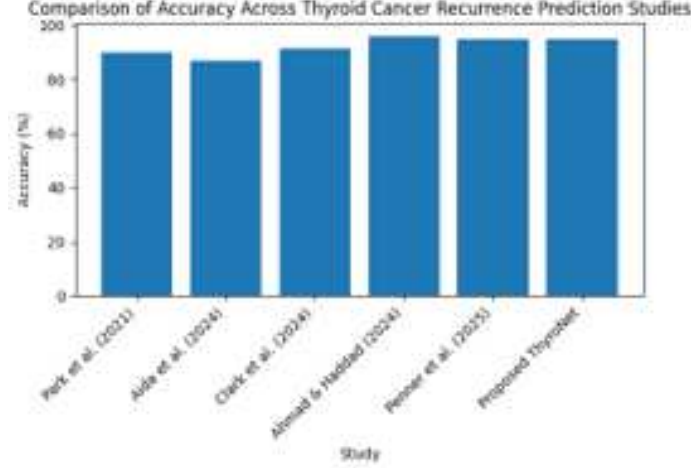


Fig. 6 Accuracy Comparison Graph

data. As a result of preprocessing, resampling using SMOTE and class balanced learning, the model had precision of 99.77% for training, and 94.81% for testing, with AUC of about 0.97 and the model was robust high precision, high recall, and high F1-score. These findings suggest that ThyroNet can serve as a feasible clinical decision support tool to predict patients at high-risk for recurrence. It is worth noting that our future work will involve further validation using larger multi-center datasets or incorporating medical imaging with multimodal learning, incorporating explainable AI (XAI) to enhance interpretability, and investigating advanced architectures such as attention mechanisms, transformers, and graph neural networks to push the performance of prediction even further.

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- Funding : NA
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- Ethics approval and consent to participate : NA
- Consent for publication : NA
- Data availability : The dataset used in this study is publicly available (<https://www.kaggle.com/datasets/ankushpanday2/colorectal-cancer-global-dataset-and-predictions>).
- Materials availability: NA
- Code availability : code used in this research is available with corresponding author
- Author contribution: All authors contributed equally.

References

- [1] Marion, I., Schulz, S., Glasner, C., Kather, J.N., Truhn, D., Eckstein, M., Mueller, C., Fernandez, A., Marquard, S., Metzger, M.O., Roth, W., Gaida, M.M., Strobl,

- S., Wagner, D.-C., Schad, A., Jesinghaus, M., Hartmann, N., Musholt, T.J., Staubitz-Vernazza, J.I., Foersch, S.: Deep learning discovers new morphological features while predicting genetic alterations from histopathology of papillary thyroid carcinoma. *Thyroid* **35**(7), 771–780 (2025) <https://doi.org/10.1089/thy.2024.0691>
- [2] Nakamura, Y., Nishimura-Yano, Y., Nishimura, M., Kokubo, T., Daino, K., Takabatake, M., Imaoka, T.: Spontaneous and radiation-induced mammary and thyroid tumorigenesis in *lew* and *(sd×cop) f1 brca1l63x/+* rats. *Anticancer Research* **45**(11), 4869–4880 (2025)
- [3] Kobayashi, N., Nakaura, T., Yoshida, N., Nagayama, Y., Kidoh, M., Uetani, H., Hirai, T.: Impact of deep learning reconstruction on radiation dose reduction and cancer risk in ct examinations: A real-world clinical analysis. *European Radiology* **35**(6), 3499–3507 (2025)
- [4] Germer, S., Sauerberg, M., Johanns, O., Rudolph, C., Gundler, C., Meisegeier, S., Abnaof, K., Kim-Wanner, S.-Z., Krauß, A., Langholz, M., Luttmann, S., Rath, N., Rausch, K., Katalinic, A., Handels, H., Nennecke, A., Kusche, H.: Harmonizing regional cancer registry data to facilitate germany-wide epidemiological analyses. *International Journal of Medical Informatics* **220**, 106586 (2026) <https://doi.org/10.1016/j.ijmedinf.2026.106586>
- [5] Gräfe, W., Scheibe, S., Schwarz, J., Liebig, L., Voigt, K., Schübel, J.: The myth of iodine: A systematic review and meta-analysis on the relationship between iodine and thyroid nodule. *Journal of Endocrinological Investigation*, 1–14 (2025)
- [6] Kim, J., Kim, M.-H., Lim, D.-J., Lee, H., Lee, J.J., Kwon, H.-S., Kim, M.K., Song, K.-H., Kim, T.-J., Jung, S.L., Lee, Y.O., Baek, K.-H.: Deep learning technology for classification of thyroid nodules using multi-view ultrasound images: Potential benefits and challenges in clinical application. *Endocrinology and Metabolism* **40**(1), 216–224 (2025) <https://doi.org/10.3803/EnM.2024.2058>
- [7] Vahdati, S., Khosravi, B., Robinson, K.A., Rouzrokh, P., Moassefi, M., Akkus, Z., Erickson, B.J.: A multi-view deep learning model for thyroid nodules detection and characterization in ultrasound imaging. *Bioengineering* **11**(7), 648 (2024) <https://doi.org/10.3390/bioengineering11070648>
- [8] Zhao, H., Zheng, C., Zhang, H., Rao, M., Li, Y., Fang, D., Huang, J., Zhang, W., Yuan, G.: Diagnosis of thyroid disease using deep convolutional neural network models applied to thyroid scintigraphy images: A multicenter study. *Frontiers in Endocrinology* **14**, 1224191 (2023) <https://doi.org/10.3389/fendo.2023.1224191>
- [9] Ram Kumar, R.P., Sri Lakshmi, M., Ashwak, B.S., Rajeshwari, K., Zaid, S.M.: Thyroid disease classification using machine learning algorithms. In: *E3S Web of Conferences*, vol. 391, p. 01141 (2023). <https://doi.org/10.1051/e3sconf/202339101141>

- [10] Penner, M.A., *et al.*: Machine learning in differentiated thyroid cancer recurrence prediction. *Applied Sciences* **15**(17), 9397 (2025) <https://doi.org/10.3390/app15179397>
- [11] Ahmad, M.A.S., Haddad, J.: An explainable ai model for predicting the recurrence of differentiated thyroid cancer. *arXiv preprint* (2024) [arXiv:2410.10907](https://arxiv.org/abs/2410.10907) [cs.LG]
- [12] Clark, E., *et al.*: Predictive analytics for thyroid cancer recurrence: A machine learning approach. *Knowledge* **4**(4), 557–570 (2024) <https://doi.org/10.3390/knowledge4040029>
- [13] Aida, N., Saragih, T.H., Kartini, D., Nugroho, R.A., Nugrahadi, D.T.: The comparison of extreme learning machine and hidden markov model algorithm in predicting the recurrence of differentiated thyroid cancer using smote. *Journal of Electronic, Electromedical Engineering and Medical Informatics* **6**(4), 429–444 (2024) <https://doi.org/10.35882/jeeemi.v6i4.467>
- [14] Park, Y.M., *et al.*: Machine learning-based prediction model using clinicopathological features for thyroid cancer recurrence. *Scientific Reports* **11**(1), 4948 (2021) <https://doi.org/10.1038/s41598-021-84504-2>
- [15] Ketschau, J., Grabenhorst, A., Singer, H., Ritschl, L.M.: Deep learning for pre-therapeutic tumor and nodal classification in head and neck squamous cell carcinoma: A systematic review and network meta-analysis. *SSRN Electronic Journal* (2025) <https://doi.org/10.2139/ssrn.5953242>
- [16] Grothey, B., Odenkirchen, J., Brkic, A., Schömig-Markiefka, B., Quaas, A., Büttner, R., Tolkach, Y.: Comprehensive testing of large language models for extraction of structured data in pathology. *Communications Medicine* **5**(1), 96 (2025) <https://doi.org/10.1038/s43856-025-00895-z>
- [17] Yang, N., Li, K., Liu, B., Chen, X., Jiang, A., Qi, C., others, Luo, P.: Decision-making performance of large language models vs. human physicians in challenging lung cancer cases: A real-world case-based study. *Intelligent Oncology*, 100039 (2026) <https://doi.org/10.1016/j.inton.2026.100039>
- [18] Liu, Y., Qu, J., Hu, C., Zhao, W., Zhang, Y., Luo, Y., Qu, Y.: Relationship between red cell distribution width and lung cancer: Evidence from mendelian randomization and national health and nutrition examination survey. *Discover Oncology* **16**(1), 867 (2025) <https://doi.org/10.1007/s12672-025-02092-5>
- [19] Brown, J.D., Lenchik, L., Doja, F., Kaviani, P., Judd, D., Probyn, L., others, Retrouvey, M.: Leveraging large language models in radiology research: A comprehensive user guide. *Academic Radiology* (2025) <https://doi.org/10.1016/j.acra.2025.05.020>
- [20] Wagner, J., Oldenburg, J., Nath, N., Simm, S.: Explainable ai model reveals

- informative mutational signatures for cancer-type classification. *Cancers* **17**(11), 1731 (2025) <https://doi.org/10.3390/cancers17111731>
- [21] Yoon, C., Park, E., Kim, D., Park, B., Kim, C.: Label-free optical microscopy with artificial intelligence: A new paradigm in pathology. *Biophotonics Discovery* **2**(2), 020901 (2025) <https://doi.org/10.1117/1.BIOS.2.2.020901>
 - [22] Nißler, D., Reimers-Kipping, S., Ingwersen, M., Berger, F., Niekrenz, F., Theis, B., others, Franiel, T.: Artificial intelligence-assisted biparametric mri for detecting prostate cancer: A comparative multireader multicase accuracy study. *Journal of Clinical Medicine* **14**(17), 6111 (2025) <https://doi.org/10.3390/jcm14176111>
 - [23] Zheng, G., Wei, P., Li, D., Li, X., Zafereo, M., Li, C., others, Li, G.: A deep learning survival model for evaluating the survival prognosis of papillary thyroid cancer: A population-based cohort study. *Annals of Surgical Oncology* (2025) <https://doi.org/10.1245/s10434-025-17592-4>
 - [24] Aytaç, Z.İ., İşeri, İ., Dandil, B.: A hybrid coot-based cnn model for thyroid cancer detection. *Computer Standards & Interfaces* **92**, 104018 (2025) <https://doi.org/10.1016/j.csi.2025.104018>
 - [25] Sun, Y., Jia, Y., Fu, K., Yang, X., Wang, P., Yuan, Z.: Global thyroid cancer patterns and predictive analytics: Integrating machine learning for advanced diagnostic modelling. *Journal of Cellular and Molecular Medicine* **29**(13), 70676 (2025) <https://doi.org/10.1111/jcmm.70676>