Assessing the Effectiveness of Le Net in Detecting Thyroid Malignancies

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ABSTRACT : *This research addresses the imperative need for early detection of thyroid malignancy, emphasizing the thyroid gland's pivotal role in regulating physiological functions. Leveraging Convolutional Neural Networks (CNNs), specifically the LeNet model, exhibits promise in thyroid malignancy detection due to its success in computer vision tasks and adeptness in multi-class classification. Employing the Digital Database of Thyroid Ultrasound Images (DDTI) and adopting the Thyroid Imaging Reporting and Data System (TIRADS) for patient classification, the LeNet model undergoes rigorous evaluation. The study reveals a 60% overall accuracy with exceptional specificity and positive predictive value, signifying proficiency in identifying benign cases. However, a noteworthy sensitivity limitation (11.11%) prompts the need for refinement in accurately detecting malignant cases. A 57.89% negative predictive value underscores potential for improvement, necessitating consideration of adjustments such as fine-tuning or dataset augmentation for enhanced model performance, particularly in sensitivity and negative predictive value.*

KEYWORDS – *Convolutional Neural Networks (CNNs), Image classification, LeNet, Malignancy (CNNs), Thyroid*

I. INTRODUCTION

The thyroid gland is an essential endocrine gland located in the neck [1]. It consists of two lobes connected by an isthmus and is responsible for producing and releasing thyroid hormones that regulate various bodily functions. These hormones, triiodothyronine (T3) and thyroxine (T4), are derived from tyrosine and play a vital role in metabolism, energy regulation, and the normal functioning of organs and systems throughout the body [2]. The proper functioning of the thyroid gland is crucial for maintaining overall health and well-being [3]. Thyroid malignancy, or thyroid cancer, can have various reasons such as genetic factors, exposure to radiation, or certain pre-existing thyroid conditions [4]. The effects of thyroid malignancy can range from a low degree of malignancy with a good prognosis to invasive and potentially life-threatening cancers [5]. For this reason, early detection of thyroid malignancy becomes necessary.

Convolutional Neural Networks have emerged as a powerful tool for various image analysis tasks, including medical image classification [6]. Their ability to automatically learn and extract relevant features from images makes them particularly well suited for tasks such as thyroid malignancy detection, where accurate analysis of medical images is crucial for diagnosis and treatment planning [7]. By leveraging the hierarchical nature of CNNs, these networks can effectively analyze different aspects of thyroid imaging data, such as texture, shape, and structural patterns [8].The LeNet model, a specific type of Convolutional Neural Network, has several benefits for thyroid malignancy detection.First, the LeNet model is widely used in computer vision tasks and has a proven track record of success [9]. Its architecture, consisting of alternating convolutional and pooling layers, allows for effective feature extraction and dimensionality reduction [10]. Furthermore, the LeNet model's capability to handle multi-class classification tasks is beneficial for thyroid malignancy detection, as it allows for the differentiation of benign and malignant thyroid nodules [11].

In this study, the performance of LeNet is scrutinized for its effectiveness in detecting thyroid malignancies. The evaluation metrics encompass accuracy, sensitivity, specificity, positive predictive value and negative predictive valueserving as comprehensive indices of performance.

II. LITERATURE SURVEY

Ma et al. [12] devised a model built on cascade deep convolutional neural networks (CNNs), featuring two distinct CNNs and an innovative splitting approach. The initial CNN utilized ground truth data to acquire knowledge of segmentation probability maps. Subsequently, a splitting method was implemented to partition the segmentation probability maps into various relevant sections. Finally, the second CNN was deployed for the automatic detection of thyroid tumors from sonographic thyroid images.Liu et al. [13] conducted the transfer of a CNN model trained on a considerable standard dataset to a new ultrasound image dataset, addressing the challenge of limited samples. This approach facilitated the extraction of high-level deep features. The integration of semantic deep features with conventionally obtained low-level features resulted in the formation of a blended feature plot.Chi et al. [14] employed feature extraction by fine-tuning the pre-trained GoogleLeNet model. Subsequently, these features were fed into a Random Forest classifier for the classification of images into cancerous and non-cancerous cases.Ko SY et al. [15] developed a deep convolutional neural network that exhibited diagnostic performance on par with experienced radiologists.Peng et al. [16] introduced ThyNet, a deep learning AI model designed for the diagnosis and management of thyroid nodules. This model underwent evaluation in a multicenter diagnostic study. Chan et al. [17] conducted the retraining of InceptionV3, ResNet101, and VGG19 convolutional neural networks (CNNs) through transfer learning. The objective was to classify thyroid tumors as either malignant or benign.Clark et al. [18] utilized a supervised deep learning classifier, adapting the BiT-M ResNet-50x1 architecture for the differentiation of benign and malignant thyroid nodules. The model incorporated pretrained weights from the ImageNet-21k dataset, with fine-tuning applied to specific blocks.Qi et al. [19] introduced the Mask-RCNN18 network model, which integrates ResNet and FPN for feature extraction. The model utilizes RPN for classification and bounding box regression for ROI generation, specifically designed for the detection of extrathyroidal extension in cases of thyroid cancer.

III. MATERIAL AND METHODS

This segment is structured into three main parts: dataset ,data preprocessing, LeNet Model.

3.1. Dataset

This research utilizes the Digital Database of Thyroid Ultrasound Images (DDTI), a publicly accessible dataset comprising 347 B-mode thyroid ultrasound images. Radiologists employ the Thyroid Imaging Reporting and Data System (TIRADS) for patient classification in this study [20].

3.2. Data Preprocessing

The images undergo cropping to specific dimensions, ensuring that the cropped region retains a square shape. Following this, the images are converted to a single channel to ensure data consistency, decrease dimensionality, and facilitate grayscale-specific processing by transforming RGB images into grayscale. A series of further image processing operations, such as thresholding, denoising, contour detection, and resizing, is employed to produce processed images, prepared for subsequent analysis or application

3.3. LeNet Model

In the field of computer vision, LeNet is a notable model architecture that played a crucial role in shaping the deep learning landscape. Introduced in 1998 by YannLeCun et al, the LeNet model architecture was one of the pioneering convolutional neural networks that revolutionized image processing and recognition tasks [21].LeNet consisted of a series of convolutional and pooling layers, followed by fully connected layers. The LeNet model architecture had a total of seven layers. These layers included two convolutional layers, each followed by a max-pooling layer, and then three fully connected layers. The LeNet model architecture made use of convolution, parameter sharing, down-sampling, and fully connected neural networks [22]. These operations helped LeNet extract features and perform classification and recognition tasks efficiently while minimizing computational costs. Furthermore, the LeNet model architecture employed a specific set of parameters to optimize its performance. These parameters included the use of ReLU activation functions, maxpooling, and dropout after the dense hidden layer [23].

Table 1: LeNet architecture

Layer	Filters/neurons	Filter Size	Stride	Size of feature map	Activation function
Input	-	-	-	32X32 X1	
Conv 1	6	5*5	1	28X28 X6	tanh
Avg.pooling 1		2*2	2	14X14 X6	
Conv 2	16	5*5	1	10X10 X16	tanh
Avg.pooling 2		2*2	2	5X5X16	
Conv 3	120	5*5	1	120	tanh
Fully Connected 1	-	-	-	84	tanh
Fully Connected 2	-	-	-	10	Softmax

IV. EXPERIMENTAL RESULTS

This section presents a thorough examination of the conducted experiments and their results, covering three essential components: the experimental setup, evaluation indices, and the discussion of results.

4.1. Experimental Setup

The experiment was conducted on a computer equipped with an NVIDIA RTX A5000 graphics card with 24 gigabytes (GB) of GPU memory. The experimental configuration runs on a 64-bit Windows 10 operating system. The deep learning environment is built on Python 3.10 and Keras 2.3.1, utilizing TensorFlow GPU 1.16 as the backend.

4.2. Evaluation Indexes

a) Accuracy - This metric is determined by the ratio of correctly classified cases to the overall count of cases.
ACCURACY= (TNC+ TPC)/ (TNC+ TPC+ FNC +FPC);
Where, TNC=True negative cases tally; TPC= True positive cases tally; FNC=False negative cases tally; FPC=False positive cases tally

b) Sensitivity - This metric gauges the capability of a classification system to accurately detect malignant cases.
SENSITIVITY=TPC/ (TPC+FNC);
Where, TPC= True positive cases tally; FNC=False negative cases tally

c) Specificity - This metric assesses the classification system's proficiency in accurately detecting benign cases.
SPECIFICITY=TNC/ (FPC+ TNC)
Where, TNC=True negative cases tally; FPC=False positive cases tally

d) Positive Predictive Value (PPV) - This metric represents the probability of correctly identifying true positives while avoiding false positives when the result indicates malignancy.
PPV = TPC/ (FPC+ TPC)
Where, TPC= True positive cases tally; FPC=False positive cases tally

e) Negative Predictive Value (NPV) - This metric denotes the probability of correctly identifying true negatives while avoiding false negatives when the result indicates benignity.
NPV = TNC/ (FNC+TNC)
Where, TNC=True negative cases tally; FNC=False negative cases tally

4.3. Results and Discussion

S.No.	Performance Index	LeNet Performance
1.	Accuracy	0.60
2.	Sensitivity	0.1111
3.	Specificity	1
4.	Positive Predictive Value (PPV)	1
5.	Negative Predictive Value (NPV)	0.5789

LeNet exhibits a moderate overall accuracy of 60%, indicating room for improvement. While achieving a perfect specificity of 100% and positive predictive value of 100%, demonstrating proficiency in identifying benign cases, the model's sensitivity is notably low at 11.11%. This suggests a limited ability to accurately detect malignant cases. The negative predictive value is 57.89%, suggesting potential enhancements are needed to reduce false negatives in predicting benign cases. Consideration of adjustments, such as fine-tuning or dataset augmentation, may enhance the model's performance, particularly in sensitivity and negative predictive value.

V. Conclusion

In summary, this research underscores the crucial need for early detection of thyroid malignancy, emphasizing the thyroid gland's regulatory role in physiological functions. The application of Convolutional Neural Networks (CNNs), specifically the LeNet model, demonstrates promise in thyroid malignancy detection, leveraging its established success in computer vision tasks and proficiency in multi-class classification. The study employs the Digital Database of Thyroid Ultrasound Images (DDTI) and adopts the Thyroid Imaging Reporting and Data System (TIRADS) for patient classification. Rigorous evaluation of the LeNet model reveals a moderate overall accuracy of 60%, with exceptional specificity and positive predictive value, indicative of its adeptness in identifying benign cases. However, a notable limitation is observed in sensitivity, necessitating refinement for enhanced accuracy in detecting malignant cases. The negative predictive value also signals a potential for improvement to reduce false negatives in predicting benign cases. The study provides an exhaustive analysis of the experimental setup, evaluation indices, and results discussion, laying the groundwork for prospective model enhancements through techniques such as fine-tuning and dataset augmentation.

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