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EVALUATING THE EFFICACY OF ALEXNET FOR DETECTION OF THYROID CANCER

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Abstract: The increasing incidence of thyroid cancer cases and the challenge of unreliable false positive diagnostic rates in expert-reviewed ultrasound images emphasize the critical need for precise tumor diagnosis. Convolutional Neural Networks (CNNs), a state-of-the-art deep learning technique, exhibit remarkable capabilities in addressing computer vision challenges. This study introduces a specialized AlexNet CNN model designed for the detection of thyroid cancer in pre-processed ultrasound (US) images. The experimental outcomes reveal that the proposed model achieves an accuracy of 0.5, sensitivity of 0.3846, specificity of 0.7143, Positive Predictive Value (PPV) of 0.7143, and Negative Predictive Value (NPV) of 0.385.

Keywords: AlexNet; CNN, Cancer, Thyroid, Ultrasound

I. INTRODAUCTION

The thyroid gland, located in the neck, is a crucial endocrine gland responsible for regulating important bodily functions such as body temperature, heart rate, blood pressure, and the basal metabolic [1][2]. Without a properly functioning thyroid gland, various physiological imbalances and health issues can occur. Thyroid cancer can occur due to various reasons, and understanding the causes is crucial for early detection and intervention. Some common reasons for thyroid cancer include genetic factors, exposure to radiation, certain inherited genetic syndromes, and dietary factors [3][4]. It is important to be aware of these risk factors and undergo regular check-ups to detect any abnormalities in the thyroid gland. Early detection and prompt medical attention are vital in managing thyroid cancer effectively. Thyroid cancer is the predominant type of endocrine malignancy, representing around 2.1% of worldwide cancer cases [5]. The incidence of thyroid cancer has steadily increased in various countries over the past few decades. It now holds the ninth position among the most common cancers in males and the fifth position among females [1] [6].

Convolutional Neural Networks (CNNs) represent a prevalent form of deep learning methodology distinguished by fully trainable models [7][8]. They are widely recognized as a state-of-the-art technique in the realm of image classification. LeNet, AlexNet, NIN, ResNet, GoogLeNet, Xception, and VGG encompass a variety of Convolutional Neural Networks (CNNs) [9]. AlexNet model , which was introduced in 2012, is considered as one of the pioneering CNN architectures that propelled the field forward [10]. AlexNet, distinguished by its innovative architecture, has significantly impacted image classification by offering several key advantages. Its deep architecture, featuring multiple convolutional layers, allows it to excel in large-scale image classification tasks, effectively learning intricate features from input [11]. Advanced techniques like local response normalization and overlapping pooling enhance the network's ability to generalize, contributing to its overall robustness across diverse image classification challenges. The use of the rectified linear unit activation function addresses the vanishing gradient problem, promoting efficient training and convergence. Moreover, AlexNet's pioneering incorporation of data augmentation and dropout techniques plays a crucial role in regularization, preventing overfitting and bolstering performance, particularly in scenarios with limited training data [12].

This study critically examines the efficacy of AlexNet in detecting thyroid cancer, utilizing comprehensive evaluation metrics such as accuracy, sensitivity, specificity, positive predictive value, and negative predictive value. These metrics collectively serve as thorough indices to assess the overall performance of the model.

II. LITERATURE SURVEY

Zhu et al. have created a three-layer feed-forward artificial neural network (ANN) model with a 6-8-1 configuration [13]. Ma et al. have devised a model centered around cascade deep convolutional neural networks (CNNs), incorporating two distinct CNNs alongside an innovative splitting method. In the first CNN, ground-correct data have been employed to establish a grasp of segmentation probability maps, and the second CNN has been used for the automated detection of thyroid tumors within sonographic thyroid images [14]. Liu et al. have conducted a transfer of a CNN model trained on a substantial reference dataset to a novel ultrasound image dataset to address the challenge of limited sample size. Hybrid classification has been employed on a hybrid feature space, formed by amalgamating traditional features with deep features [15]. Chi et al. have utilized feature extraction through fine-tuning the pre-trained GoogleLeNet model, and then for classification, the random Forest classifier has been fed with extracted features [16]. Li et al. have devised a hybrid model by combining ResNet-50 and Darknet-19 architectures [17]. Zhang et al. have introduced an innovative approach that involved the utilization of two integrated classification modules to effectively segregate thyroid nodules [18]. Ko et al. have utilized pre-trained imagenet-vgg-f and pre-trained imagenet-vgg-verydeep16, in the recognition task after undergoing a fine-tuning process [19]. Moussa et al. have conducted fine-tuning of the resNet-50 model for thyroid malignancy detection [20]. Nguyen et al. have combined ResNet and InceptionNet CNN models to enhance information extraction [21]. Liang et al. have classified thyroid and breast nodules through a multi-organ Computer-Aided Diagnosis (CAD) system employing convolutional neural networks (CNNs) to classify thyroid and breast nodules. They have explored the effects of various preprocessing approaches on diagnostic efficiency [22]. Wang et al. have conducted a comparative analysis between radiomics and a deep learning-based technique, i.e., fine-tuned VGG-16 for classifying thyroid nodules [23]. Xie et al. have introduced a unique structural design that combines local binary pattern with deep learning methodologies [24]. Liu et al. have devised an innovative joint convolutional neural network (CNN) that leverages information fusion techniques. This advanced CNN architecture comprises two distinct branched pathways, each dedicated to profound feature extraction [25]. Vadhiraj et al. have performed a relative analysis between artificial neural network (ANN) classification algorithms and the support vector machine (SVM) [26]. Li et al. have created a holistic automated system for recognizing and classifying CT images of thyroid tumors. Their approach has hinged on convolutional neural networks (CNNs) to drive the recognition and classification processes seamlessly [27]. Hang has presented a method that entails amalgamating conventional features with deep features to create a combined feature domain. A comparison between two models: ResNet18, an 18-layer residual convolutional neural network, and Res-GAN has been done [28]. Peng et al. have created the ThyNet model, which has amalgamated ResNet, DenseNet, and ResNeXt architectures [29]. Qi et al. have developed a comprehensive network model named Mask-RCNN18. This model has incorporated the feature pyramid network (FPN) and the residual network (ResNet) for feature extraction, employed the region proposal network (RPN) for classification, and integrated bounding box (BB) regression for generating Regions of Interest (ROI) to detect the existence of significant extrathyroidal extension (ETE) in cases of thyroid cancer [30]. Liu et al. have created a deep-learning model known as ThyNet-LNM, designed specifically for assessing Lymph Node Metastasis (LNM) [31]. Ajilisa et al. have integrated inception modules with squeeze and excitation networks to enhance the recognition accuracy of the inception network. Additionally, as a bridging dataset, breast ultrasound images have been used for multi-level transfer learning [32].

III. MATERIAL AND METHODS

This segment is structured into two main parts:

A. *Dataset and Data Preprocessing*

In this study, the Digital Database of Thyroid Ultrasound Images (DDTI), a publicly accessible dataset consisting of 347 B-mode thyroid ultrasound images has been utilized. Radiologists have employed the Thyroid Imaging Reporting and Data System (TIRADS) for patient classification [33][34]. The images underwent cropping to specific dimensions, ensuring a maintained square shape in the cropped region. Following this, the images were converted to a single channel to ensure data consistency, reduce dimensionality, and facilitate grayscale-specific processing by transforming RGB images into grayscale. A series of additional image processing operations, such as thresholding, denoising, contour detection, and resizing, were applied to generate processed images ready for subsequent analysis or utilization. The dataset was then partitioned into training, validation, and test sets.

B. *AlexNet Model*

Krizhevsky et al proposed the AlexNet architecture in 2012. It consists of five convolutional layers and three fully connected layers. The first five layers of AlexNet are convolutional layers, which apply filters to the input image to extract features [33][34]. These convolutional layers are followed by maxpooling layers, which downsample the feature maps to reduce their spatial dimensions. The last three layers of AlexNet are fully connected layers, where each neuron is connected to all neurons in the previous layer. The final fully connected layer of AlexNet uses a softmax activation function to classify the input image into one of the 1000 predefined classes [35].

Table 1: AlexNet architecture

Layer	#filters / neurons	Filter size	Stride	Padding	Size of feature map	Activation function
Input	**-**	**-**	**-**	**-**	**227X227X3**	**-**
Conv1	**96**	**11X11**	**4**	**-**	**55X55X96**	**ReLU**
Max pool 1	**-**	**5X5**	**2**	**-**	**27X27X96**	**-**
Conv 2	**256**	**3X3**	**1**	**2**	**27X27X256**	**ReLU**
Max pool 2	**-**	**5X5**	**2**	**-**	**13X13X256**	**-**
Conv 3	**384**	**3X3**	**1**	**1**	**13X13X256**	**ReLU**
Conv 4	**384**	**3X3**	**1**	**1**	**13X13X384**	**ReLU**
Conv 5	**256**	**3X3**	**1**	**1**	**13X13X256**	**ReLU**
Max pool 3	**-**	**3X3**	**2**	**-**	**6X6X256**	**-**
Dropout 1	**Rate= 0.5**	**-**	**-**	**-**	**6X6X256**	**-**

IV. EXPERIMENTAL RESULTS

This section provides a comprehensive analysis of the experiments undertaken, encompassing three vital aspects: the experimental setup, evaluation indices, and the discourse on the outcomes.

A. Experimental Setup

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

B. Evaluation Indexes

- **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
- **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
- **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
- **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
- **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

C. Results and Discussion

Table 2: AlexNet Performance

S.No.	Performance Index	AlexNet Performance
1.	Accuracy	0.5
2.	Sensitivity	0.3846
3.	Specificity	0.7143
4.	Positive Predictive Value (PPV)	0.7143
5.	Negative Predictive Value (NPV)	0.385

AlexNet with an accuracy of 0.5, the model's predictions align with random guessing, indicating limited effectiveness. The sensitivity score of 0.3846 implies a challenge in accurately identifying positive instances, while the specificity of 0.7143 showcases a relatively better ability to correctly identify negative cases. The positive predictive value (PPV) of 0.7143 indicates that when the model predicts positive instances, it is accurate about 71.43% of the time. However, the negative predictive value (NPV) at 0.385 suggests a lower accuracy in predicting negative instances. In summary, while AlexNet demonstrates certain strengths in negative predictions and positive precision, overall improvements are needed to enhance its performance across all aspects of the classification task.

V. CONCLUSION

In conclusion, the study has systematically examined the performance of AlexNet in the context of a classification task, utilizing key metrics such as accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). The obtained results, with an accuracy of 0.5, indicate a performance level equivalent to random guessing. The model's ability to correctly identify positive instances, as reflected in the sensitivity score of 0.3846, reveals room for improvement. While demonstrating a comparatively stronger performance in correctly identifying negative cases (specificity of 0.7143) and positive precision (PPV of 0.7143), the model's overall effectiveness is hindered by its limited accuracy and sensitivity. These findings underscore the necessity for further refinement and optimization of the AlexNet architecture or exploration of alternative models to enhance classification performance in the specific domain under consideration. Future work could involve fine-tuning hyperparameters, exploring different architectures, or incorporating additional preprocessing steps to address the identified limitations and advance the model's efficacy in the given task.

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