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Taylor-Based Mean Poisson Loss for Lung Cancer Detection

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Abstract

Lung cancer is the most typical disease, leading to death around the globe; thus, timely diagnosis is vital to decrease the mortality rate. Deep Learning (DL) techniques have been typically exploited to assess Computed Tomography (CT) scans automatically, which helps radiologists in identifying cancerous cells. Nevertheless, classical DL schemes failed to maintain the accuracy rate because of overfitting risks and false detections, thereby decreasing the overall performance during the detection process. Hence, a novel scheme termed Taylor Mean Poisson EfficientNetB7 (TMPENetB7) is developed to identify lung cancer. In addition, the attained features are forwarded to the diagnosis phase, where the lung cancer is identified by applying the TMPENetB7 and is established by advancing the learning rule of EfficientNetB7 with Taylor-based Mean Poisson Loss (TMPoL).

Keywords: Lung cancer, Computed Tomography, Gabor filter, Multi-Window Uncertainty-Guided Segmentation Network, Deep Learning

1. Introduction

Cancer is a life-threatening disease with rapidly increasing mortality and incidence rate among elderly people, and poses a serious health hazard. Smoking, second-hand smoke, drinking water with high arsenic, and air pollution have been considered as the major risks for cancer, while smoking is the leading cause of cancer in people around the world [1]. The World Health Organization (WHO) survey reports that cancer is the second leading cause of mortality, leading to nearly 10 million fatalities. Cancer can affect individuals of all age groups, and it can occur in any body part [2]. There are around 100 diverse forms of cancer; each has its unique behaviours and characteristics. Further, breast, liver, lung, and colorectal cancers are regarded as the widespread forms of cancer. Lung cancer originates within the lungs, which are a pair of organs that are used for performing respiration, helping the body to breathe by exchanging oxygen and carbon dioxide [3].

Globally, lung cancer is a deadly and commonly occurring disease. Further, lung cancer mostly leads to death, especially when the disease is diagnosed late. This disease occurs due to the emergence of malignant cells that begin to develop in the pulmonary tract and usually spread quickly over the body. Lung cancer is characterized by uncontrolled cell proliferation, affecting the typical pulmonary function and accelerating the disease in patients. This disease includes two types, namely Non-Small Cell Lung Cancer (NSCLC) and Small-Cell Lung Cancer (SCLC). Here, SCLC is more intense and spreads rapidly, whereas mostly 85% of all lung cancer cases are NSCLC, which makes it the most common lung disease.

Periodic examinations of high-risk individuals enable timely identification. Timely diagnosis of lung cancer is regarded as challenging for physicians. For diagnosing lung cancer, it is essential to exploit a wide range of approaches, such as physical and imaging examinations. More recently, lung cancers are commonly detected and treated employing a variety of imaging approaches [4]. Besides, radiotherapists diagnose lung cancer, especially CT. A non-invasive technique for early disease detection is provided by frequently understanding and assessing the CT images of patients. CT imaging is an effectual medical screening tool exploited for diagnosing diseases by detecting cancerous cells. Moreover, significant pathological and anatomical information about the human body can be provided by these CT scans [5].

Recently, DL and Machine Learning (ML)-based schemes are exploited for interpreting and diagnosing diseases. Here, DL models have a better ability than ML in rapidly mining the patterns in generating the

predictions, even from huge databases. More recently, the implementation of DL techniques has significantly improved and is being widely used in the medical sector. Moreover, AI-based schemes have demonstrated robust potential in the timely detection of complex diseases, like lung cancer. By assessing CT scans automatically, the automated technique can optimize the accuracy and speed of the detection process [6]. Since AI has advanced, DL models become increasingly popular in assessing medical CT scans. DL techniques have exhibited high potential for the timely diagnosis of lung cancer employing CT images [7]. In addition to this, DL processes a huge amount of data more rapidly than skilled clinicians. Further, this scheme is also exploited for segmenting, categorizing, and identifying pulmonary nodules. Besides, Convolutional Neural Networks (CNNs) have attained effectual outcomes in excerpting robust and potent features from the CT scans.

2. Literature Review

You Only Look Once, version 8 (YOLOv8) with Tumor, Node, Metastasis Classifier (TNM Classifier) was presented by Wehbe, A., *et al.* [8] to identify lung cancer. This scheme exhibited better generalization ability and high computational efficiency. Nonetheless, this method did not concentrate on the features that are mined from YOLO and failed to advance a Content-Based Image Retrieval (CBIR) to offer additional information for better detection. EfficientNetB0 was formulated by Shatnawi, M.Q., *et al.* [7] for diagnosing lung cancer. This scheme was more effectual in real-world practices, acquired high accuracy with fewer computational requirements. Nevertheless, this scheme demanded technical constraints and limited high-quality data to maximize the performance. Saha, A., *et al.* [9] developed the VER-Net for identifying lung cancer. This approach mitigated error and addressed overfitting and under fitting risks. However, this scheme did not have the capability to assess the progression of lung cancer, and the accuracy in the detection process was reduced. A Generative Adversarial Network- Attention Gated Network (GA-AGN) was devised by Joseph, S., *et al.* [10] for identifying lung cancer. This technique decreased overfitting by attaining high computational speed and generalization. Still, this model failed to minimize the computational time while maintaining a high accuracy rate.

A model named Deep Nodule-Detect was introduced by Abe, A.A., *et al.* [12] for diagnosing lung cancer. This model had high processing speed and demanded less computational overhead. But this technique failed to exploit in huge lung cancer databases across several imaging models, like PET and MRI. Ozdemir, B., *et al.* [13] devised CNNs with Vision Transformers (ViTs) to diagnose lung cancer. This scheme attained high efficacy in managing intricate features, decreased processing power requirements, and memory storage. Still, failed to refine the model by testing its generalization and expanding its accessibility to other imaging modalities across distinct databases for optimizing the clinical impact. 3D-ResNet was proposed by Crasta, L.J., *et al.* [14] to diagnose lung cancer. This approach lessened false negatives and mitigated the parameters required. Still, this technique failed to integrate data from distinct imaging modalities for offering a better interpretation of nodules to further optimize an accuracy rate. Hammad, M., *et al.* [15] introduced a custom CNN for diagnosing lung cancer. This scheme demanded less computation time and decreased prediction errors, which made it more robust. Nonetheless, this approach failed to include extensive and distinct databases by cooperating with various data sources and medical institutions.

3. Proposed Taylor Mean Poisson Efficientnetb7 for Lung Cancer Detection

Lung cancer is considered a serious disease, where malignant cells proliferate quickly and form tumours in lungs, affecting the function of the lungs and spreading to other body parts. Hence, early identification via medical imaging tools, like CT scans, is vital in providing better treatments. Further, prevailing DL-based approaches have attained promising performance in medical image assessment; however, they failed to achieve high accuracy due to false alarms. Consequently, a novel TMPENetB7 is designed for identifying lung cancer. At first, the lung CT scan is subjected to image de-noising with a Gabor filter [16]. Subsequently, lung nodule region segmentation is performed using the MUS-Net [17]. After segmentation, techniques such as flipping, shearing, and colour jittering are applied [18] for image augmentation. Next, features, namely Nodule Irregularity Index [19], Nodule Solidity [20], and Nodule Equivalent Diameter along with texture-based features, like Dominant Rotated Local Binary Pattern (DRLBP) [21] and Gray Level Co-occurrence Matrix (GLCM)

features [22], are extracted. Finally, lung cancer is identified employing the TMPENetB7, which is developed by updating the learning rule of EfficientNetB7 with TMPoL. Figure 1 represents the structural view of TMPENetB7 to diagnose lung cancer.

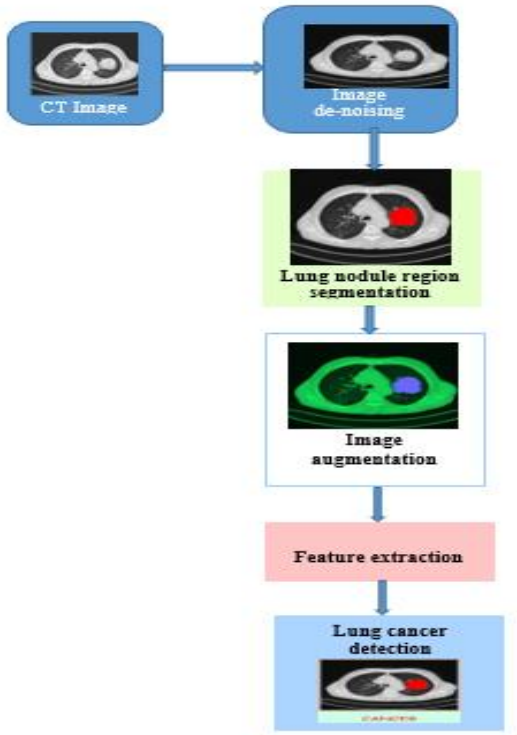


Fig. 1. Proposed TMPENetB7 method to diagnose lung cancer.

A. Acquisition of CT Scan

Assume a database α comprises δ number of images used to identify lung cancer, and is represented as,

$$\alpha = \{\alpha_1, \alpha_2, ..., \alpha_\lambda, ..., \alpha_\delta\} \quad (1)$$

where, α_λ characterizes the λ^{th} image considered for the detection task.

B. Denoising using a Gabor filter

Denoising approaches are applied for improving the significant structure in the lungs by decreasing irrelevant variations. This process assists in highlighting abnormal tissue patterns, tumors, and small nodules, indicating the existence of lung cancer. The approach attains better visibility of lung nodules and a high accuracy rate in diagnosis. It helps the automated detection system in detecting early-stage cancerous cells more effectually. Denoising also minimizes the false positives by eradicating the random noise and maintaining the important structural details. Furthermore, the noise from an input image α_λ is eliminated by exploiting a Gabor filter[17], and is elaborated below.

Gabor filter [17] is a type of linear filter, in which the Gabor function is employed as a kernel for accumulating the data on the direction and frequency of local visual elements, namely textures and edges. Here, the sinusoidal plane wave is incorporated with the Gaussian function to examine the image at diverse orientations and frequencies. This technique is used for attaining better localization in both frequency and spatial domains, thereby enhancing the image details, and achieving better performance in disease detection systems.

C. Segmenting Lung Nodule Rregion using MUS-Net

Segmenting lung nodule areas from the denoised image is considered an important step. It is utilized to isolate the nodule region from the surrounding lung tissues in the image. It is also employed for locating the boundaries of lung nodules accurately, which enables the system to concentrate on the specific region that contains excessive tissue growth in the lungs. By segmenting lung nodule, the accuracy rate of automated systems for further processing can be increased with better visualization of tumor boundaries. The influence of background information can also be minimized, thereby supporting the timely identification of lung cancer for more precise and faster diagnosis. Here, the lung nodule area is segmented by applying MUS-Net [18], by considering the denoised image as input.

D. Image Augmentation

This process is used for artificially expanding the database via diverse transformations on the segmented image. This approach is exploited to learn more generalized and robust features when applied to nodules in different sizes, orientations, and intensity variations. Also, this technique is exploited for decreasing overfitting and data imbalances by attaining a high accuracy rate and better generalization to unseen data. By increasing the diversity of the database, the augmentation process ensures that the automated system can be reliable across diverse imaging scenarios and patients. Here, color jittering [19], shearing [19], and flipping [19] are employed to augment the segmented image.

E. Feature extraction

In order to detect and isolate relevant features from the augmented image σ , feature extraction is applied, which aids in distinguishing between cancerous and healthy tissues. By converting the augmented image into a meaningful feature, the ability of the automated systems to concentrate on the image's most informative aspects is enhanced, thereby decreasing the complexity with a better performance rate. In addition, this process can lessen the computational load with high accuracy, better interpretability of results, and high capability to leverage even under limited databases. Moreover, this process assists the model in identifying complex abnormalities early and thus contributes to reliable and timely diagnosis.

F. Lung Cancer Detection using TMPENetB7

Lung cancer is characterized by the abnormal and uncontrolled spread of cells in the lungs. This disease is mostly diagnosed at the last stage because of the absence of early symptoms, which significantly lessens the survival rate. Hence, timely diagnosis is vital for offering effective treatment and attaining better patient outcomes. DL methods have outperformed traditional models in automating the detection of cancers from medical images. Nevertheless, most of the schemes struggle with overfitting risks, which leads to high false alarms. Thus, the novel scheme known as TMPENetB7 is devised to diagnose lung cancer from CT scans. Here, TMPENetB7 is modelled by modifying the learning rule of EfficientNetB7 [23]with TMPoL, which is devised by fusing MDElog [25], Taylor concept [24], and Poisson loss [26].

a) EfficientNetB7 architecture

EfficientNetB7 [23] is a Deep CNN framework often employed in medical image analysis for attaining better results with a more accurate rate. This network maximizes the performance rate while maintaining computational efficacy. This scheme attains better performance by maintaining the parameter count. Furthermore, the feature vector X_{ρ} is subjected to EfficientNetB7 as input. EfficientNetB7 is more robust than existing EfficientNet versions, since it captures intricate visual patterns, resulting in more precise detection. Moreover, EfficientNetB7 includes several benefits, namely effectual use of computational resources, high reliability, and flexibility in detecting cancerous cells. Further, EfficientNetB7 offers high generalizability, which makes it an effective network for precise lung cancer diagnosis.

b) TaylorMean Difference Poisson Loss-based Learning Rule

The TMPoL-based learning rule is designed for improving the detection ability and efficacy of EfficientNetB7 [23]by assimilating three modules, namely MDElog [25], Taylor concept[24], and Poisson loss[26]. Here, Taylor concept [24] approximates the intricate nonlinear loss behavior by lessening the computational complexity and preserving the gradient information. MDElog[25]is employed for assessing the average discrepancy between the targeted and predicted values by reducing the impact of large deviations and stabilizing the error scale. In addition, Poisson loss [26]is exploited to model the distribution of abnormal patterns in CT scans. Furthermore, the incorporation of these three modules offers high convergence stability, better handling of class imbalance, and less overfitting, resulting in more reliable early-stage diagnosis of lung cancer.

4. Results and Discussion

The experimental outcomes of TMPENetB7 for normal and cancer cases are illustrated figure 2. The image samples of TMPENetB7 for the normal and cancer cases are considered and indicated in the respective images.

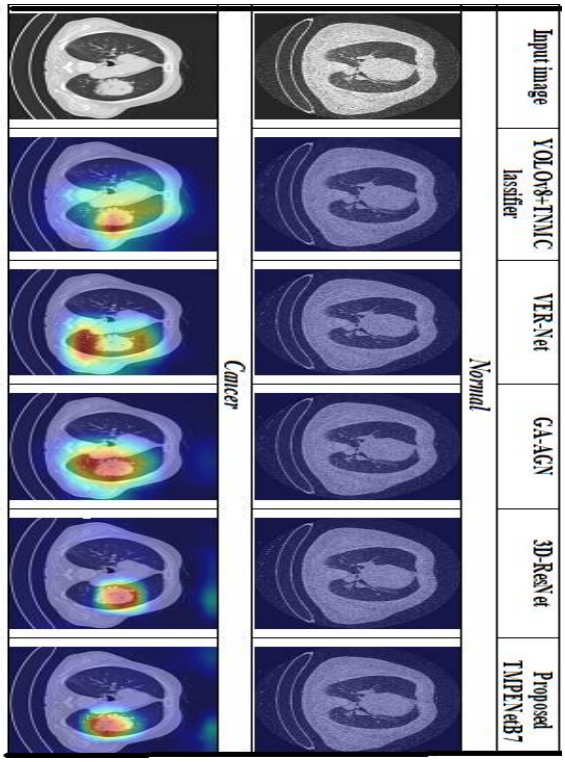


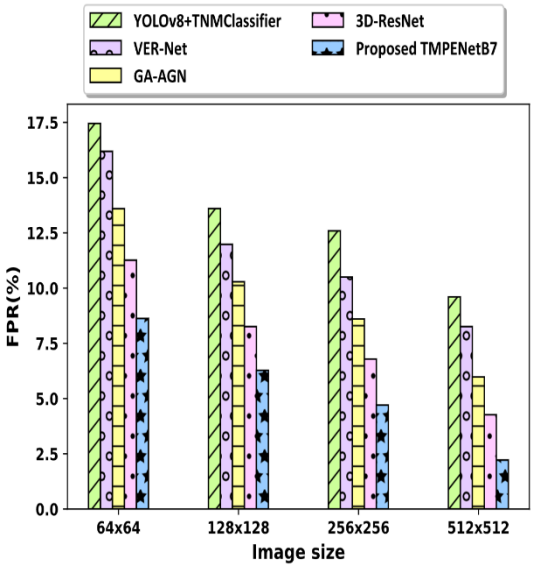
Fig. 2. Experimental Results of TMPENetB7 for normal and cancer cases.

Grad-CAM is applied for examining the novel TMPENetB7's interpretability by concentrating on nodule areas impacting the detection outcomes. Besides, the gradient transmitted into the Convolution layer is exploited by this analysis, which is performed to produce heat maps emphasizing the affected areas on the given CT scan. Besides, this assessment is carried out by correlating TMPENetB7 with other baseline schemes, namely YOLOv8+TNMClassifier [5], VER-Net [9], GA-AGN [11], and 3D-ResNet [13], exploiting representative CT scans. The input CT scan, together with corresponding heat maps created by YOLOv8+TNMClassifier [5], VER-Net [9], GA-AGN [9], 3D-ResNet [13], and TMPENetB7 are delineated in Figure 2. Consequently, TMPENetB7 attained more precise activations over clinically significant areas of CT lung scans, allowing the model to capture complex patterns that are associated with early-stage lung cancer. Hence, the false detections are reduced gradually, thereby optimizing the robustness and applicability of the detection system.

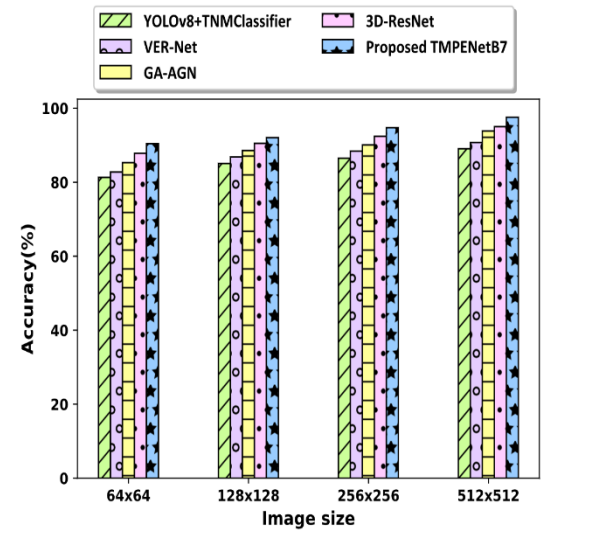
A. *Scalability Assessment*

Multiple classical schemes, namely YOLOv8+TNMClassifier [5], VER-Net [9], GA-AGN [11], 3D-ResNet [13], are correlated with the novel TMPENetB7 to assess its superiority in diagnosing lung cancer.

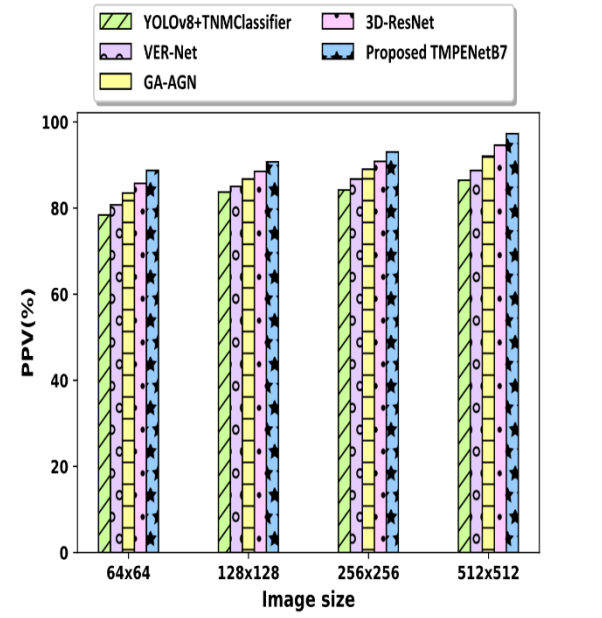
The estimation of TMPENetB7 with multiple parameters by altering image size is indicated in Figure 3. The estimation of TMPENetB7 regarding FPR is signified in Figure 3(a).



(a)



(b)



(c)

Fig. 3 Scalability estimation of TMPENetB7 (a) FPR, (b) Accuracy, and (c) PPV

Here, the FPR figured by TMPENetB7 for image size 128 X 128 6.279%, while the classical schemes, including YOLOv8+TNMClassifier, VER-Net, GA-AGN, and 3D-ResNet, gained the FPR of 13.603%, 11.981%, 10.289%, and 8.260%. The valuation of TMPENetB7 related to accuracy is depicted in Figure 7(b). The YOLOv8+TNMClassifier, VER-Net, GA-AGN, 3D-ResNet, and novel TMPENetB7 at image size 256 X 256 computed an accuracy of 86.476%, 88.397%, 90.086%, 92.396%, and 94.729%. The TMPENetB7's efficacy over VER-Net is boosted by 6.69%. The PPV-based estimation of TMPENetB7 is delineated in Figure 3(c). At image size 64 X 64, the PPV quantified by

TMPENetB7 is 88.740%, YOLOv8+TNMClassifier is 78.396%, VER-Net is 80.744%, GA-AGN is 83.491%, and 3D-ResNet is 85.739%. The TMPENetB7's effectiveness over existing schemes is increased 11.66%, 9.01%, 5.92%, and 3.38%.

5. Conclusion

Lung cancer diagnosis mostly focuses on detecting the malignant nodules in CT scans during the early phase of the disease. Recently, DL models have been introduced widely to automatically examine CT images, which helps the radiologists in identifying abnormal lung tissues. Nonetheless, traditional DL methods mostly failed in maintaining high accuracy because of the class imbalance issues. Hence, a novel scheme termed TMPENetB7 is introduced to identify lung cancer. Furthermore, the TMPENetB7 recorded the minimal FPR of 2.217%, and maximal accuracy, and PPV of 97.283% and 97.573%. Future scope aims to implement transfer learning, decreasing the demand for large labeled databases and effectively capturing intricate patterns, thereby attaining better generalization on unseen medical images.

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