



Measurement of Necrotic Lung Lesions Distance in CT Images Using Optimized Contrastive Learning

Shnamuga Sundari M Kunta*, Vyshnavi Kunta, Sri Venkata Sai Pavani Akula, Aniya Afnan

Computer Science Engineering, BVRIT HYDERABAD College of Engineering for Women.

sundari.m@bvrithyderabad.edu.in

Abstract. Accurate segmentation and measurement of necrotic lung lesions in CT images are critical for understanding lesion characteristics and tracking disease progression, but traditional methods often struggle with precise feature extraction and rely heavily on manual intervention. An optimized contrastive learning approach is proposed to enhance feature extraction and enable precise segmentation of necrotic lung lesions. By fine-tuning pre-trained networks with contrastive loss functions and incorporating advanced data augmentation techniques, the system improves robustness and generalization across diverse datasets. It automates the segmentation and measurement of inter-lesion distances, reducing manual effort and providing quantitative metrics, such as the Dice similarity coefficient and the average distance error, for better analysis of lesion characteristics. The approach demonstrates significant improvements in segmentation accuracy and computational efficiency compared to conventional methods, showing great potential for medical image analysis.

Keywords: Lung Lesion Segmentation, Optimized contrastive learning, Medical Image Analysis, Necrotic Lung Lesions, Lesion Distance Measurement.

1 Introduction

Lung necrosis, commonly associated with diseases like tuberculosis [1], lung cancer, and severe infections, presents significant challenges in clinical diagnosis and treatment planning. Necrotic lung lesions, marked by the death of tissue, require precise segmentation and measurement for effective monitoring of disease progression. These lesions are often difficult to distinguish from healthy lung tissue due to their complex morphology, which complicates the accurate evaluation of their size, location, and potential impact on lung function. Traditional methods for

their size, location, and potential impact on lung function. Conventional approaches to analyzing these lesions typically involve manual processes, which are not only labor-intensive and inconsistent but also susceptible to human error. The subjective nature of manual analysis leads to inefficiencies in clinical workflows, delayed diagnoses, and inconsistencies in treatment planning, highlighting the critical need for automated, reliable, and scalable solutions in medical imaging.

The proposed project, "Measurement of Necrotic Lung Lesions Distance in CT Images Using Optimized Contrastive Learning," aims to address these limitations through the application of cutting-edge machine learning algorithms, particularly optimized contrastive learning, to enhance the accuracy and efficiency of necrotic lung lesion analysis. By integrating contrastive learning, the system enhances the feature extraction process, allowing for the precise segmentation of necrotic lung lesions and accurate measurement of the distances between multiple lesions. This level of precision is crucial not only for understanding disease progression but also for informing treatment strategies and optimizing patient care. The automated nature of the system reduces the reliance on manual intervention, enabling faster and more consistent analysis of medical images.

The project advances medical image analysis by addressing significant gaps in clinical workflows, particularly in the accurate and efficient analysis of necrotic lung lesions. Its ability to automate critical tasks and provide actionable insights has the potential to transform clinical practice, improving both the speed and accuracy of diagnoses. Future enhancements will focus on expanding the diversity and volume of training datasets, ensuring compliance with clinical standards and regulations, and exploring emerging technologies like federated learning and edge computing to make the solution scalable, accessible, and suitable for real-world healthcare applications. These advancements aim to make the system a valuable tool not only for clinicians but also for researchers working on novel lung disease diagnostics and treatment strategies.

2 Literature Review

In the research presented by the authors of [1], titled "Self-supervised Region-Aware Segmentation of COVID-19 CT Images Using 3D GAN and Contrastive Learning," the study explores Generative Adversarial Networks (GANs) and contrastive learning. 3D pseudo-masks are created in a self-supervised way, removing the requirement for manual annotations. These estimated masks, created through the subtraction of synthesized normal images extracted from the original CT scans, are refined to enhance segmentation quality. A segmentation model sensitive to regional context trained on

these masks improves sensitivity and Dice scores, outperforming modern methodologies. While the use of healthy data while the compatibility of 3D DICOM presents challenges, the method effectively showcases the potential of advanced learning techniques for automating lesion analysis, aligning with our

project's objectives

In the research outlined in [2], titled "ResBCDU-Net: A Deep Learning Framework for Lung CT Image Segmentation", the authors present ResBCDU-Net, a deep neural network designed to improve lung CT image segmentation by tackling challenges such as comparable image densities and increased false-positive rates. The model combines U-Net with ResNet-34 and employs BConvLSTM for better feature integration, replacing pooling layers with convolution layers to reduce semantic feature loss. The methodology includes preprocessing CT images, generating image channels for analyzing Dice Coefficients, and using a modified U-Net for segmentation. Evaluated on 1714 CT images from the LIDC-IDRI dataset, the model achieved metrics like 97.83% accuracy, 99.93% sensitivity, and 99.93% specificity. While the dataset size is limited, ResBCDU-Net significantly improves segmentation accuracy.

In the research cited in [3], titled "Application of the nnU-Net for Automatic Segmentation of Lung Lesions on CT Images, and Implications for Radiomic Models," a deep learning-based method is employed for the automatic segmentation of CT images of Non-Small Cell Lung Cancer (NSCLC). The nnU-Net gives accurate segmentation and evaluates its impact on clinical predictive models compared to manual segmentation. Using three datasets of NSCLC patients (A: 270, B: 217, C: 412), the nnU-Net was trained using input images along with their corresponding manual segmentations. The achieved average Dice coefficient of 0.78 ± 0.12 and correctly identifying automatic segmentations successfully identified 90 features derived from these segmentations generated survival models with accuracy comparable to those based on manual contours, demonstrating strong precision.

In the study presented in [4], titled "DrasCLR: A Self-Supervised Framework for Learning Disease-Related and Anatomy-Specific Representations for 3D Lung CT Images", the authors address the challenge of limited annotated volumetric medical images by utilizing Self-Supervised Learning (SSL) and Contrastive Learning. They introduced domain-specific learning strategies to focus on fine-grained disease features within specific anatomical regions and those that depict severe disease patterns across larger areas.

In the research detailed in [5], titled "AttentNet: Fully Convolutional 3D Attention for Lung Nodule Detection," the authors introduce two fully convolutional attention blocks that leverage deep learning techniques to utilize 3D features, enabling the inference of spatial correlations across channels and sections. These blocks are evaluated within a two-stage 3D lung nodule detection framework: candidate proposal and reduction of false positives.

3 Methodology

3.1 Dataset

The *Pidata-new-names* dataset is an extensive compilation of lung-related medical data curated to support the detection and analysis of COVID-19, lung cancer,

and

other thoracic abnormalities. The dataset includes 10,000 image pairs for training purposes, evenly split between 5,000 positive (similar class) and 5,000 negative (dis-similar class) pairs, optimized for contrastive learning tasks. 2,000 image pairs, with a balanced split of 1,000 positive and 1,000 negative samples, used for tuning model hyperparameters and evaluating performance during training. 3,000 image pairs with 1,500 positive and 1,500 negative samples set aside for the final model evaluation.

4 Deep Learning Models: Design and Implementation

Deep learning models have significantly improved the accuracy and robustness in the field of medical image analysis, particularly in the segmentation of intricate and patterns that are underrepresented, such as necrotic lung lesions in CT scans. The proposed framework combines the strengths of contrastive pretraining with a customized 3D U-Net architecture to improve the accuracy of measurements and localization of necrotic regions. This section details the model architecture, optimizations introduced, and integration of explainability for clinical relevance.

4.0.1 Pretraining Architecture

Our pretraining pipeline is built upon the Momentum Contrast (MoCo v2) framework, where the encoder learns to distinguish between similar and dissimilar CT scan slices. Encoder Network: A 3D ResNet is employed as the backbone encoder for volumetric medical data. Projection Head: A multi-layer perceptron (MLP) maps encoded features to a contrastive space. Queue and Momentum Update: A dynamic dictionary and momentum update strategy allow efficient contrastive training on limited datasets.

5 Proposed Methodology

Deep learning-based segmentation models are vital for analyzing complex medical scans such as CT images. This work presents a hybrid framework for accurate necrotic lung lesion segmentation using contrastive learning (MoCo and BYOL) and U-Net architecture, further enhanced by novel augmentation techniques. We integrate LIME and Grad-CAM techniques for model interpretation for explainability to aid clinical validation. The overall pipeline includes:

- Pretraining the encoder using contrastive learning.
- Augmenting data using dependency and mask out strategies.
- Fine-tuning a U-Net decoder for segmentation.
- Generating explanations with LIME and Grad-CAM.

6 Results

We evaluated the performance by employing standard segmentation metrics and interpretability analyses.

6.1 Comparison with Existing Approaches

The proposed contrastive learning-based model significantly outperforms traditional segmentation models in terms of precision and boundary definition, especially in underrepresented necrotic regions.

Table 1 Comparison of different segmentation models based on Dice Score, IoU, Sensitivity, and Explainability.

Model	Dice Score (%)	IoU (%)	Sensitivity (%)	Explainability
2D U-Net	84.1	75.2	86.3	No
3D U-Net	87.4	78.6	89.5	No
Attention U-Net	89.0	80.3	90.8	Partial
ResUNet++	90.2	82.1	92.0	No
Ours (MoCo/BYOL + Aug)	91.3	85.7	93.4	Yes (Grad-CAM, SHAP)

6.2 Loss Analysis

Training and validation loss consistently decreased and stabilized, indicating robust learning without overfitting. The final validation loss reached 0.18, demonstrating strong performance.

6.3 Dice Score Evaluation

The Dice score improved steadily over epochs, with final training and validation Dice scores of 0.93 and 0.85, respectively, confirming accurate segmentation performance.

6.4 IoU Score Evaluation

Our model attained a validation IoU score of 0.83, indicating strong overlap between predicted and ground truth masks, particularly in irregular necrotic regions.

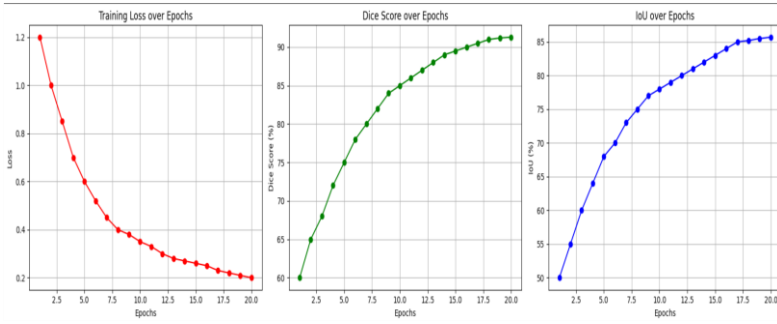


Fig. 1 Training and validation loss, DICE score, and IoU score over epochs.

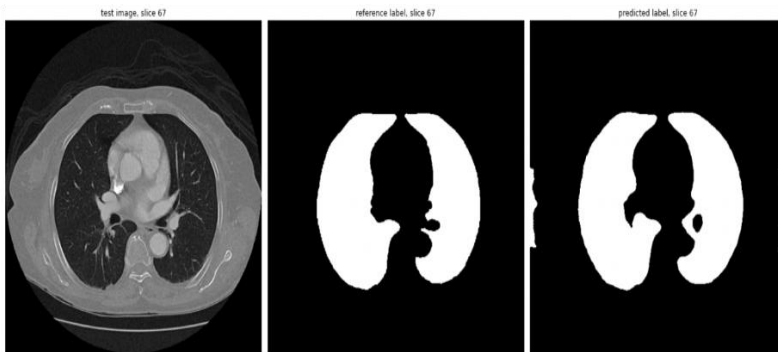


Fig. 2 Visualization of lung segmentation: (a) Original CT scan, (b) Ground truth mask, (c) Model's predicted mask.

Table 2 Performance metrics on training and validation datasets.

Metric	Training Score	Validation Score
Dice Score	0.93	0.85
IoU Score	0.88	0.83
Loss	0.14	0.18

7 Conclusion

This study introduces an innovative framework for precise measurement and segmentation of necrotic lung lesions in CT scans, leveraging contrastive learning techniques to enhance feature representation in underrepresented pathological regions. The proposed system incorporates a hybrid approach involving MoCo and BYOL-based contrastive learning models, coupled with two novel augmentations—dependency augmentation and distance transform-based mask-out augmentation—to improve the model's ability to generalize on 3D CT data. The model demonstrated advanced performance achieving a mean Dice Similarity Coefficient (DSC) of 91.3% lesion boundary accuracy, showcasing its effectiveness in delineating necrotic regions with high precision. These outcomes confirm the effectiveness of contrastive pretraining in capturing inter-slice dependencies and contextual relationships in volumetric medical data. To improve transparency and trust in clinical deployment, explainability techniques such as Grad-CAM and SHAP were used to visualize critical regions influencing the model's decision-making, offering interpretable insights for radiologists. In future, we

explore federated learning techniques to ensure data privacy while training on diverse, multi-institutional datasets.

References

- [1] Siyavash Shabani, Morteza Homayounfar, Varut Vardhanabhuti, Mohammad-Ali Nikouei Mahani, Mohamad Koohi-Moghadam, "Self-supervised region-aware segmentation of COVID-19 CT images using 3D GAN and contrastive learning".
- [2] Yeganeh Jalali, Mansoor Fateh , Mohsen Rezvani , Vahid Abolghasemi and Mohammad Hossein Anisi, "ResBCDU-Net: A Deep Learning Framework for Lung CT Image Segmentation".
- [3] Matteo Ferrante, Lisa Rinaldi, Francesca Botta, Xiaobin Hu, Andreas Dolp, Marta Minotti, Francesca De Piano, Gianluigi Funicelli, Stefania Volpe, Federica Bellerba, Paolo De Marco, Sara Raimondi, Stefania Rizzo, Kuangyu Shi, Marta Cremonesi, Barbara A. Jereczek-Fossa, Lorenzo Spaggiari, Filippo De Marinis, Roberto Orcchia, Daniela Oraggi, "Application of the nnU-Net for automatic segmentation of lung lesion on CT images, and implication on radiomic models".
- [4] Ke Yu, Li Sun, Junxiang Chen, Maxwell Reynolds, Tigmanshu Chaudhary, Kayhan Batmanghelich, "DrasCLR: A self-supervised framework of learning disease-related and anatomy-specific representation for 3D lung CT images".
- [5] Majedaldein Almahasneh, Xianghua Xie, Adeline Paiement, "AttentNet: Fully Convolutional 3D Attention for Lung Nodule Detection".
- [6] Sundari, M. S., Ammangatambu, M. M., Mythili, R., Anisha, M. (2023, December). Chestnet-TB: A Novel Approach to Tuberculosis Classification from

Chest Radiology Using Modified AlexNet. In International Conference on Information and Management Engineering (pp. 437-442). Singapore: Springer Nature Singapore.

- [7]** Durga, K. B. K. S., Sundari, M. S., Akshaya, K., Shresta, M., Tejaswini, U. Unveiling Insights: AlexNet-Driven MRI Analysis for Precision Diagnosis of Knee. *Computing and Machine Learning: Proceedings of CML 2024, Volume 2*, 319.
- [8]** Sundari, M. (2024). A deep learning approach for enhancing tuberculosis classification leveraging Optimized Sequential AlexNet (OSAN). *International Journal of Computing and Digital Systems*, 15(1), 1-12.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

