Utilization of deep learning in early detection of lung cancer through CT Scan images: thematic analysis in medical diagnosis innovation

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ABSTRACT

Early detection of lung cancer is a major challenge in the global healthcare system, particularly due to the often asymptomatic nature of the disease in its early stages. CT imaging (Computed Tomography) has become a key tool in early diagnosis, but it still faces challenges in terms of accuracy, interpretation time, and reliance on radiological expertise. This study aims to analyze the use of deep learning technology in increasing the effectiveness of lung cancer detection through CT scan images. This study uses a systematic literature review approach and thematic analysis of a number of popular deep learning models such as CNN (Convolutional Neural Network), U-Net, and ResNet. The results show that deep learning can significantly improve the sensitivity and specificity of diagnosis, while speeding up the detection process. The implications of this study open up great opportunities for the transformation of cancer diagnostic systems that are more efficient, accurate, and affordable.

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1. INTRODUCTION

Lung cancer is one of the leading causes of cancer deaths globally. According to GLOBOCAN 2020 data, lung cancer is ranked the first cause of cancer death, with an estimated 1.8 million deaths worldwide. In Indonesia, the trend of lung cancer cases also shows an increase, both in terms of the number of new cases and mortality rates. The biggest challenge in the management of lung cancer is generally late detection, where most patients are diagnosed at an advanced stage, so treatment options become limited and the prognosis deteriorates.

Early detection of lung cancer can significantly increase the life expectancy of patients. One approach that has proven effective for early screening is the use of low-dose computed tomography (CT) images, or low-dose CT (LDCT). This technology allows the identification of small, potentially malignant lung nodules. However, manual interpretation of CT images by radiologists requires time, high expertise, and is susceptible to variation between individuals. This encourages the need for an artificial intelligence-based clinical decision support system that is able to perform image analysis automatically, quickly, and accurately.

Deep learning, as a branch of machine learning that relies on the structure of artificial neural networks to detect complex patterns, has shown tremendous potential in the classification of medical images, including in the detection of lung cancer. With the ability to perform feature extraction automatically without the need for manual feature engineering, deep learning can identify the microscopic structure and visual characteristics of cancer nodules that are not easily captured by human vision. As model architectures such as convolutional neural networks (CNN), ResNet, DenseNet, and 3D-CNN advance, the performance of deep learning-based systems in lung cancer diagnosis is approaching—even exceeding—human radiological accuracy levels.

Nonetheless, various approaches in the development of deep learning models for lung cancer detection show mixed results. Some studies emphasize network architecture, while others focus on image segmentation techniques, dataset processing, or clinical performance evaluation. This raises the need to conduct a systematic synthesis of knowledge on existing research trends. In addition, although many models achieve high levels of accuracy on public datasets such as LIDC-IDRI and LUNA16, there are still limitations in their application to more varied and complex real-world data.

Based on this background, this article aims to present a thematic analysis based on a literature review of various deep learning approaches used in the early detection of lung cancer through CT scan images. The main focus is on the model architecture used, segmentation techniques, performance evaluation, and clinical suitability. By summarizing the latest research, this article is expected to provide an in-depth understanding of the artificial intelligence-based medical diagnosis innovation landscape and open up new directions for future research development and applications.

2. METHOD

2.1 Research Type and Design

This research is a qualitative study based on thematic analysis of relevant scientific literature. This design was chosen to explore and identify key themes related to the use of *deep learning* in early detection of lung cancer using CT scan images. The main focus is directed at mapping the model architecture, performance effectiveness, and the challenges and opportunities of its implementation in clinical practice.

2.2 Data Sources

Data were obtained from scientific articles published in internationally reputable journals and accredited indexes such as Scopus, PubMed, IEEE Xplore, and ScienceDirect. Inclusion and exclusion criteria are used to filter the literature to fit the topic of the study.

criteria Inclusive:

a. Articles published in the 2018–2024 time frame;
b. Explicitly discuss the application of *deep learning* algorithms (such as CNN, ResNet, U-Net, etc.) for lung cancer detection through CT scan images;
c. Available in English;
d. Load data or test results of model performance (accuracy, sensitivity, specificity, AUC, etc.).

Exclusion Criteria:

a. Literature studies that are not accompanied by technical data on model performance;
b. Articles that only discuss cancer detection by methods other than CT scans;
c. Articles in languages other than English or not available in full text (full text unavailable).

2.3 Article Search and Selection Strategy

Literature searches are conducted systematically using a combination of keywords:

("deep learning" OR "convolutional neural network" OR "CNN") AND ("lung cancer" OR "pulmonary nodules") AND ("CT scan" OR "computed tomography") AND ("early detection")

The selection steps include:

a. Initial Identification: 165 articles were found from 4 main databases.
b. Title and Abstract Filtering: Filtered into 72 articles based on topic relevance.
c. Full Text Evaluation: Thoroughly read and evaluated as many as 34 articles.
d. Selected Articles for Analysis: A total of 20 articles that met the criteria were selected as thematic analysis materials.

2.4 Data Analysis Procedures

The author uses a thematic analysis approach based on the framework of Braun and Clarke (2006) which consists of the following six stages:

a. Data Familiarization: Authors read and record summaries of selected articles, including model types, evaluation metrics, and study context.

b. Initial Code Generation: Codes such as "model accuracy", "nodule segmentation", "interpretation difficulties", and "clinical response" are found.
c. Theme Search: The initial codes are grouped into main themes, such as *model performance*, *data augmentation techniques*, *clinical systems integration*, and *ethical challenges*.
d. Theme Review: The theme is evaluated to see if it reflects the data as a whole and does not overlap.
e. Theme Definition and Naming: Labeled that reflects the deep content and meaning of each theme.
f. Preparation of Thematic Analysis Narrative: The final result is prepared in the form of a logical and interconnected scientific narrative between themes.

2.5 Validity and Credibility

To ensure the validity of the analysis, the following steps are performed:
a. Triangulation of sources by comparing results between articles from different journals;
b. peer debriefing, which is discussion with peers in the field of computer science and medicine;
c. Trail audit, which is the systematic recording of the selection and analysis process so that it can be re-traced transparently.

3. RESULTS AND DISCUSSION

3.1 General Characteristics of the Reviewed Study

A total of 20 scientific articles from internationally reputable journals such as *Nature Medicine*, *IEEE Transactions on Medical Imaging*, *Radiology*, and *Journal of Thoracic Oncology* were analyzed in this study. The main focus of the entire article is the use of *deep learning* algorithms in the early detection of lung cancer based on Low-Dose Computed Tomography (LDCT) images.
The most commonly used datasets are:
a. LIDC-IDRI (Lung Image Database Consortium Image Collection)
b. LUNA16 (LUng Nodule Analysis 2016)
c. National Lung Screening Trial (NLST)
d. Unpublished hospital dataset (proprietary hospital data)

The dominant deep learning models used include:
a. 2D dan 3D Convolutional Neural Networks (CNN)
b. Residual Networks (ResNet)
c. Dense Convolutional Networks (DenseNet)
d. EfficientNet
e. U-Net, specifically for nodule segmentation
f. Some studies use a combination approach, such as U-Net + CNN and CNN + LSTM

3.2 Quantitative Evaluation of Model Performance

The reviewed studies reported model prediction accuracy ranging from 85.3% to 92.1%, sensitivity ranging from 88.7% to 94.6%, specificity ranging from 82.4% to 89.2%, and AUC values ranging from 0.916 to 0.963.

Table 1. Summary of the Performance of Deep Learning Models in Lung Cancer Detection

Model Deep Learning	Dataset	Accuracy (%)	Sensitivitas (%)	Specificity (%)	AUC	Source
2D-CNN	LIDC-IDRI	88.2	91.3	84.5	0.935	Wang et al. (2020)
ResNet-50	LUNA16	90.4	93.1	87.6	0.951	Li et al. (2021)
3D-CNN	RS Dataset (USA)	92.1	94.6	89.2	0.963	Ardila et al. (2019)
U-Net + CNN	NLST + LIDC	87.6	89.9	85.3	0.927	Chen et al. (2022)
EfficientNet-B0	LIDC-IDRI	89.7	92.5	87.0	0.943	Zhao et al. (2021)
DenseNet-121	Kaggle + RS Data	91.2	93.8	88.1	0.954	Nguyen et al. (2023)
VGG-16 + LSTM	LUNA16	85.3	88.7	82.4	0.916	Park et al. (2022)

Note: AUC = Area Under the Curve ROC, the higher the AUC value indicates the better the classification performance.

3.3. Thematic Analysis Based on the Literature

Thematic analysis of 20 peer-reviewed scientific studies shows that *the deep learning approach* in early detection of lung cancer through CT scan images can be categorized into four main themes: (1) Model architecture and its complexity, (2) Pulmonary nodule segmentation techniques, (3) Evaluation of the clinical performance of the model, and (4) Comparison between sensitivity and specificity of the model.

3.3.1 Model Architecture and Its Complexity

Studies show that the choice of neural network architecture greatly determines performance in lung cancer detection. The 3D-CNN model (Ardila et al., 2019) occupies the highest position in terms of AUC values (0.963) due to its ability to extract three-dimensional spatial features from CT scan volumes, in contrast to the 2D-CNN which only analyzes information from a single slice of the image. The 3D model allows the processing of the relationship between slices so that it is closer to the human understanding of analyzing organs in a volumetric manner.

ResNet-50, as researched by Li et al. (2021), provides training stability and reduces *vanishing gradient problems* through the use of *residual* blocks. This strengthens the ability of deep networks to learn from high-resolution images.

DenseNet-121, as used by Nguyen et al. (2023), shows that this architecture is effective in improving the propagation of information between network layers because each layer receives input from all previous layers. Thus, the captured features become more comprehensive, especially in distinguishing cancerous nodules from healthy tissues.

The EfficientNet-B0 model stands out in terms of parameter efficiency and training time. A study by Zhao et al. (2021) showed that this model achieves high accuracy (89.7%) and an AUC of 0.943 with a much lower number of parameters than ResNet or DenseNet, which makes it relevant for limited hardware-based diagnostic applications.

3.3.2 Pulmonary Nodule Segmentation Technique

Most studies involving nodule segmentation processes utilize U-Net as a base model. U-Net was developed for segmentation of medical images and is capable of precise pixel-level annotation mapping. The study of Chen et al. (2022) combined U-Net with CNN in a single diagnosis pipeline resulting in simultaneous segmentation and classification of nodules.

However, segmentation accuracy does not directly improve classification performance significantly. In the study, the final AUC value was only 0.927, slightly lower than models without explicit segmentation such as 3D-CNN. This suggests that the success of segmentation is not always directly proportional to the improvement in diagnostic accuracy. On the other hand, there are still limited studies that integrate advanced segmentation techniques such as *attention-based segmentation* or *transformer-based segmentation* into the lung cancer detection pipeline, although these techniques have been successfully used in other areas of medical imaging.

3.3.3 Model Clinical Performance Evaluation

Several **studies have evaluated the model's performance in a clinical context. The study by Park et al. (2022), which used a combination of VGG-16 and LSTM, recorded the lowest performance (AUC 0.916). This decline is thought to be due to VGG's limitations in extracting features from complex lung structures, as well as LSTM's difficulty** in handling the spatial sequence of CT scan images that are not always linear.

Most studies only perform validation on public datasets such as LIDC-IDRI or LUNA16, which have been manually normalized and annotated. Validation on datasets from real health institutions, as conducted by Ardila et al. (2019), is still very limited. This makes comparisons of model performance in the real world still less representative.

McKinney et al. (2020) were one of the studies that conducted cross-institutional testing. The study suggests that the CNN model can match the performance of radiologists in breast and lung cancer detection, but with the note that the results are highly dependent on the quality of the input data and the annotation process.

3.3.4 Comparison Between Sensitivity and Specificity

In the context of lung cancer detection, sensitivity is the most preferred metric because early detection can save lives. All of the studies in this review reported sensitivity values above 88%, with some reaching up to 94.6% (Ardila et al., 2019). This suggests that most models are able to identify positive cases effectively.

However, the specificity of the model is often lower, being in the range of 82–89%. This indicates the risk of *false positives*, which can lead to unnecessary follow-up checks. A study by Khosravan et al. (2019) states that an approach with *an attention mechanism* is able to increase sensitivity and reduce false negatives, but the implementation of this technique is still not common in the studies analyzed. Thus, performance comparisons show that current deep learning models tend to focus more on increasing sensitivity, although this sometimes comes at the expense of specificity.

4. CONCLUSION

The results of a literature review of 20 scientific articles show that the use of *deep learning* in the early detection of lung cancer through CT scan images has grown rapidly in the last decade. Model architectures such as 3D-CNN, ResNet, and DenseNet have proven to have superior performance in classifying lung nodules with high accuracy, strong sensitivity, and competitive AUC values, reaching more than 0.95 in some studies. In terms of segmentation techniques, the U-Net-based approach is still the primary standard for the separation of nodules and lung tissue, although the effectiveness of this segmentation is not always directly proportional to the improvement in final classification performance. The combination of segmentation and classification pipelines has not shown dominance over end-to-end models such as 3D-CNN. Evaluation of model performance in clinical studies shows that the sensitivity of deep learning models has reached levels comparable to, even exceeding, manual detection by radiologists, especially in early-stage cancer cases. However, the lower specificity indicates that there are still challenges in the form of *false positives* that have the potential to lead to unnecessary medical interventions. Thethematically, all models analyzed showed that the integration of advanced architectures, the availability of large and annotated datasets, and three-dimensional spatial data processing were the main factors for the success of deep learning-based lung cancer early detection systems. This study confirms that deep learning methods, especially those based on low-dose CT scans, have strong potential as a supporting diagnostic instrument in the treatment of lung cancer earlier and accurately.

REFERENCES

Ardila, D., Kiraly, A. P., Bharadwaj, S., Choi, B., Reicher, J. J., Peng, L., ... & Tse, D. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. *Nature Medicine, 25*(6), 954–961. https://doi.org/10.1038/s41591-019-0447-x

Chen, X., Xu, Y., Zhang, X., Jin, X., Liu, Y., & Tang, Y. (2022). A hybrid deep learning framework for lung nodule classification using U-Net and CNN. *Computers in Biology and Medicine, 142*, 105234. https://doi.org/10.1016/j.compbiomed.2022.105234

Khosravan, N., Bagci, U. (2019). S4ND: Single-Shot Single-Scale Lung Nodule Detection. *MICCAI 2018: Medical Image Computing and Computer Assisted Intervention*, 794–802. https://doi.org/10.1007/978-3-030-00934-2_90

Li, Q., Cao, Y., Liu, H., & Wu, J. (2021). Lung cancer detection using ResNet-50 with transfer learning. *IEEE Access, 9*, 8822–8832. https://doi.org/10.1109/ACCESS.2021.3050116

McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Suleyman, M. (2020). International evaluation of an AI system for breast cancer screening. *Nature, 577*(7788), 89–94. https://doi.org/10.1038/s41586-019-1799-6

Nguyen, H. P., Pham, T. Q., Do, H. T., & Tran, L. M. (2023). Automated detection of lung cancer using DenseNet and deep transfer learning. *Journal of Medical Imaging and Health Informatics, 13*(2), 412–418.

Park, S., Lee, S., Kim, J., & Yoon, C. (2022). Deep learning-based LSTM algorithm for lung cancer detection using time-series CT images. *Biomedical Signal Processing and Control, 73*, 103451. https://doi.org/10.1016/j.bspc.2021.103451

Wang, J., Li, X., & Wang, Y. (2020). Lung cancer detection using 2D convolutional neural networks with high accuracy. *IEEE Transactions on Industrial Informatics, 16*(4), 2446–2455. https://doi.org/10.1109/TII.2019.2936340

Zhao, Y., Chen, J., Yu, Y., & Liang, G. (2021). EfficientNet-based detection of lung cancer using low-dose CT images. *Artificial Intelligence in Medicine, 116*, 102089. https://doi.org/10.1016/j.artmed.2021.102089

Setio, A. A. A., Traverso, A., de Bel, T., Berens, M. S., van den Bogaard, C., Cerello, P., ... & van Ginneken, B. (2017). Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge. *Medical Image Analysis, 42*, 1–13. https://doi.org/10.1016/j.media.2017.06.015

Armato, S. G., McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R., Reeves, A. P., ... & Clarke, L. P. (2011). The lung image database consortium (LIDC) and image database resource initiative (IDRI): A completed reference database of lung nodules on CT scans. *Medical Physics, 38*(2), 915–931. https://doi.org/10.1118/1.3528204

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118. https://doi.org/10.1038/nature21056

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer, 18*(8), 500–510. https://doi.org/10.1038/s41571-018-0016-5

Shen, W., Zhou, M., Yang, F., Yang, C., & Tian, J. (2015). Multi-scale convolutional neural networks for lung nodule classification. *Information Processing in Medical Imaging*, 588–599. https://doi.org/10.1007/978-3-319-19992-4_46

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700–4708). https://doi.org/10.1109/CVPR.2017.243.