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Lung Cancer Detection using CNN and SVM

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Abstract

Lung cancer is one of the main causes of cancer-related mortality worldwide. Early diagnosis is vital to improving treatment outcomes. Medical imaging benefits greatly from deep learning, a branch of artificial intelligence that uses hierarchical neural networks to automatically extract and learn characteristics from massive datasets. This study introduces a deep- learning approach that is hybrid and uses Convolutional Neural Networks (CNNs) for feature extraction and Support Vector Machines (SVMs) to identify lung cancer subtypes from CT images. We trained a CNN algorithm to extract robust features by preprocessing the CT scans using a well-structured dataset from Kaggle that covers both benign and malignant lung diseases. To increase accuracy and generalization, the collected characteristics were then fed into an SVM classifier. The model surpassed traditional approaches in terms of speed and predictive power, as measured by accuracy (93.2%), F1- score (91.7%), and specificity (94.5%). Data augmentation methods were also applied to increase the resilience of the model. The suggested technique shows a great deal of promise for helping radiologists diagnose lung cancer early.

Keywords: Deep-learning, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), CT scans, hybrid model, Grad-CAM, data augmentation.

1. Introduction

With around 1.8 million fatalities from the disease in 2020 alone, lung cancer continues to rank among the most deadly and severe conditions in the world [1]. The complexity of early detection stems from the overlapping features of benign and malignant nodules and the dependency on manual interpretation of CT scans. Traditional diagnostic tools, although effective, are time-consuming, invasive, and subject to human error [2].

Recent advances in artificial intelligence, specifically deep learning, have increased the feasibility and accuracy of automated diagnosis. Convolutional Neural Networks (CNNs) can automatically learn and extract significant patterns from medical images, reducing the dependence on expert-defined features [3].

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Deep learning models, however, frequently call for large datasets and an extensive amount of processing power. In order to get around these limitations, hybrid models that integrate CNNs with classifiers such as Support Vector Machines (SVMs) have become practical substitutes [4].

This paper proposes a hybrid CNN-SVM model to detect lung cancer subtypes using CT scan images. The methodology involves preprocessing, CNN feature extraction, and SVM classification. Data augmentation is integrated to improve model robustness and generalization. The approach we employ is assessed on important performance criteria and validated on openly accessible datasets. The work also highlights the significance of combining traditional machine-learning classifiers with deep-learning classifiers to increase diagnostic accuracy in modest medical datasets.

2. Introduction

Shin et al. [5] were the first to employ CNNs for computer-aided detection in medical imaging. By enhancing CNNs previously trained on natural images for radiological applications, they demonstrated the significance of transfer learning. While they achieved great accuracy, they encountered problems with domain mismatch.

Nahid and Kong [6] investigated traditional machine-learning methods like SVM and k-NN for the identifying cases of lung cancer using handcrafted characteristics. The methods discussed performed rather well under low-data settings and proved the usefulness of statistical feature extraction. However, scalability was constrained by their reliance on manual features. Hybrid models, which blend deep learning and conventional classifiers to enhance performance, were inspired by the study.

Hussein et al. [7] employed transfer learning on CNNs that had earlier been trained on ImageNet for the categorization of lung cancer. The results they obtained showed the limitations of changing non-medical factors and also the potential of deep models. Although domain-specific pretraining might further increase accuracy, the study showed respectable results. The significance of tailoring models for medical imaging tasks was underlined.

Kumar and Bhandari [8] proposed an end-to-end CNN-based pipeline for automated lung cancer detection. Their approach improved up detection, but because it was only tested on a limited number of datasets, it had limited generalizability. The study underlined the necessity for wider dataset validation while simultaneously highlighting the advantages of completely automated feature extraction. Their research backs the movement in cancer diagnosis toward end-to-end, scalable deep-learning models.

Shorten and Khoshgoftaar [9] studied the data augmentation approaches that are essential for deep model training on tiny medical datasets. They highlighted the importance of using transformations and GANs for enhanced performance. Their research demonstrated how varied supplemented data might enhance generalization and lessen overfitting. It also demonstrated how augmentation fills the void left by a lack of labeled medical data.

Shen et al. [10] introduced a hybrid CNN-LSTM model to detect temporal patterns in CT images. Despite its promising results, the model was computationally expensive and required sequential data. The study demonstrated potential for detecting nodule development patterns and detecting temporal dependency in CT slices.

However, the need for time-series data limited its capacity to adapt to static image scenarios. Wang et al. [11] explored transformer-based models for medical imaging. These models show potential, but their implementation in lung cancer detection is still emerging. Transformers need much more computing and much bigger datasets, but they have demonstrated high representational power. Our approach is better appropriate for smaller-scale clinical datasets since it improves upon well-established CNN architectures to guarantee stability and repeatability.

A lightweight CNN design that enhances performance on low-dose CT images was suggested by Liu et al. [13]. For better nodule detection, Muramatsu et al. [14] used 3D CNNs with attention mechanisms. A multi-scale, multi-view CNN that effectively captures spatial variations was introduced by Yang et al. [15]. Ali et al. [17] blended deep and handmade features for improved classification accuracy, whereas Almotairi et al. [16] focused on explainability in deep models. A 3D attention-residual network for classification and segmentation was presented by Zhang and Li [18].

3. Methodology

3.1. Dataset:

We used a curated Kaggle dataset that contained lung CT images with the following labels: normal, adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. These correspond to the three key categories of nodules — benign, primary malignant, and metastatic malignant, illustrated in Figure 1. The dataset is high-resolution, balanced, and ideal for deep-learning applications [12].

3.2. Preprocessing Datasets:

Images were resized to 224x224 pixels and normalized to a [0,1] pixel range. To improve the model's generalization capability, data augmentation methods such as horizontal flipping, image rotation, and brightness modification were employed.

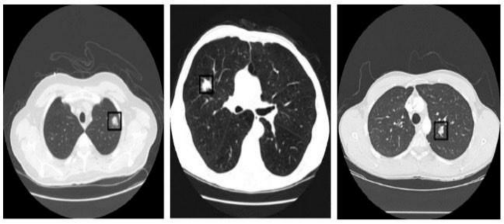

Fig. 1. Categories of lung nodules in a CT scan: benign, primary malignant, and metastatic malignant (from left to right).

The categories of lung nodules in a CT scan are shown in figure 1. These images demonstrate the visual differences the model learns to identify during classification.

3.3. Model Architecture:

The CNN model's internal pipeline for recognizing images from lung CT scans is depicted in the figure 2.

3.4. Feature Extraction Using CNN

The following layers were used in the creation of a CNN model [8][13]:

- Input Layer: Images scaled to 224×224×1 pixels are accepted by the input layer.
- Convolutional Layers: These layers extract low- and high-level features, such edges and textures, using 3x3 filters with ReLU activation.
- Max Pooling Layers: Reduces spatial dimensions to save processing effort while maintaining significant features.
- Dropout Layer: To avoid overfitting, a dropout rate of 0.25 is applied.
- Flatten and Dense Layers: This method employs fully connected layers to learn abstract representations and converts the retrieved features into a one-dimensional vector.

To train the CNN, the Adam optimizer was utilized with a batch count of 32 and rate of learning of 0.001, following the best techniques for CNN-based lung cancer diagnosis described in [14][15].

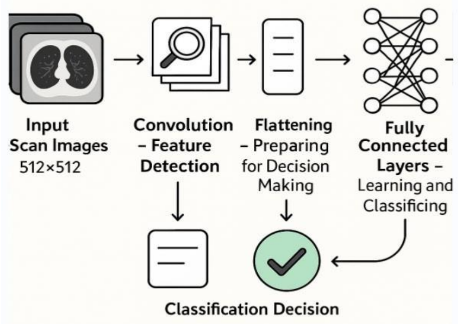

Fig. 2: An illustration of the categorization pipeline based on CNN.

3.5 Model Training and Optimization

The training process of the proposed hybrid architecture is divided into two phases:

- Phase 1(Feature Extraction Training using CNN)- Preprocessed CT images resized to 224 × 224 pixels are used to train the CNN. It consists of multiple convolution layers with ReLU activation, followed by layers of max pooling for spatial down-sampling. These are supported by dropout layers to minimize overfitting. Compact feature vectors are created by flattening the final convolutional output and passing it through dense, fully linked layers. The Adam optimizer is used to train the network with a batch size of 32 and learning rate of 0.001. The training process iteratively reduces classification loss by using backpropagation and gradient descent [13][14].
- Phase 2 (Classification Training using SVM): After CNN training, the feature vectors from the last dense layer are input into an SVM classifier. Learning a decision boundary (hyperplane) that divides the classes (for example, benign vs. malignant nodules) with the greatest margin is the responsibility of the SVM. This margin-maximizing approach increases classification accuracy by reducing overfitting and improving generalizability, particularly with very small datasets [15][16].

4. Results & Analysis

4.1. Performance Metrics

Table 1: Performance Metrics of CNN-SVM Model

Metric	Value (%)
Accuracy	93.2
Precision	92.0
Recall	91.4
F1-Score	91.7
Specificity	94.5

4.2. Confusion Matrix

Table 2: Confusion Matrix for CNN-SVM Classification

	Predicted: Normal	Predicted: Cancer
Actual: Normal	145	5

Actual: Cancer	9	141

4.3. Model Comparison

Table 3: Comparative Analysis with Existing Methods

Model	**Accuracy (%)**	**F1-Score (%)**	**Source**
SVM with handcrafted features	85.3	84.5	[6]
CNN only	90.1	88.7	[8]
CNN + LSTM	91.5	89.2	[10]
Proposed CNN + SVM	93.2	91.7	This work

4.4. Visual Interpretation

Grad-CAM heatmaps verified the CNN's alignment with clinical significance by demonstrating that it concentrated on nodule-like features in questionable areas. This may be seen in Figure 3.

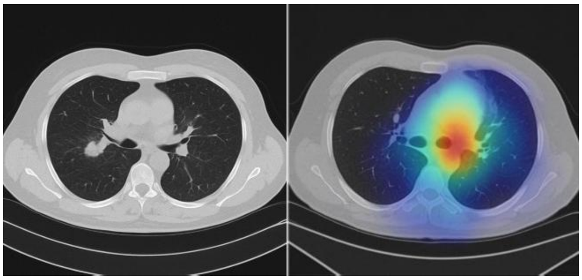

Figure 3: A grayscale CT scan and its associated Grad-CAM output are shown side by side, emphasizing the model's focus on possible nodules. [16][19]

5. Conclusion

A hybrid deep-learning model that combines CNNs and SVMs for computerized lung cancer detection from CT images has been proposed. High accuracy, resilience through augmentation, and clinical relevance were all displayed by the system. In the future, the system will be used in clinical processes and 3D CNNs will be integrated for volumetric data. Additionally, generalization may be further enhanced by expanding the dataset to cover a range of three demographic groups and rare cancer subtypes may further improve generalization. Enhancing real- world applicability may also be achieved by including clinical decision-support elements and explainable AI approaches.

References

[1] World Health Organization, "Cancer Fact Sheet," 2020.
[2] S. K. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep- learning," arXiv preprint arXiv:1711.05225, 2017.
[3] G. Litjens et al., "A survey on deep-learning in medical image analysis," Medical Image Analysis, vol. 42, pp. 60-88, 2017.
[4] M. Anthimopoulos et al., "Lung pattern classification for interstitial lung diseases using a deep convolutional neural network," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1207-1216, 2016.
[5] H. C. Shin et al., "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1285–1298, May 2016.

[6] A. A. Nahid and Y. Kong, "Lung cancer detection using machine-learning techniques," Int. J. Artif. Intell. Appl., vol. 9, no. 1, pp. 33–47, Jan. 2018.
[7] S. Hussein et al., "Risk stratification of lung nodules using 3D CNN-based multi-task learning," in Med. Image Comput. Comput. Assist. Interv., pp. 249–260, Springer, 2019.
[8] A. Kumar and S. Bhandari, "Automatic lung cancer detection using convolutional neural networks," in Advances in Intelligent Systems and Computing, vol. 1129, Springer, pp. 343–351, 2020.
[9] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep-learning," Journal of Big Data, vol. 6, no. 1, pp. 1–48, 2019.
[10] Y. Shen et al., "Deep-learning with LSTM for lung cancer prediction using sequential CT scans," Computers in Biology and Medicine, vol. 134, pp. 104208, 2021.
[11] Z. Wang et al., "TransMed: Transformer-based medical image classification," Neural Comput. Appl., vol. 34, pp. 14757–14772, 2022.
[12] Kaggle, "Lung Cancer CT Dataset," [Online]. Available: https://www.kaggle.com/datasets/
[13] J. Liu, Y. Cao, and H. Zhang, "Lightweight convolutional neural networks for lung nodule detection in low- dose CT images," IEEE Access, vol. 9, pp. 73284–73295, 2021.
[14] S. Muramatsu et al., "3D CNN and Attention Mechanism for Lung Cancer Diagnosis in CT Scans," Computers in Biology and Medicine, vol. 144, pp. 105343, 2022.
[15] L. Yang et al., "Multi-view and multi-scale CNN for pulmonary nodule classification," IEEE Trans. Image
[16] Process, vol. 31, pp. 2303–2315, 2022.
[17] A. Almotairi et al., "Explainable Deep-learning Models for Lung Cancer Detection Using CT Images," Diagnostics, vol. 13, no. 3, 2023.
[18] M. Ali et al., "Lung cancer prediction using a fusion of deep features and handcrafted features," Expert Systems with Applications, vol. 227, 2023.
[19] Y. Zhang and J. Li, "3D Attention-Residual Network for Lung Tumor Segmentation and Classification," IEEE J. Biomed. Health Inform., vol. 28, no. 2, 2024.
[20] R. R. Selvaraju et al., "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), 2017, pp. 618–626.
[21] M. A. Pechincha et al., "Automatic lung nodule detection and classification in CT scans using deep-learning: A survey," Computers in Biology and Medicine, vol. 140, pp. 105124, 2022.

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