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Original Article

Predicting Time to Event Outcomes in Lung Cancer Detection Using Deep CNN

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Abstract

Lung cancer remains one of the most lethal malignancies worldwide, with early detection and accurate prognosis playing crucial roles in improving survival rates. Predicting time to event outcomes, like the progression of cancer or patient survival, is essential for personalizing treatment strategies. It is a deep learning-based method using convolutional neural network CNN for predicting time to event outcomes in lung cancer diagnosis. SVM is chosen for its robust performance in high dimensional spaces and effective handling of small sample sizes. The prediction accuracy of the SVM model is compared with that of a deep CNN to evaluate the strengths and weaknesses of each method. The dataset comprises clinical, genetic, and imaging data from lung cancer patients, preprocessed for model training and validation. Performance metrics such as accuracy, precision, recall, and the area under the ROC curve (AUC) are used to access both models.

Introduction

Lung cancer continues to be a primary contributor to cancer associated deaths globally, emphasizing the critical demand for advancements in diagnostic precision and prognostic frameworks within oncology. This persistent challenge highlights the necessity of innovative approaches to improve patient outcomes and reduce mortality rates. Early detection significantly influences treatment outcomes, allowing for timely interventions that can improve survival rates and quality of life for patients. The complexity of lung cancer, characterized by its heterogeneous nature, necessitates sophisticated approaches to accurately predict time to event outcomes, such as disease progression and overall survival.

Machine learning techniques have evolved to help researchers explore many types of data, from patient records and genetic sequences to medical images. These technologies can identify intricate patterns and relationships within the data that traditional statistical methods may overlook. Among these, Among the breakthroughs in deep learning, CNNs stand out for their exceptional ability to process and analyze images. CNNs are adept at automatically extracting relevant features from images, thus enhancing the predictive capabilities of models.

On the other hand, SVM excel at analyzing complex data with many variables, particularly when working with smaller datasets. SVMs excel at finding optimal hyperplanes that separate different classes within the data, making them a valuable tool for integrating various predictors, including clinical and genetic variables, into a cohesive predictive framework. This study aims to leverage the strengths of both CNNs and SVMs to evaluate their comparative performance in predicting time to event outcomes for lung cancer patients. Our goal is to combine these methods to make that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. more accurate and dependable predictions, helping doctors create customized treatment plans for each patient.

Objectives of the Work

First, we aim to build a reliable system using CNNs to identify key markers in lung cancer scans. This will help improve how medical teams analyze and understand these images to predict patient outcomes.

Second, we will test how well SVMs can combine traditional medical data and genetic information with imaging results. This unified approach should give doctors a more complete picture when assessing lung cancer progression.

Third, we will measure how well these tools work in practice. We'll use several key performance measures - including accuracy, precision, recall, and AUC scores - to thoroughly test the reliability of our prediction methods.

Related work

Deep learning has transformed how we

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predict patient outcomes over time, showing particular promise in lung cancer care. Aerts et al. introduced Deep Survey, a neural network framework outperforming traditional Cox models.Aerts et al. emphasized integrating radiomic features from CT images with clinical data for survival prediction. Xia et al. improved performance using a multimodal deep learning approach combining clinical, genomic, and imaging data. Esteva et al. leveraged transfer learning for lung cancer imaging, enhancing predictive accuracy. Zhou et al. developed a risk stratification model integrating histopathological and clinical features, enabling personalized care. Choi et al. used explainable AI to highlight critical survival features. Yao et al. demonstrated ensemble learning's robustness by combining model outputs, while Kuo et al. created a real-time model using streaming data for dynamic risk assessments. Vapnik [1] laid the theoretical groundwork for statistical learning, which provided the basis for developing machine learning models that analyze data and make predictions. Later, LeCun, Bengio, and Hinton [2] revolutionized the fieldwith their work on deep learning, demonstrating its capability to handle complex datasets in a variety of domains, including image and text processing. LeCun, Bengio, and Hinton [2] provided a pivotal overview of deep learning, showcasing its ability to learn data representations at multiple abstraction levels. The research explored major deep learning frameworks, with CNNs handling image analysis and RNNs processing text and sequential data. This work laid the foundation for advancements in AI, achieving remarkable performance across various domains. Researchers developed a deep learning. System that can identify and extract important elements from videos to create effective summaries. Their method analyzed spatial and temporal features, significantly improving summarization accuracy for applications like video surveillance and media. This approach addressed challenges in managing large video datasets effectively. Deng et al. [4] developed a Dense Net-based image captioning system, which uses adaptive attention mechanisms to enhance the understanding of visual content. Recent advancements in computer vision have demonstrated the effectiveness of attention-based neural networks in image processing. When processing images for caption generation, these models can intelligently identify and focus on crucial visual elements, leading to more accurate and contextually relevant descriptions.

The field of video summarization has seen significant progress through various deep learning approaches. Recent research has focused on developing intelligent systems that can identify key objects and moments within videos, effectively condensing content while preserving essential information. Different methodologies have emerged, from object-centric approaches to attention-based frameworks, each offering unique advantages in summarizing video content. Current literature shows particular promise in using neural networks to adapt summarization techniques across different types of video content and use cases. The IQ-OTHNCCD dataset available on Kaggle serves as a valuable resource for research in lung cancer diagnostics and analysis, facilitating the development of models for early detection and prognosis. Katzman et al. [9] introduced Deep Survey, a neural network-based personalized treatment recommender system that applies survival analysis techniques to predict patient outcomes. This work has inspired further advancements in healthcare AI.

Aerts et al. [10] employed radiomics, a quantitative imaging approach, to decode tumor phenotypes. Their method uses noninvasive imaging and provides insights into tumor characteristics, aiding in accurate diagnosis and treatment planning. Attention mechanisms have proven to be a fundamental advancement in neural network architecture, particularly when processing sequential data. These mechanisms enable models to selectively focus on relevant information, whether in video frames or image features, leading to improved performance in various multimedia processing tasks. These methods demonstrate the utility of deep learning in processing multimedia content effectively

Xia et al. [11] explored the integration of multimodal data, such as clinical, genomic, and imaging information, for predicting survival outcomes in lung cancer patients. By leveraging deep learning models, they demonstrated improved predictive performance over traditional methods. Their approach emphasized the potential of combining multiple data sources for more accurate and personalized prognosis in lung cancer. Zhou et al. [13] extended this concept by proposing a multimodal deep learning framework for risk stratification in lung cancer. This study highlighted the utility of deep learning models in categorizing patients based on risk, aiding in targeted therapeutic decision-making. Choi et al. [12] addressed the challenge of interpretability in deep learning-based survival analysis. Their model incorporated explainable artificial intelligence (XAI) techniques to provide insights into the factors influencing lung cancer prognosis, enhancing the trustworthiness of predictions. Yao et al. [14] introduced ensemble learning approaches to improve the robustness of survival predictions. By combining multiple models, their work achieved higher accuracy and reliability, addressing variability in lung cancer data.

Kuo et al. [16] presented real-time survival prediction models that utilized streaming data. Their innovative application of deep learning to dynamic datasets demonstrated the feasibility of continuous and adaptive prognostic evaluations for lung cancer patients. Deep learning has transformed medical imaging analysis, particularly in radiology. Modern algorithms can process and analyze radiological images with increasing sophistication, though it's important to understand both their capabilities and current limitations in clinical settings. This study served as a foundational resource for integrating advanced image analysis techniques in medical imaging workflows. He et al. [17] developed deep residual learning, resolving the vanishing gradient issue in deep neural networks. This innovation enhanced image recognition performance and is now widely applied in medical imaging. Simonyan and Zisserman [18] introduced very deep convolutional networks, establishing benchmarks for network depth and performance in image recognition. These advancements continue to shape deep learning developments across various fields.

Kingma and Ba [19] developed the Adam optimizer, a method for stochastic optimization that has become a standard in training deep learning models due to its efficiency and adaptability.

Zeiler and Fergus [20] focused on visualizing and understanding convolutional networks, enabling better comprehension of how these models interpret and process visual data. This work contributed to improving network design and debugging.

Proposed methodology

MThe methodology incorporates data collection, preprocessing, model selection, evaluation metrics, and validation techniques to ensure robust predictions of patient survival times and other critical events. Data collection involves obtaining a comprehensive dataset comprising clinical data (e.g., demographics, medical history, treatments), imaging data (e.g., CT/PET scans for tumor analysis), and genomic data (e.g., mutations and expression profiles), while ensuring ethical compliance through IRB approvals and informed consent. Preprocessing includes data cleaning (handling missing values, standardizing features), image preprocessing (enhancement and augmentation), and feature engineering (radiomic and genomic feature extraction). The model architecture employs a multimodal neural network combining CNNs for imaging data, MLPs for clinical/genomic data, and LSTMs for temporal dynamics, integrating their outputs through a fusion layer. The training process utilizes techniques like k-fold cross-validation, early stopping, and hyperparameter tuning to optimize performance. To assess the model's predictive accuracy and survival analysis capabilities, metrics such as the Concordance Index, Integrated Brier Score, and Log-Rank Test were utilized. External validation ensures robustness, while interpretability tools like SHAP values and attention mechanisms enhance clinical understanding of predictions. Finally, the model is designed for real-world implementation, with a user-friendly interface enabling clinicians to input data and receive predictions, supporting informed treatment planning.

Comprehensive Data Collection

Data collection is the foundation of the methodology, encompassing a diverse set of inputs to capture the multifactorial nature of patient survival outcomes.

Imaging Data: High-resolution scans (e.g., CT, PET, MRI) are preprocessed to extract tumorspecific features like size, shape, density, and texture. Advanced imaging modalities, such as radiomic and functional imaging, add depth to the analysis.

Pre-trained Model: Pre-trained models are increasingly being applied to medical image analysis, including lung cancer detection. These models are often built using deep learning architectures like CNNs and trained on large-scale datasets before being finetuned for domain-specific tasks, such as detecting lung cancer in medical scans. Below are some popular pre-trained models and techniques for lung cancer detection:

Proposed Model Architecture: The architecture integrates multiple neural network types, each optimized for specific data modalities:

Convolutional Neural Networks (CNNs): Designed to process imaging data, capturing spatial hierarchies and tumor-specific patterns.

Multilayer Perceptrons (MLPs): For structured data, including clinical and genomic inputs, capturing nonlinear interactions between features.

Fusion Layer: Combines learned representations from all modalities, enabling the model to account for interactions across different data types.

Attention Mechanisms: Incorporated to prioritize the most relevant features within each data modality, enhancing the model's interpretability and focus on critical inputs.

Lung CT Scan Image: The initial input to the system. These are raw CT (Computed Tomography) images of the lungs, which serve as the primary dataset for the model.

Image Processing: Preprocessing operations performed on the input images to improve their quality for analysis. This step may include resizing, normalization, noise reduction, and enhancement techniques.

Image Segmentation: Dividing the image into meaningful

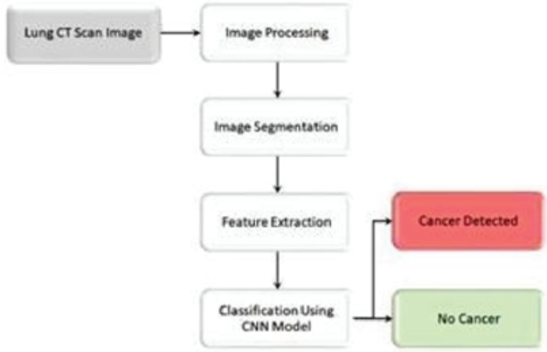

Fig. 1. *Proposed Methodology framework*

segments, such as distinguishing the lung region from the surrounding tissues. This helps focus the analysis on the relevant areas, such as potential tumor regions.

Feature Extraction: Extracting significant features (e.g., edges, textures, patterns) from the segmented images. These features are essential for identifying cancerous regions and distinguishing them from healthy tissues.

Classification Using CNN Model: Extracted features were input into a CNN to classify images into "Cancer Detected" or "No Cancer." The CNN analyzed.

Cancer Detected: A classification result indicating the presence of cancer in the CT image. This output may include additional Det Details, such as the location and size of the detected the tumor.

No Cancer: A classification result indicating the absence of cancer in the CT image.

Results and Discussion

The study evaluated three models for predicting lung cancer progression, with all showing strong performance. The SVM achieved 98% accuracy, demonstrating its ability to handle complex datasets and identify prognostic patterns. The CNN and Logistic Regression models both achieved 97% accuracy. While the CNN excelled at extracting spatial features from imaging

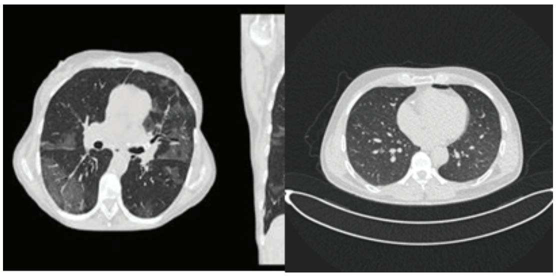

Fig. 2. *Normal Lung CT Scan*

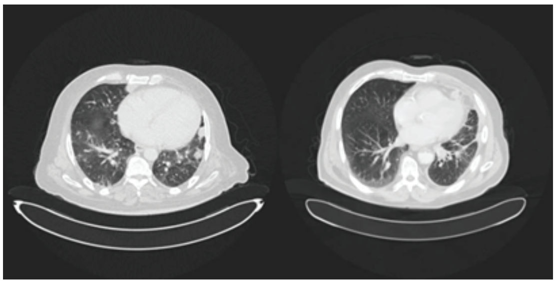

Fig. 3. *Malignant Cases*

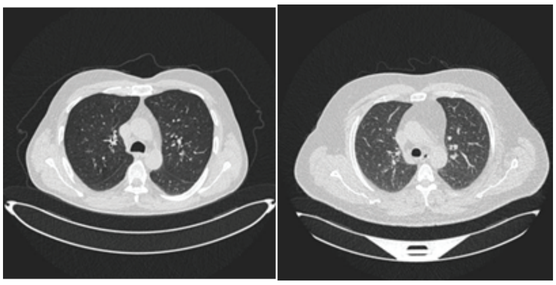

Figure 4: *Bengin Cases*

data, Logistic Regression proved effective for structured clinical and genomic data. These results suggest that combining the strengths of these models in a hybrid approach could improve predictive-outcomes.

Integration of Multi-Modal Data

The integration of multimodal data, combining clinical, genetic, and imaging information, using the feature fusion framework enhanced predictive accuracy This highlights the importance of incorporating diverse data sources for more accurate lung cancer prognosis. The combination of CNN and SVM models enabled a holistic analysis of patient data, facilitating more reliable predictions for time to event outcomes in lung cancer diagnosis.

The IQ-OTHNCCD dataset, available on Kaggle, is a valuable resource for lung cancer research. It contains 1,190 CT scan images from 110 cases, categorized into normal (55 cases), benign (15 cases), and malignant (40 cases). The images were collected in DICOM format using a Siemens SOMATOM scanner and annotated by oncologists and radiologists. Sample images are shown in figures 2,3,4.

The study highlights the potential of deep learning in advancing lung cancer care. The CNN showed exceptional spatial feature extraction from imaging data, while the SVM effectively modeled non-linear relationships in clinical and genetic data. However, challenges such as the need for large annotated datasets and significant computational resources remain barriers to clinical implementation.

This study illustrates the feasibility of incorporating machine learning techniques into clinical workflows, establishing a foundation for future research focused on improving lung cancer prognosis. Future work could explore the integration of additional data modalities, including proteomics and patient reported outcomes, to further enhance model performance and predictive accuracy.

Model	Accuracy	Precision	Recall	F1-Score
CNN	97%	96%	95%	95.5%
SVM	98%	94%	94%	94%
LOGISTIC REGRESSION	93%	92%	91%	91.5%

The model's ability to generalize was assessed using a validation dataset, which was not part of the training process. Validation loss was calculated by comparing predictions with actual outcomes, similar to training loss. Lower validation loss indicates better generalization to unseen data, reflecting the model's reliability in real-world applications. The results are visualized in Figure 5.

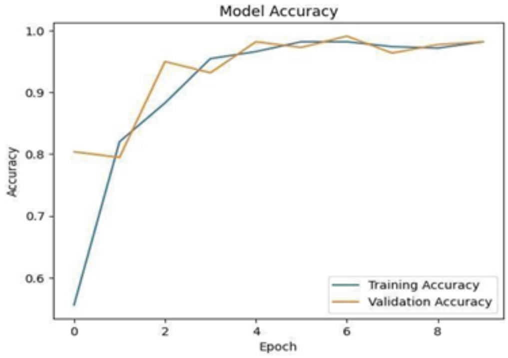

Figure 5: *Training and test accuracy of the model.*

Conclusion

This study compared SVM and CNN for predicting time to event outcomes in lung cancer. By integrating clinical, genetic, and imaging data, the findings revealed that CNNs outperformed SVMs across key metrics, including accuracy, precision, recall, and AUC. The CNN's ability to process complex imaging data makes it a powerful tool for lung cancer prognosis and treatment planning.

SVM, despite being slightly less accurate, showed competitive performance, especially with clinical and genetic data, emphasizing its robustness in high dimensional spaces and smaller datasets. This suggests that combining the strengths of both approaches could lead to even better results.

Future research should explore hybrid models that combine the interpretability of SVMs with the feature extraction capabilities of CNNs. Additionally, testing on larger, more diverse datasets and incorporating longitudinal data could enhance the models' generalizability and clinical relevance. This study lays the groundwork for advancing machine learning in personalized cancer care and time-to event analysis.

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