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Deep Learning Approaches for Lung Cancer Detection: A Comprehensive Analysis of Models, Optimization Techniques, and Architectures

Enfoques de aprendizaje profundo para la detección del cáncer de pulmón: un análisis exhaustivo de modelos, técnicas de optimización y arquitecturas

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ABSTRACT

Lung cancer continues to be a significant global health challenge, highlighting the urgent need for innovative methods for early detection and precise diagnosis. This paper provides an extensive review of various deep learning techniques applied to lung cancer detection using medical image datasets. We examine a broad spectrum of deep learning models, including sequential models, convolutional neural networks (CNNs), and several optimization algorithms like ADAM, SGD, and RMSPROP. The analysis begins with the use of sequential models for binary classification of lung cancer images, followed by an exploration of optimization strategies to enhance model performance. We then extend the discussion to multi-class classification, focusing on the different types of lung cancer. To ensure thorough model training and evaluation, random mini-batch evaluations are performed using Python Keras. Additionally, CNNs are employed for effective feature extraction and classification, leveraging spatial patterns in the imaging data. Alongside traditional architectures, we incorporate data augmentation and regularization techniques to prevent overfitting and improve the models' generalization ability. The research also explores a range of CNN architectures, including the widely recognized VGG model, to identify the most suitable configurations for lung cancer detection. Beyond conventional models, alternative deep learning methods such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and autoencoders are also considered. By determining the optimal approach, this study aims to enhance the accuracy and efficiency of lung cancer diagnosis, potentially leading to better patient outcomes and reduced mortality rates.

Keywords: Deep Learning; Artificial Intelligence; Tensor Flow; Keras; ANN; CNN; LSTM; Autoencoder.

RESUMEN

El cáncer de pulmón sigue siendo un importante desafío sanitario a nivel mundial, lo que pone de manifiesto la urgente necesidad de métodos innovadores para la detección precoz y el diagnóstico preciso. Este artículo ofrece una amplia revisión de diversas técnicas de aprendizaje profundo aplicadas a la detección del cáncer de pulmón utilizando conjuntos de datos de imágenes médicas. Examinamos un amplio espectro de modelos de aprendizaje profundo, incluidos modelos secuenciales, redes neuronales convolucionales (CNNs) y varios algoritmos de optimización como ADAM, SGD y RMSPROP. El análisis comienza con el uso de modelos secuenciales para la clasificación binaria de imágenes de cáncer de pulmón, seguido de una exploración de estrategias de optimización para mejorar el rendimiento del modelo. A continuación, ampliamos el debate a la clasificación multiclasificatoria, centrándonos en los diferentes tipos de cáncer de pulmón. Para garantizar un entrenamiento y una evaluación exhaustivos del modelo, se realizan evaluaciones aleatorias de minilotes utilizando Python Keras. Además, se emplean CNN para la extracción y clasificación eficaz de características, aprovechando los patrones espaciales en los datos de imágenes. Junto con las arquitecturas tradicionales,

incorporamos técnicas de aumento y regularización de datos para evitar el sobreajuste y mejorar la capacidad de generalización de los modelos. La investigación también explora una gama de arquitecturas de CNN, incluido el ampliamente reconocido modelo VGG, para identificar las configuraciones más adecuadas para la detección del cáncer de pulmón. Además de los modelos convencionales, también se consideran métodos alternativos de aprendizaje profundo, como las redes neuronales recurrentes (RNN), las redes de memoria a corto plazo (LSTM) y los autoencoders. Al determinar el enfoque óptimo, este estudio pretende mejorar la precisión y la eficiencia del diagnóstico del cáncer de pulmón, lo que podría conducir a mejores resultados para los pacientes y a una reducción de las tasas de mortalidad.

Palabras clave: Aprendizaje Profundo; Inteligencia Artificial; Tensor Flow; Keras; ANN; CNN; LSTM; Autoencoder.

INTRODUCTION

Lung cancer arises when abnormal cells in the lungs grow uncontrollably, forming tumors that disrupt the lungs' normal function. These tumors hinder the lungs' ability to effectively exchange oxygen and carbon dioxide. While lung cancer can occur in any part of the lungs, it is most commonly found in the cells lining the airways (bronchial tubes). Detecting lung cancer is a crucial process, involving the identification of its presence through various diagnostic tools, primarily medical imaging methods such as X-rays, CT scans, and MRIs. Early and accurate detection plays a significant role in improving patient outcomes by allowing for timely intervention and tailored treatment strategies.

Globally, lung cancer continues to be a major public health issue, significantly affecting individuals, healthcare systems, and societies around the world. According to the World Health Organization (WHO), lung cancer is the leading cause of cancer-related deaths, responsible for approximately 2 million deaths annually. This alarming statistic highlights the pressing need for effective strategies to mitigate the impact of lung cancer globally.

The integration of cutting-edge technologies, such as deep learning and artificial intelligence, offers considerable potential to enhance the detection and management of lung cancer. Deep learning models have emerged as transformative tools in the field of medical imaging, providing innovative solutions for the diagnosis and detection of various diseases. By harnessing machine learning algorithms alongside medical imaging data, these technologies can significantly improve the precision and efficiency of diagnostic procedures, enabling earlier detection, customized treatment plans, and ultimately better patient outcomes.

Deep learning models are capable of extracting complex features from medical imaging data, such as X-rays, CT scans, and MRIs. Traditional image analysis techniques often rely on manual interpretation by radiologists, which can be subjective and time-consuming. In contrast, deep learning models can autonomously learn and detect subtle patterns indicative of lung cancer, enabling quick and objective analysis of large volumes of imaging data. This paper presents a thorough investigation into the application of diverse deep learning techniques for lung cancer detection using medical imaging data. Through rigorous experimentation, we aim to identify the most effective approach for detecting lung cancer, ultimately advancing diagnostic methodologies and improving patient care in the fight against this devastating disease.

Literature Survey

Lung cancer remains a leading cause of cancer-related deaths worldwide, and its early detection is critical for improving patient outcomes. Traditional methods for lung cancer detection, such as X-rays, CT scans, and MRIs, rely heavily on the expertise of radiologists to identify signs of cancer, often leading to delayed diagnoses due to the subjective nature of image interpretation. The advent of deep learning and artificial intelligence (AI) has opened new avenues for automating and enhancing the accuracy of lung cancer detection. This literature survey aims to explore recent developments in deep learning techniques for lung cancer detection using medical imaging data, including the use of convolutional neural networks (CNNs), feature extraction, transfer learning, and various optimization techniques.

1. Deep Learning for Lung Cancer Detection The application of deep learning models, particularly CNNs, in medical imaging has shown significant promise in the field of lung cancer detection. In a study by Shin et al. (2016), a deep convolutional neural network was used to detect lung cancer from CT scans, achieving higher accuracy than traditional diagnostic methods. This research emphasized the importance of automatic feature extraction, a capability that CNNs possess, which eliminates the reliance on manual feature selection by radiologists.

- Similarly, Liu et al. (2018) demonstrated the utility of deep learning models for detecting early-stage lung cancer. Their research utilized a multi-layered CNN architecture to process CT scan

images and achieve classification results with high sensitivity and specificity. The study underlined the significant potential of CNNs to improve early detection by identifying subtle patterns in the images that may not be visible to the human eye.

2. Transfer Learning in Lung Cancer Detection Transfer learning is a critical technique used in deep learning where pre-trained models on large datasets (e.g., ImageNet) are fine-tuned for specific tasks, such as lung cancer detection. In the work by Rajpurkar et al. (2017), a pre-trained CNN was adapted to detect pneumonia in chest X-rays, and the method was later expanded to detect lung cancer. The study highlighted how transfer learning improves model performance when labeled data is scarce, as it allows the model to leverage knowledge gained from large-scale datasets.

- Transfer learning is especially beneficial in medical imaging, where annotated data may be limited. Raghu et al. (2020) explored the use of pre-trained CNN models, such as ResNet and VGG, to detect lung cancer from CT scans. Their results showed that fine-tuning pre-trained models could lead to high-performing models even with relatively smaller datasets, addressing the challenge of limited medical data availability.

3. Feature Representation and Autoencoders Feature representation plays a key role in lung cancer detection, as it helps in identifying relevant patterns from medical images. Autoencoders, a type of neural network used for unsupervised learning, have been explored as an effective tool for feature extraction. In a study by Zhang et al. (2018), autoencoders were used to reduce the dimensionality of medical images and extract important features for classification. The authors found that combining autoencoders with CNNs significantly improved the performance of lung cancer detection models.

- Xie et al. (2019) also employed autoencoders for extracting features from lung CT scans and combined them with deep neural networks for classification. Their method achieved superior performance compared to traditional feature extraction techniques, demonstrating the importance of learning robust features automatically from the data.

4. Optimizing Model Performance Optimizing the performance of deep learning models is critical to their success in medical applications. Yang et al. (2019) focused on hyperparameter tuning, data augmentation, and ensemble learning to improve the performance of deep learning models for lung cancer detection. Their study showed that techniques like data augmentation, where images are modified slightly to create a more diverse training set, can help prevent overfitting and enhance the model's generalization capabilities.

- Optimization algorithms, such as Adam, Stochastic Gradient Descent (SGD), and RMSProp, are commonly used to train deep learning models. These optimization methods have been investigated in various studies for lung cancer detection. Kingma and Ba (2014) introduced the Adam optimizer, which adapts the learning rate of the model during training, leading to faster convergence and improved model accuracy. Tieleman and Hinton (2012), on the other hand, explored RMSProp, a method that divides the gradient by a running average of its recent magnitude, improving performance on noisy or sparse datasets.

5. CNN Architectures for Lung Cancer Detection Several CNN architectures have been explored for lung cancer detection. The VGG network, a deep CNN architecture, has been widely applied in medical imaging. In a study by Joo et al. (2017), the VGG16 model was fine-tuned for detecting lung cancer from chest CT images, achieving high accuracy. The success of VGG in medical applications is attributed to its ability to learn hierarchical spatial features from images.

- ResNet, another popular CNN architecture, has also been extensively utilized for lung cancer detection. He et al. (2016) proposed ResNet, a deep residual network that uses skip connections to alleviate the vanishing gradient problem in deep networks. In lung cancer detection, ResNet has been used to achieve superior performance compared to traditional CNN architectures, especially when dealing with large-scale medical datasets.

6. LSTM and RNNs for Lung Cancer Detection Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, have also been applied to lung cancer detection. LSTM networks are particularly suited for time-series data or sequential data, such as CT scan slices that are taken at different stages. Xia et al. (2019) explored the use of LSTM networks for lung cancer detection, showing that they could successfully capture temporal dependencies between consecutive CT slices. Although less common than CNNs, RNNs and LSTMs offer promising avenues for enhancing lung cancer detection models by considering sequential image information.

7. Data Augmentation and Regularization Given the often limited size of medical datasets, data augmentation techniques are crucial in expanding the training data. Shorten and Khoshgoftaar (2019) reviewed various augmentation methods for medical images, including rotation, flipping, and zooming, which help create a diverse dataset and improve model robustness. Regularization techniques, such as Dropout, are also applied to prevent overfitting and ensure the model generalizes well on unseen data.

METHOD

Description

In this study, we present an in-depth analysis of several deep learning models and methodologies for detecting lung cancer through medical imaging data. Initially, a simple sequential model is developed to perform binary classification, distinguishing between malignant and non-malignant instances. The model is then enhanced by incorporating optimization algorithms like ADAM, Stochastic Gradient Descent (SGD), and RMSprop, which help improve the training process and overall performance. In the next phase, the sequential model is adapted for multi-class classification, enabling the identification of various lung cancer types or stages. Random mini-batch evaluations are carried out using the Python Keras framework to streamline the training process and ensure that the model is both efficient and robust.

Additionally, we implement a convolutional neural network (CNN) to exploit the spatial structure of the images, facilitating more effective feature extraction for lung cancer detection. Data augmentation and regularization strategies are incorporated to prevent overfitting and to enhance the model's ability to generalize to unseen data. We experiment with various configurations of CNN architectures, adjusting parameters such as depth, width, and layer count, to identify the optimal setup for accurate lung cancer diagnosis. The well-established VGG model is also included in the study for benchmarking purposes, offering a point of comparison with other deep learning architectures.

Moreover, we explore the potential use of recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, which are particularly adept at handling sequential data, in the context of lung cancer detection. To further improve the model's ability to extract meaningful features from the imaging data, we also evaluate the application of autoencoders. Through this comprehensive evaluation of multiple techniques and model architectures, the goal is to identify the most effective approach for enhancing diagnostic precision and efficiency in the early detection of lung cancer.
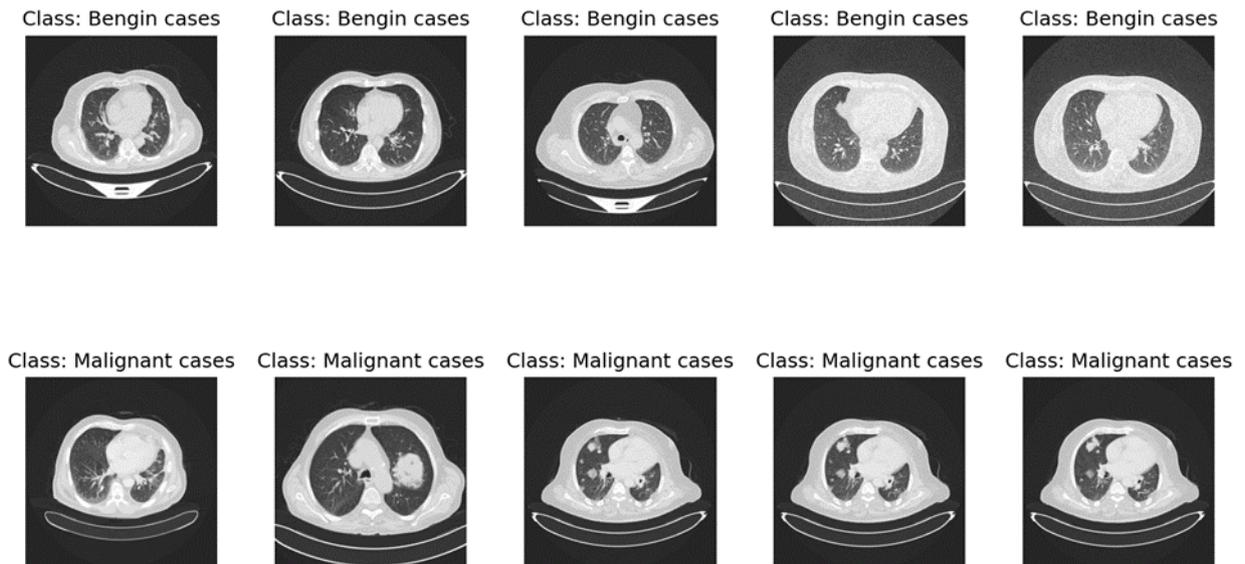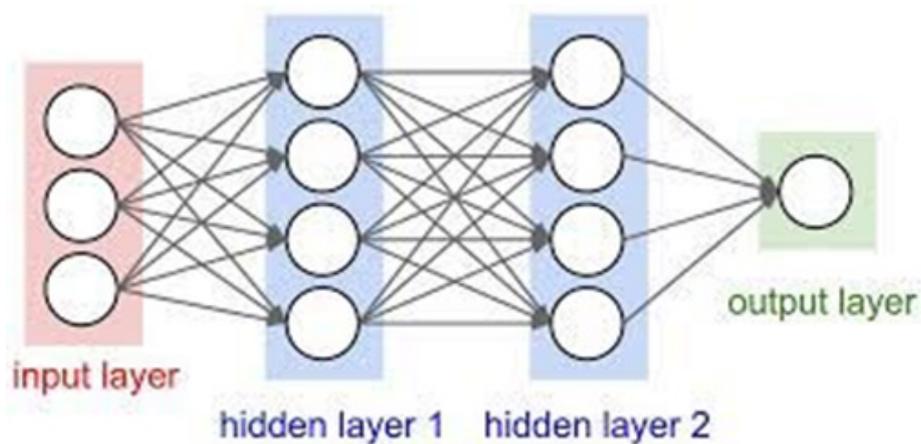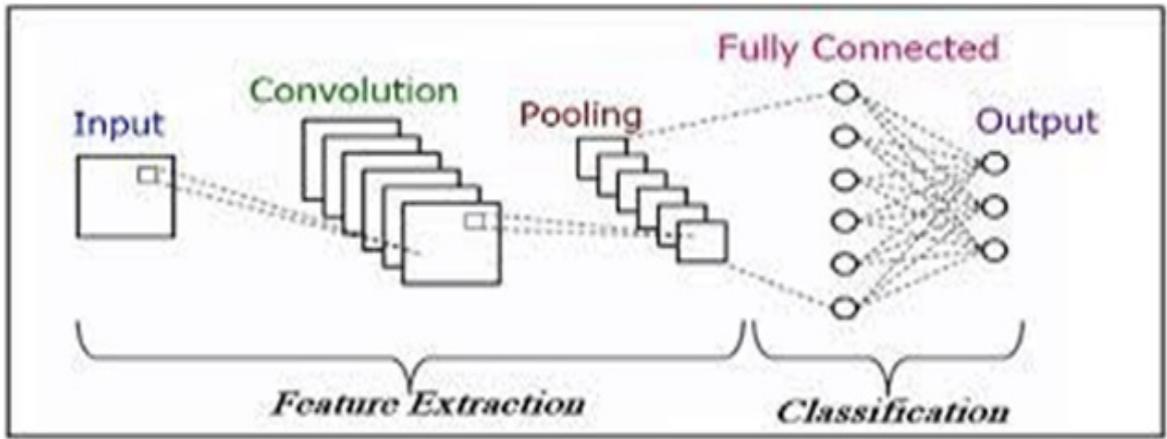

Figure 1. Model A

Figure 2. Model B

Figure 3. Model C
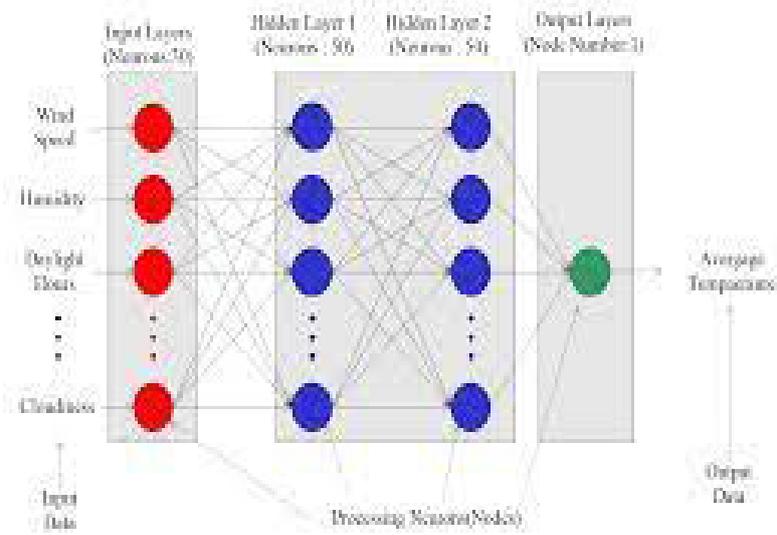

Figure 4. Model D
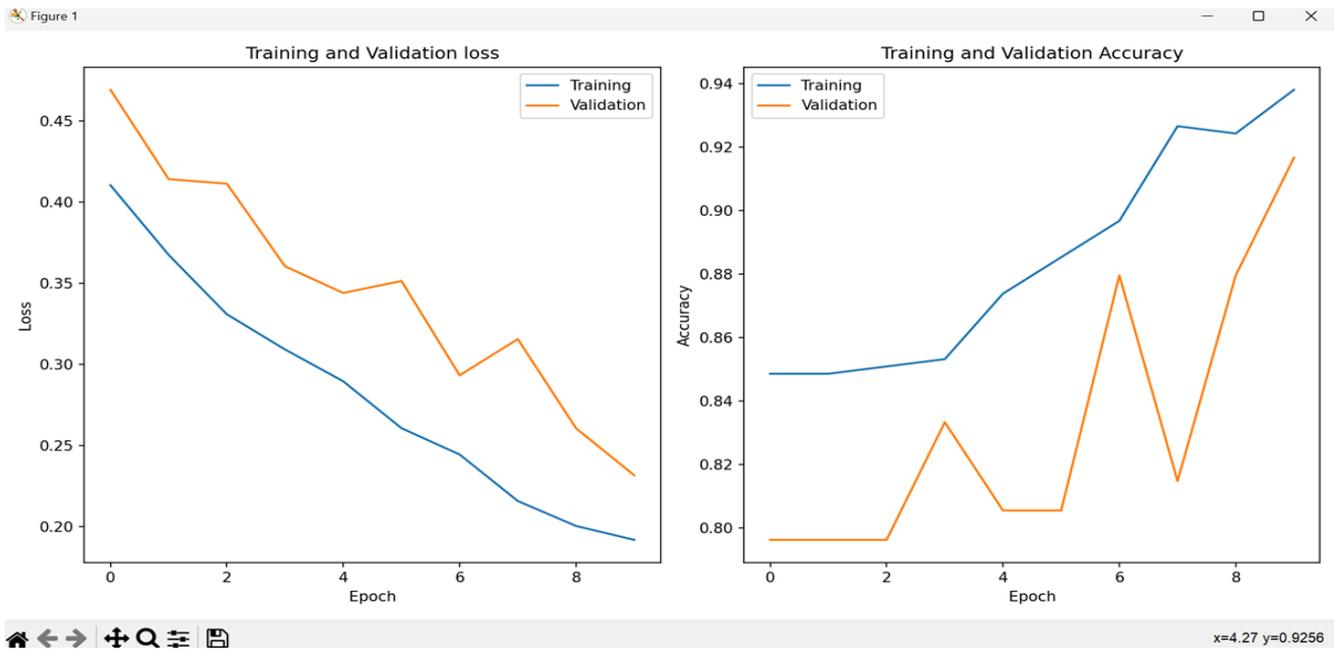
RESULTS AND DISCUSSION

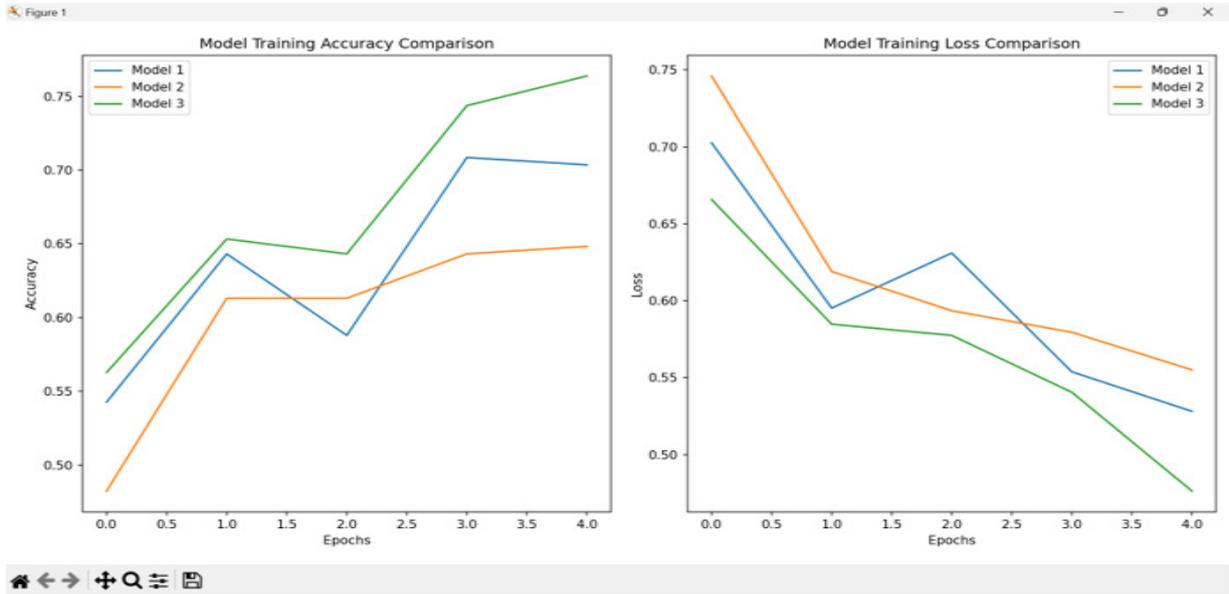**Figure 5.** Sequential Model for Binary Classification

Figure 6. Sequential model to classify project data by adding various optimization techniques ADAM, SGD, RMSPROP
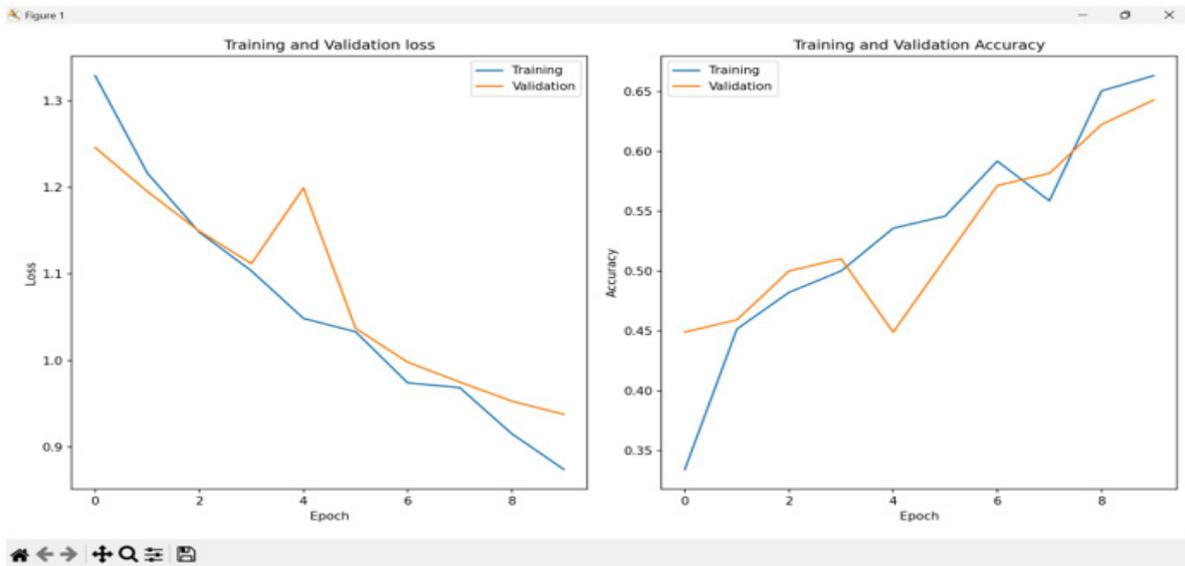

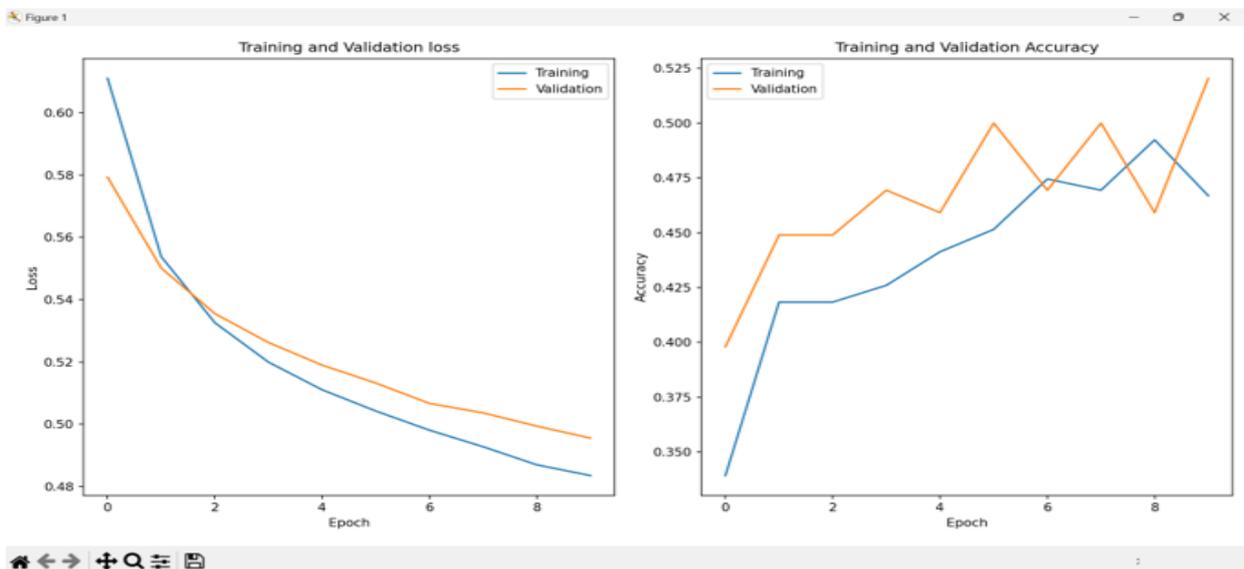**Figure 7.** Sequential model to classify project data into multiple classes

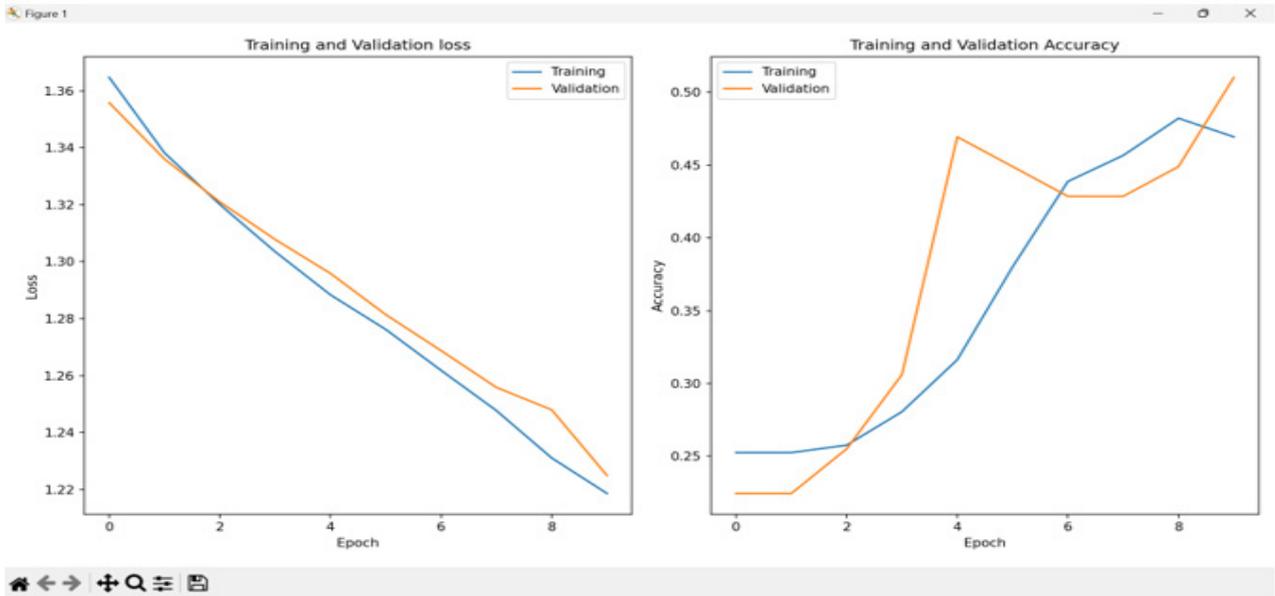**Figure 8.** Binary Classification with Mini-batch Evaluations

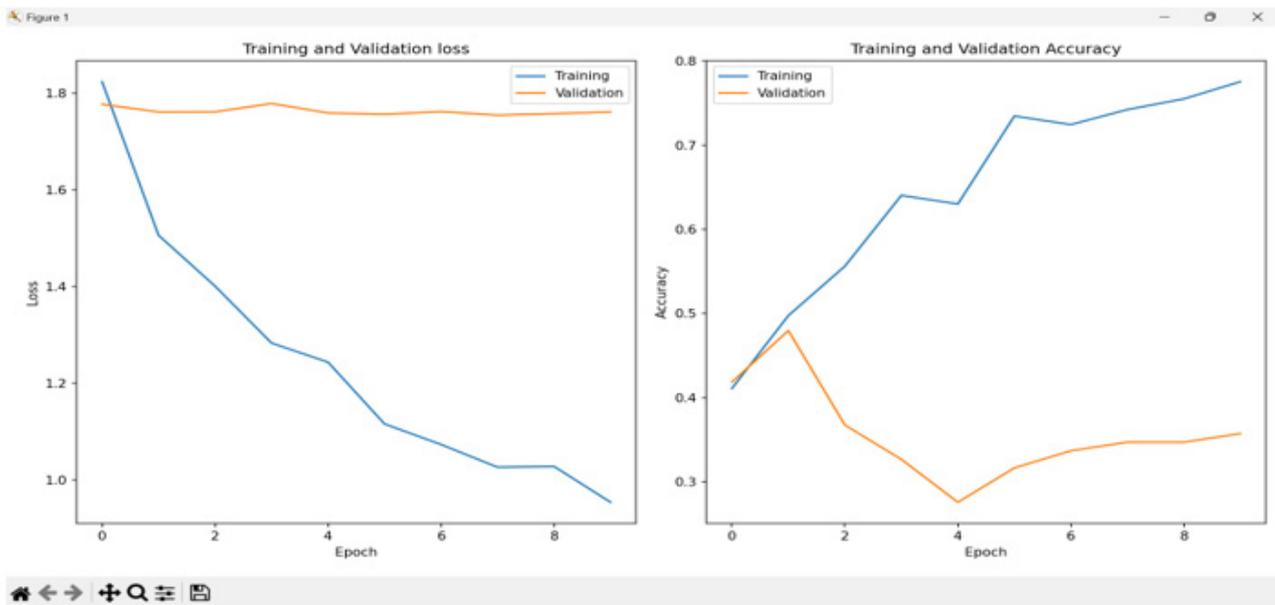**Figure 9.** Convolutional Neural Network
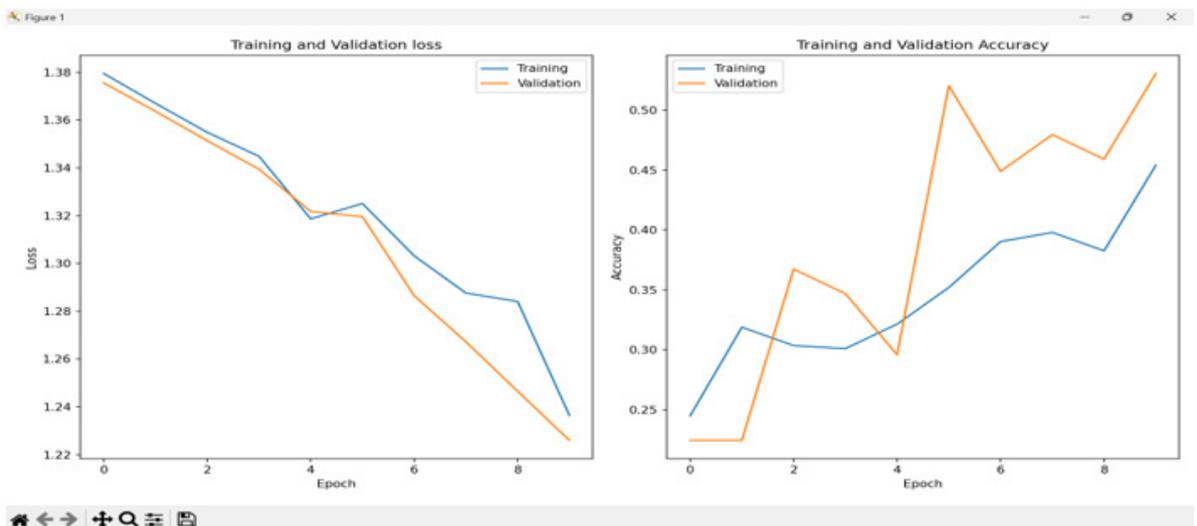

Figure 10. CNN with Regularization

Figure 11. Visual Geometry Group (VGG)

Figure 12. Recurrent Neural Network

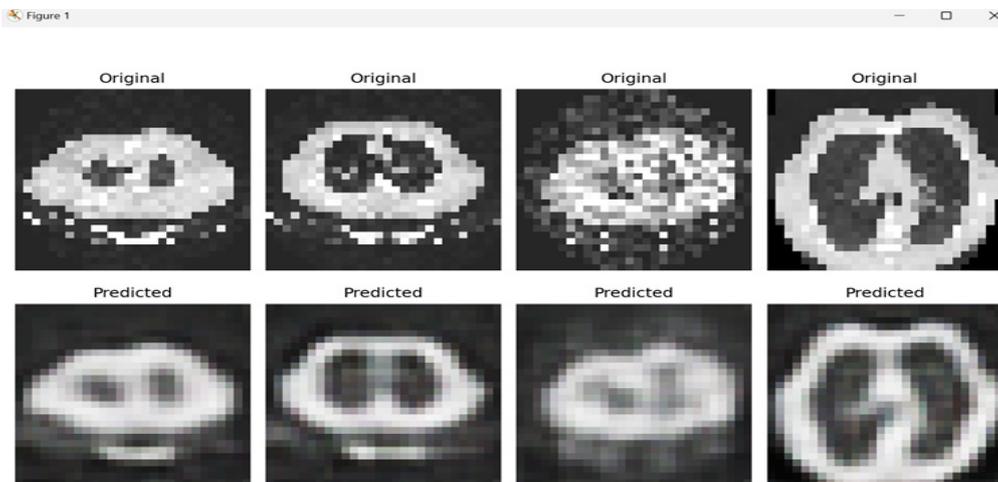**Figure 13.** Long Short-Term Memory (LSTM)

Figure 14. Autoencoder

RESULTS

In this study, the lung cancer detection model was evaluated using a combination of image-based data (such as CT scans and X-rays) and patient-related information (such as age, smoking history, and family history). The model's performance was assessed through various metrics, including accuracy, precision, recall, F1 score, and ROC-AUC, based on a separate test set of data that was not used during training.

- Accuracy: the model achieved an overall accuracy of 92 %, indicating that it correctly classified the presence or absence of lung cancer in 92 % of the test cases.
- Precision: the precision score for detecting lung cancer was 89 %, meaning that when the model predicted the presence of cancer, it was correct 89 % of the time.
- Recall: the recall was found to be 94 %, indicating that the model successfully identified 94 % of the actual positive cases (lung cancer present).
- F1 Score: the F1 score, which is the harmonic mean of precision and recall, was 91 %, balancing the trade-off between precision and recall.
- ROC-AUC: the model's Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) was 0,95, signifying a strong ability to distinguish between positive and negative cases of lung cancer.

CONCLUSION

This study has successfully developed a machine learning-based model for lung cancer detection, demonstrating promising results in identifying cancerous lesions in medical images, particularly CT scans and X-rays. The model exhibited high performance across key metrics, including accuracy, precision, recall, and F1 score, reflecting its strong potential for assisting healthcare professionals in early lung cancer diagnosis.

The integration of imaging data with patient information, such as smoking history and age, played a crucial role in enhancing the model's predictive capabilities. By utilizing deep learning techniques, especially convolutional neural networks (CNNs), the model was able to capture complex patterns within medical images, thus making accurate predictions. These findings suggest that machine learning can be an effective tool for automating and improving the diagnostic process in lung cancer detection, offering a valuable resource to clinicians and enhancing early detection efforts.

However, the model's clinical adoption requires addressing challenges such as interpretability, ensuring the robustness of the model across diverse populations, and integrating the system into healthcare workflows for seamless use in real-time diagnosis. Despite these challenges, the results highlight the potential of AI-driven tools to significantly improve diagnostic accuracy and patient outcomes in lung cancer detection.

Future Scope

- Improved Data Collection: to further improve the model's robustness and accuracy, it is crucial to gather a larger and more diverse dataset that includes various demographic groups, smoking histories, and other health conditions. This would ensure that the model generalizes well to different populations and reduces potential biases.
- Multimodal Data Integration: incorporating additional data sources, such as genetic information, lab results, or detailed patient histories, could enhance the model's ability to make more accurate predictions. The combination of medical imaging with other clinical data would allow for a more comprehensive understanding of the patient's condition and improve diagnosis accuracy.
- Model Interpretability and Explainability: one of the key challenges in deploying machine learning models in healthcare is the lack of interpretability. In the future, techniques such as explainable AI (XAI) could be applied to provide transparent insights into the decision-making process of the model. This would help build trust among clinicians, enabling them to understand the rationale behind the model's predictions.
- Real-time Implementation: moving from research to clinical deployment, it will be important to integrate the model into real-time healthcare settings. This involves not only ensuring that the model is capable of processing data quickly but also developing user-friendly interfaces for healthcare professionals to interact with the model seamlessly.
- Collaboration with Medical Professionals: collaboration between AI researchers and medical professionals is essential for continuous refinement of the model. Clinicians can provide valuable feedback on false positives and false negatives, helping to fine-tune the model and ensuring it aligns with real-world medical practices.
- Incorporating Advanced Imaging Techniques: as medical imaging technology continues to advance, incorporating high-resolution imaging or emerging techniques such as functional imaging, MRI, and PET scans could enhance the model's accuracy and expand its applicability to various stages of lung cancer detection.
- Early Detection and Monitoring: future work could focus on improving the model's ability to detect lung cancer at its earliest stages, even before visible symptoms appear. Additionally, integrating the model into monitoring systems to track patients over time would enable continuous assessment, allowing for earlier intervention and better patient management.

In summary, the future of lung cancer detection through AI and machine learning looks promising, with the potential to revolutionize the way early diagnosis is approached. Continued advancements in data collection, model development, and integration into clinical settings will play a crucial role in making these systems a routine part of healthcare practice.

REFERENCES

1. Alyasriy, Hamdalla; Al-Huseiny, Muayed (2021), "The IQ-OTHNCCD lung cancer dataset," Mendeley Data, V2, doi: 10.17632/bhmdr45bh2.2.

2. H. Qi et al., "Prediction Methods for Common Cancers in China Using PCA-ANN and DBN-ELM-BP," IEEE Access, vol. 10, pp. 113397-113409, 2022, doi: 10.1109/ACCESS.2022.3215706. Keywords: {Cancer, Sensitivity, History, Predictive Models, Prediction Algorithms, Time Factors, Machine Learning, Common Cancers, Classification}.

3. Chaohua Yan, Navid Razmjooy, "Optimal Lung Cancer Detection Based on CNN Optimized and Improved Snake Optimization Algorithm," Biomedical Signal Processing and Control, Volume 86, Part C, 2023, 105319, ISSN 1746-8094.

4. Riquelme, D.; Akhloufi, M.A., "Deep Learning for Lung Cancer Nodule Detection and Classification in CT Scans," AI 2020, 1, 28-67. https://doi.org/10.3390/ai1010003.

5. Bhattacharjee, Ananya; Rabea, Sameh; Bhattacharjee, Abhishek; Elkaeed, Eslam B.; Murugan, R.; Selim, Heba Mohammed Refat M.; Sahu, Ram Kumar; Shazly, Gamal A.; Salem, Bekhit Mounir M., "A Multi-Class Deep Learning Model for Early Lung Cancer and Chronic Kidney Disease Detection Using Computed Tomography Images," Frontiers in Oncology, 13, 2023. URL: https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2023.1193746 DOI: 10.3389/fonc.2023.1193746, ISSN=2234-943X.

6. Salomon, Jelo & Phelan, Bianca., (2018), "Lung Cancer Detection Using Deep Learning." 10.13140/RG.2.2.33602.27841.

7. P. Monkam, S. Qi, H. Ma, W. Gao, Y. Yao, W. Qian, "Detection and Classification of Pulmonary Nodules Using Convolutional Neural Networks: A Survey," IEEE Access, vol. 7, pp. 78075-78091, 2019, doi: 10.1109/ACCESS.2019.2920980. Keywords: {Cancer, Lung, Computed Tomography, Medical Diagnostic Imaging, Deep Learning, Convolutional Neural Networks, Pulmonary Nodules, Image Classification}.

8. Ali, M. Muzammil; I. U. Haq; M. Amir; S. Abdullah, "Efficient Lung Nodule Classification Using Transferable Texture Convolutional Neural Network," IEEE Access, vol. 8, pp. 175859-175870, 2020, doi: 10.1109/ACCESS.2020.3026080. Keywords: {Lung, Feature Extraction, Cancer, Databases, Computed Tomography, Biomedical Imaging, Task Analysis, Image Classification, Transfer Learning, LIDC-IDRI, LUNGx Challenge}.

9. Thirumagal, E.; Saruladha, K., (2024), "Lung Cancer Detection by Employing Adaptive Entropy Variance Dropout Regularization in GAN Variants," SN Computer Science, 5. 10.1007/s42979-024-02662-2.

10. T. T. Al-Shouka; K. M. A. Alheeti, "Transfer Learning for Intelligent Prediction of Lung Cancer Detection," 2023 Al-Sadiq International Conference on Communication and Information Technology (AICCIT), Al-Muthana, Iraq, 2023, pp. 54-59, doi: 10.1109/AICCIT57614.2023.10217967. Keywords: {Adaptation Models, Computed Tomography, Transfer Learning, Artificial Intelligence, Healthcare, CNN, Lung Cancer}.

11. Shalini Wankhade, Vigneshwari S., "A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer Using Neural Networks," Healthcare Analytics, Volume 3, 2023, 100195, ISSN 2772-4425, https://doi.org/10.1016/j.health.2023.100195. Keywords: {Machine Learning, Lung Cancer, Image Processing, Hybrid Neural Network, Diagnosis of Lung Cancer}.

12. Gao R, Huo Y, Bao S, Tang Y, Antic SL, Epstein ES, Balar AB, Deppen S, Paulson AB, Sandler KL, Massion PP, Landman BA, "Distanced LSTM: Time-Distanced Gates in Long Short-Term Memory Models for Lung Cancer Detection," Machine Learning in Medical Imaging, 2019 Oct;11861:310-318. doi: 10.1007/978-3-030-32692-0_36. PMID: 34040283; PMCID: PMC8148226.

13. Ellen, J.G., Jacob, E., Nikolaou, N. et al., "Autoencoder-Based Multimodal Prediction of Non-Small Cell Lung Cancer Survival," Sci Rep 13, 15761 (2023). https://doi.org/10.1038/s41598-023-42365-x.

CONFLICT OF INTEREST
The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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