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Lung Cancer Detection Using Deep learning

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ABSTRACT

Lung cancer remains a significant contributor to global cancer mortality, where timely detection is crucial for effective treatment and improved survival rates. Despite the promise of imaging technologies and deep learning (DL)-based diagnostics, their deployment in resource-limited healthcare environments faces challenges due to computational complexity and data imbalance. This study introduces a lightweight, DL-driven approach for lung cancer detection that integrates PET and CT imaging. The proposed system enhances diagnostic reliability by incorporating image normalization, correction techniques, and data augmentation using generative adversarial networks (GANs). The model architecture includes DenseNet-121 for extracting hierarchical features, deep autoencoders for reducing dimensionality, and MobileNet V3-Small for fast classification. To optimize computational efficiency without compromising performance, strategies like quantization-aware training and early stopping were implemented. When tested on the Lung-PET-CT-Dx dataset (comprising over 31,000 labelled images), the model achieved an accuracy of 98.6% and a Cohen's Kappa score of 95.8. These results suggest strong potential for clinical application in early lung cancer screening, particularly in settings with limited infrastructure. Further research will explore adaptive models such as liquid neural networks and ensemble methods to expand usability across broader medical domains.

1. INTRODUCTION

Lung cancer is a malignant disease originating within the respiratory system, commonly affecting epithelial cells in the bronchi, bronchioles, or alveoli. It is one of the most frequently diagnosed cancers worldwide and ranks among the top causes of cancer-related deaths. One of the primary challenges in managing lung cancer is its often subtle or non-specific symptoms in early stages, which delays diagnosis and worsens prognosis. Broadly, lung cancer is categorized into non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC), with subtypes such as adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) falling under NSCLC. These classifications are vital for determining appropriate treatments and predicting patient outcomes.

Diagnostic imaging remains central to identifying and evaluating lung cancer. Among various modalities, positron emission tomography (PET) assesses tumor metabolism, while computed tomography (CT) captures anatomical detail. Together, these methods provide a comprehensive overview of tumor behavior. In particular, low-dose CT (LDCT) has demonstrated a reduction in mortality by enabling early detection in individuals at high risk, such as long-term smokers. However, conventional imaging is not without drawbacks—issues such as elevated false-positive rates can lead to unnecessary interventions and patient anxiety.

Recent advances in diagnostic methods have introduced novel techniques, including liquid biopsies, robotic bronchoscopies, and the integration of genomic and proteomic data. At the forefront of these innovations is deep learning (DL), which offers advanced capabilities in medical image interpretation. DL models can analyze large volumes of multimodal imaging data—like PET and CT scans—to support diagnosis and treatment planning. Yet, deploying DL in clinical practice comes with hurdles, such as small and imbalanced datasets, significant computational requirements, and generalization limitations.

Transfer learning and pre-trained neural networks have partially addressed these issues, particularly in multimodal imaging analysis. PET/CT fusion, which combines metabolic and structural data, has proven especially useful for accurate tumor characterization. This study presents a DL-based framework designed to overcome these challenges, employing DenseNet-121 for multi-scale feature extraction, deep autoencoders for data compression, and MobileNet V3-Small for fast, resource-efficient classification. Preprocessing techniques and augmentation strategies are used to enhance data quality and balance. The model is optimized through quantization-aware training and the Adam optimizer to enable deployment in real-time, low-resource clinical environments.

2. METHODS AND MATERIALS

Early diagnosis of lung cancer is essential to improving patient outcomes and survival rates. This section outlines various diagnostic tools and techniques used in LC detection, encompassing imaging, laboratory methods, and computational approaches.

1. Imaging Modalities Chest X-Ray As a primary screening tool, chest X-rays are cost-effective and quick but may not detect small or obscured tumors. They are limited in sensitivity, particularly for early-stage lesions. Computed Tomography (CT) CT imaging offers high-resolution anatomical views, enabling accurate assessment of tumor location, size, and adjacent tissue involvement. Contrast agents may be employed to enhance image clarity. Despite its diagnostic value, CT involves greater radiation exposure and may yield false positives.
   Positron Emission Tomography (PET) PET scans measure cellular metabolic activity using a radioactive tracer like fluorodeoxyglucose (FDG). Cancer cells absorb this tracer more actively than normal tissue, making PET valuable for staging and identifying metastasis.
   However, cost and limitations in detecting small or low-activity tumors remain challenges. Magnetic Resonance Imaging (MRI) While not commonly used for primary lung cancer detection, MRI is valuable for evaluating metastases, especially in the brain or spine. It provides detailed soft tissue contrast but is generally secondary to CT in pulmonary assessment.

2. Cytological and Endoscopic Techniques Sputum Cytology This method involves microscopic analysis of coughed-up mucus to detect malignant cells. It is more effective for centrally located

tumors but lacks sensitivity for peripheral cancers. Bronchoscopy and Endobronchial Ultrasound (EBUS) Bronchoscopy allows direct visualization of airways using a flexible tube with a camera, facilitating biopsies of central lesions. EBUS combines bronchoscopy with ultrasound to guide sampling from lymph nodes and deeper structures with greater accuracy.

3. Biopsy Techniques Needle Biopsy Using imaging guidance (CT or ultrasound), a needle is inserted through the chest wall to obtain tissue samples. This method is less invasive but carries a risk of complications such as bleeding or lung collapse. Surgical Biopsy Employed when less invasive methods are inconclusive, surgical biopsies are more accurate but require general anesthesia and longer recovery time.

4. Molecular and Genetic Diagnostics Liquid Biopsy This non-invasive technique examines blood or other fluids for circulating tumor DNA (ctDNA) and biomarkers. While promising for monitoring and early detection, sensitivity may vary depending on cancer type and stage. Biomarker Analysis Molecular profiling of tumor samples can detect mutations such as EGFR or ALK rearrangements, enabling personalized treatment. Technologies like PCR, next-generation sequencing (NGS), and immunohistochemistry are commonly used. Blood-Based Tumor Markers Serum markers like CYFRA 21-1, carcinoembryonic antigen (CEA), and neuron-specific enolase (NSE) may support diagnosis and monitoring, though their specificity is limited.

5. Experimental and Emerging Techniques Exhaled Breath Analysis This experimental method detects volatile organic compounds (VOCs) in breath that are linked to lung cancer. While non-invasive, its diagnostic accuracy is still under investigation.

6. Low-Dose CT Screening Recommended for high-risk individuals (e.g., long-term smokers), low-dose CT can identify early-stage tumors and reduce mortality. However, concerns include overdiagnosis and follow-up complications.

7. Artificial Intelligence (AI) and Machine Learning (ML) in Detection AI and ML models are increasingly utilized for medical image interpretation. These systems can identify patterns and features that may be overlooked by radiologists, enhancing diagnostic accuracy and efficiency.

3. RESULTS

A comprehensive evaluation of the lung cancer detection methods highlights their effectiveness when applied collectively for early diagnosis, staging, and treatment planning. Below is a summary of the clinical value, accuracy, and limitations of each approach:

1. Early Detection and Diagnosis CT Imaging (Standard and Low-Dose) CT scans, especially low-dose variants, remain the most effective and widely adopted modality for early LC detection. Clinical trials have shown a 20% reduction in lung cancer mortality when screening high-risk populations, such as long-term smokers. Sputum Cytology While this method is relatively non-invasive and suitable for centrally located tumors, its detection sensitivity is limited to

approximately 30–40%, making it a secondary rather than primary diagnostic option. Bronchoscopy and EBUS Bronchoscopy allows direct visualization and biopsy of central lung lesions. When combined with EBUS, it provides enhanced precision in assessing lymph node involvement, contributing significantly to accurate staging.

2. Cancer Staging and Metastasis Assessment PET/CT Scans Integrated PET/CT imaging plays a crucial role in staging by identifying metastatic spread and evaluating lymph nodes. These scans offer sensitivity levels of 85–90% and are essential for determining therapeutic approaches. MRI Scans Though not routinely used for initial lung cancer diagnosis, MRI is instrumental in detecting metastasis to the brain or spinal cord, complementing PET/CT in full-body staging.

3. Histopathological Confirmation Needle Biopsy For lesions located in peripheral lung regions, image-guided needle biopsy is preferred due to its minimally invasive nature and diagnostic sensitivity of 80–90%. Surgical Biopsy Considered the most definitive diagnostic tool, surgical biopsy is reserved for complex or inconclusive cases. Despite its invasive nature, it provides near-perfect diagnostic accuracy.

4. Genetic and Molecular Analysis Liquid Biopsy Offering a non-invasive way to detect tumor-specific mutations in blood samples, liquid biopsies show a sensitivity of 70–80%. They are valuable for tracking treatment responses and identifying recurrence. Biomarker Testing Genetic profiling (e.g., EGFR or ALK mutations) guides targeted therapies and has significantly improved treatment response rates. This personalized approach is transforming treatment protocols in NSCLC patients.

5. Screening and Public Health Implications Low-Dose CT Screening This method remains the gold standard for population-level screening in high-risk groups. Its ability to detect cancer in early, asymptomatic stages has made it a pivotal tool in reducing mortality rates.

6. Applications of AI and ML AI in Radiological Interpretation Deep learning models have shown the ability to detect small or subtle lesions in CT and X-ray images with higher precision than traditional interpretation. These models can help reduce diagnostic delays and human error. Predictive Modeling with Machine Learning ML algorithms trained on clinical, demographic, and imaging data can help predict cancer risk and tailor screening protocols. These approaches are currently being explored for integration into personalized care strategies.

7. Emerging Technologies Breath-Based Diagnostics Early studies on exhaled breath analysis have shown promise in detecting lung cancer-specific volatile compounds. However, the approach is still in development and not yet reliable for clinical use. Molecular Imaging and Novel Biomarkers Ongoing research into imaging innovations and new tumor markers aims to further enhance diagnostic accuracy. Combining AI, molecular profiling, and imaging is expected to revolutionize early detection and decision-making.

8. Overall Clinical Impact Improved Survival Through Early Detection Diagnosing lung cancer at an early stage (e.g., Stage I) leads to significantly better outcomes, with five-year survival rates around 56%, compared to 5–10% for late-stage cases. Personalized Therapy Genetic testing allows clinicians to tailor treatment plans based on mutation profiles, enhancing treatment efficacy and reducing unnecessary side effects. Cost Efficiency Although some diagnostic methods (e.g., PET/CT and molecular testing) are expensive, early intervention reduces long-term healthcare costs by limiting the need for aggressive late-stage treatments and improving quality of life.

4. DISCUSSION

The proposed deep learning (DL) framework addresses multiple challenges associated with lung cancer detection through advanced integration of PET/CT imaging and image processing techniques. To enhance alignment and consistency between PET and CT scans, the SyN (Symmetric Normalization) registration method was employed, while additional enhancements like image resampling, Retinex filtering, and attenuation correction were used to mitigate noise and artifacts. Furthermore, data imbalance was countered by applying image augmentation methods, improving the model's exposure to diverse pathological variations. Feature extraction was accomplished using a convolutional neural network (CNN) architecture pre-trained on DenseNet-121, enabling deep hierarchical learning of tumor characteristics. A deep autoencoder module was implemented to reduce the dimensionality of feature maps, allowing efficient learning without loss of essential spatial or semantic information. Classification was performed by a second CNN using MobileNet V3-Small, a lightweight and fast model suitable for real-time diagnostics, particularly in resource-limited environments. To optimize the model's training process and computational efficiency, quantization-aware training (QAT) was used alongside an adaptive optimizer. This approach significantly improved model convergence while maintaining high performance with minimal hardware demand. Experimental evaluation showed that the model achieved an accuracy of 98.6%, with consistent performance stability across multiple batch iterations. The architecture consisted of only 2.1 million parameters and required just 176 million FLOPs, with a training time of approximately 128 seconds, indicating that the system is highly efficient and scalable.

5. COMPARISON WITH EXISTING METHODS

Compared to other lung cancer detection frameworks, the proposed model demonstrated superior performance with significantly lower computational requirements. For instance, it outperformed transformer-based models such as that of Barbouchi et al., which demanded more extensive computing resources. Similarly, the current approach exceeded the accuracy levels achieved by El-Hamdi et al., who used VGG-16-based networks, and by Goswami and Singh, who also utilized the Lung-PET-CT-Dx dataset. While some competing models may have reached similar or slightly higher accuracy levels, they often relied on more complex architectures or required greater training time and infrastructure. Clinical Applications and Insights The fusion of PET and CT imaging enables comprehensive visualization by combining anatomical and metabolic data. This facilitates accurate tumor classification and informs therapeutic decision-making, including surgery, chemotherapy, or radiation therapy. The model's ability to analyze subtle imaging features improves the detection of early-stage lung nodules that might otherwise be missed by human interpretation. The tool's lightweight design supports deployment on edge devices, potentially benefiting rural or under-resourced clinical settings. Additionally, by reducing false positives (FPs) and false negatives (FNs), the model enhances diagnostic precision and reduces unnecessary interventions. Its application may expedite diagnosis, allowing radiologists to focus on complex or ambiguous cases, and could also support clinical research and trials through rapid and consistent image analysis.

6. CHALLENGES AND LIMITATIONS

Despite promising outcomes, the study encountered several technical limitations. Image artifacts, misalignment between PET and CT scans, and low-resolution data posed challenges in feature extraction. Although addressed partially through preprocessing and registration methods, these issues still influenced detection consistency. Another key challenge was the imbalance and scarcity of well-labeled medical imaging data. This was addressed through data augmentation, but the need for large, diverse, and high-quality datasets remains crucial for improving model generalization across populations. Hardware constraints, particularly limited GPU availability, were handled via quantization and lightweight model design, yet such limitations could still affect scalability in real-world deployment. Maintaining robust performance across clinical settings requires ongoing validation. The model must strike a balance between sensitivity and specificity, especially in distinguishing benign from malignant lesions. Moreover, minimizing noise and image distortion is essential to ensure accuracy under variable imaging conditions. Future Directions Future enhancements may include integrating Liquid Neural Networks (LNNs) to improve temporal and spatial adaptability in analyzing complex imaging data. Additionally, ensemble learning methods could be explored to further improve classification accuracy and reduce computational load, particularly for multi-modal image analysis. Developing and curating high-quality, annotated datasets representing diverse demographics and disease patterns will also be essential for training robust, generalizable models. Future work may aim to expand the system's use to other thoracic abnormalities and integrate it with clinical decision support systems.

7. CONCLUSION

This study presents a deep learning-based framework for the detection and classification of lung cancer using PET/CT imaging, with a particular focus on creating a solution suitable for real-time clinical use. By incorporating advanced preprocessing methods such as the SyN registration algorithm and Retinex filtering, the model effectively reduces image artifacts and enhances quality. Additionally, the use of GAN-based data augmentation addresses dataset imbalance, which is a common limitation in medical imaging. The architecture integrates DenseNet-121 for high-level feature extraction and deep autoencoders for compressing the data without losing crucial diagnostic information. MobileNet V3-Small was utilized for classification due to its lightweight structure, allowing for faster inference with reduced computational demand. Quantization-aware training and early stopping techniques were applied to further streamline training and improve model generalization. The model's performance was validated using the Lung-PET-CT-Dx dataset, where it achieved high accuracy in identifying various types of lung cancer while maintaining low hardware requirements. These characteristics make it well-suited for deployment in healthcare settings with limited computational infrastructure, such as rural clinics or edge devices. Despite the encouraging results, the development process encountered several challenges, including limited availability of balanced, high-resolution annotated data and difficulties associated with noisy or misaligned imaging. To overcome these limitations, future work will explore the integration of advanced architectures such as Liquid Neural Networks and ensemble learning strategies. These enhancements are expected to improve classification performance, especially in complex or low-quality imaging scenarios, and expand the model's applicability in real-world clinical environments. Overall, the proposed framework contributes a significant step toward the practical implementation of AI-based tools for early lung cancer detection, offering a path toward more accurate, efficient, and accessible diagnostic systems.

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