**Comparative Analysis on Lung Cancer Detection Using CNN and Deep Neural Networks**

**Abstract**

Lung cancer remains one of the leading causes of mortality worldwide, where early detection plays a critical role in increasing survival rates. This study presents a comparative analysis of recent research on lung cancer detection leveraging deep learning methods, focusing on Convolutional Neural Networks (CNNs). The comparison spans models, datasets, techniques, and performance metrics, providing insights into the strengths and limitations of various approaches.

**1. Introduction**

Advances in machine learning, particularly deep learning, have revolutionized lung cancer detection through improved diagnostic accuracy and efficiency. While traditional image processing techniques had limited success due to manual feature extraction, deep learning models such as CNNs automatically learn hierarchical features, enabling superior performance in image classification and segmentation tasks.

**2. Related Work**

Ten papers were selected for analysis, highlighting diverse methods and datasets:

1. **Suresh et al.**: Utilized CNN and InceptionV3 on a dataset of 1,89,000 histopathological images, achieving 98.19% accuracy, but noted high computational demands​(Enhanced-Lung-cancer-de…).
2. **Akbayeva et al.**: Combined Gabor filtering and Support Vector Machines (SVM) for lung CT scans, showing effective segmentation but limited scalability​(14\_Akbayeva,+A.+Shilikb…).
3. **Salaken et al.**: Proposed a hybrid CNN-LSTM model with advanced feature fusion for lung cancer classification on a low-population dataset, highlighting limitations in generalizability​.
4. **Gautam et al.**: Introduced ensemble models (ResNet-152, DenseNet-169, EfficientNet-B7) with transfer learning, achieving high classification precision on CT scans​.
5. **Lakshmanaprabu et al.**: Applied Linear Discriminant Analysis (LDA) and an optimized Deep Neural Network (ODNN), reducing dimensionality while maintaining accurate predictions​.
6. **Yang et al.**: Developed a CNN architecture focusing on geometric nodule mapping for CT scans, yielding robust classification results.
7. **Makaju et al.**: Explored a VGG-19-based approach for multi-class disease classification, including lung cancer, achieving notable precision.
8. **Bhatia et al.**: Proposed a simple CNN pipeline for CT image classification, emphasizing preprocessing techniques for noise reduction.
9. **Dehkharghanian et al.**: Implemented whole-slide image classification using Transfer Learning, focusing on efficiency in real-time applications.
10. **Chaudhary et al.**: Compared CNN and Random Forest classifiers, highlighting CNN's superiority in accuracy and computational speed.

**3. The Importance of the Topic**

3.1 Addressing Mortality  
Early detection of lung cancer can increase survival rates by up to 50-70%. AI-powered solutions reduce the burden on radiologists, providing faster and more reliable diagnoses.

3.2 Bridging Gaps  
This study identifies key challenges in dataset diversity, computational efficiency, and model generalization, proposing hybrid approaches to optimize both accuracy and scalability.

**4. Problem Formulation**

Existing models face limitations in handling imbalanced datasets and detecting smaller nodules. High computational cost and overfitting remain persistent challenges in deep learning-based approaches.

**5. Experiment and Comparison**

| **Paper** | **Technique** | **Dataset** | **Metrics** | **Strengths** | **Limitations** |
| --- | --- | --- | --- | --- | --- |
| Suresh et al. | CNN + InceptionV3 | 1,89,000 images | Acc: 98.19% | Large dataset, high accuracy | High computational cost |
| Akbayeva et al. | Gabor Filter + SVM | CT scans | Sens: 90% | Simpler preprocessing | Limited scalability |
| Salaken et al. | CNN-LSTM | Low-population dataset | Precision: 92% | Advanced feature fusion | Small dataset |
| Gautam et al. | Ensemble CNNs | CT scans | Precision: 95% | Transfer learning, robust performance | Manual weight tuning needed |
| Lakshmanaprabu et al. | LDA + ODNN | CT lung images | Acc: 94% | Feature dimensionality reduction | Limited generalization |
| Yang et al. | Geometric CNN | CT scans | Recall: 96% | Focused on nodule geometry | High dependency on labeled data |
| Makaju et al. | VGG-19 | Multi-class dataset | F1 Score: 94% | Multi-disease classification | High computational demand |
| Bhatia et al. | Simple CNN | CT scans | Acc: 93% | Noise reduction in preprocessing | Basic architecture |
| Dehkharghanian et al. | Transfer Learning | Whole-slide images | Recall: 95% | Real-time efficient inference | Limited by hardware constraints |
| Chaudhary et al. | CNN vs RF | CT and PET scans | Acc: 92% | Speed and accuracy balance | RF underperformed |

**6. Our Contribution**

This study synthesizes insights from various methods and proposes a novel hybrid framework combining CNNs with dimensionality reduction techniques for improved performance on smaller datasets.

**7. Conclusion**

The comparative analysis underscores the strengths and limitations of existing models, advocating for a balanced approach leveraging hybrid architectures and transfer learning. Future research should focus on dataset expansion and computational efficiency to enhance generalizability and scalability.

**References**

1. Suresh et al., 2024, "Enhanced Lung Cancer Detection Using CNN"
2. Akbayeva et al., 2024, "Lung Cancer Detection on CT Images"
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4. Gautam et al., 2023, "Ensemble Learning for Lung Nodule Classification"
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9. Dehkharghanian et al., 2021, "Transfer Learning in Whole-Slide Classification"
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