# Comparative Analysis of Machine Learning Models for Lung Cancer Detection Using CT Scan Images

Muhammad Osama[1*], Ejaz Ahmed[2], Misbah Batool[1], Mohsin Saleem[3], Ahmed Salim[1]
[1]Department of Electrical Engineering, Namal University, Mianwali, Pakistan
[2]Computer Science Department, Namal University, Mianwali, Pakistan
[3]Software Development Cell, Computer Science Department, Namal University, Mianwali, Pakistan
***Correspondence**: bsee23f01@namal.edu.pk

**Citation |** Osama. M, Ahmed. E, Batool. M, Saleem. M, Salim. A, "Comparative Analysis of Machine Learning Models for Lung Cancer Detection Using CT Scan Images", IJIST, Special Issue pp 318-328 March 2025.
**Received** March 02, 2025 **Revised** | March 14, 2025 **Accepted** | March 20, 2025 **Published** | March 23, 2025.

The CT scan provides useful information but has limitations in detecting subtle patterns. Machine learning models enhance cancer detection by extracting features, reducing errors, and enabling early-stage diagnosis. Unlike earlier studies that focused on single models, this paper compares three models: CNN, RF, and SVM. A total of 995 CT images were resized to 128x128 pixels, representing both healthy individuals and patients across the full range of lung cancer types. Using a feature hierarchy, CNN achieved a 96% validation accuracy, and RF reached 95%, showing robustness. However, SVM with an RBF kernel optimization outperformed the others, achieving over 98% accuracy with superior alignment of hyperplanes, particularly in detecting fine malignant patterns. The key metrics used in this study were sensitivity, specificity, and AUC, all of which showed a low false positive rate for early lung cancer detection, bridging theoretical accuracy and clinical practicality. Data volume and processing resources remain significant challenges for applying machine learning in early lung cancer diagnosis. To address these issues, we suggest hybrid architectures (e.g., CNN-SVM) that combine hierarchical feature learning and hyperplane optimization. These findings could pave the way for AI-based clinical approaches, improving patient diagnosis and treatment.

**Keywords**: Lung Cancer Detection, Machine Learning Models, Ct Scan Image Analysis, Diagnostic Accuracy, Confusion Matrix

## Introduction:

### Background:

Medical imaging has transformed healthcare by enabling the diagnosis, monitoring, and treatment of various health conditions without surgery. Technologies like CT scans, MRIs, and X-rays have become more advanced, leading to more accurate medical diagnoses. Lung cancer remains one of the leading causes of cancer-related deaths worldwide, but early and precise detection through imaging greatly improves outcomes. However, despite these advancements, interpreting medical images manually still takes time and can lead to errors due to human limitations [1].

The approach to analyzing medical imaging data has been revolutionized. Machine learning, a branch of artificial intelligence, handles large volumes of data, identifies subtle patterns, and makes accurate predictions through its powerful processing capabilities and intelligent algorithms [2].

Deep learning, a subset of machine learning, is especially effective in analyzing images. Its advanced methods have proven highly useful in identifying diseases, particularly lung cancer, turning machine learning into a powerful tool for medical diagnostics [3], [4].

### Objectives and Novelty:

The main goals of this study are three: (1) to compare how well three machine learning models—CNN, RF, and SVM—can detect lung cancer from CT scans; (2) to enhance the methods used to identify features and classify results to help with early diagnosis and lower false positives; and (3) to carefully evaluate real-world issues (like dataset size and computing needs) when using AI-based diagnostics in hospitals.

This research offers three key contributions: First, unlike previous studies focusing on single-model approaches, we demonstrate that the SVM with RBF kernel outperforms CNN and RF in accuracy (98% compared to 96% and 95%, respectively), particularly in identifying subtle malignant patterns. Second, we confirm the clinical relevance of these models by evaluating sensitivity (for early detection) and specificity (for minimizing false positives), helping bridge the gap between theoretical performance and practical use. Third, we advocate for hybrid approaches (e.g., CNN-SVM) to combine hierarchical feature learning with hyperplane optimization—an underexplored direction in current literature.

### Importance of AI in Clinical Settings:

The scalability of artificial intelligence (AI) models allows them to be used across a wide range of medical institutions, including those with limited resources, making quality diagnoses more accessible [5]. The integration of AI into clinical workflows has significantly improved both diagnostic and therapeutic processes—particularly in lung cancer, where early detection is vital for effective treatment. AI brings major advantages by increasing the accuracy and efficiency of medical procedures. One key benefit is its ability to detect hidden issues, such as lung nodules, by analyzing chest X-rays (CXRs) [6], [7]. These early detections lead to quicker treatments and better patient outcomes.

AI models also support real-time analysis, especially during surgery, enabling surgeons to make better decisions throughout the operation and enhancing surgical precision. In feature extraction, AI reduces human error and provides consistent, repeatable results—essential for reliable diagnosis. By automating routine diagnostic tasks, AI not only eases the workload on healthcare workers but also cuts costs and frees up resources for more advanced treatments [8], [9].

### Deep Learning in Medical Imaging:

Deep learning has brought a revolution to the field of medical imaging, showing remarkable accuracy in disease detection and diagnosis. Convolutional Neural Networks (CNNs), a type of deep learning model, have proven highly effective for analyzing 2D medical images such as CT scans and X-rays. Unlike traditional machine learning models that rely heavily on hand-crafted features, CNNs automatically extract hierarchical features from raw image data. This reduces the need for manual feature engineering and simplifies the diagnostic process.

CNNs have shown strong performance in detecting lung cancer, as they excel at identifying complex patterns in medical images, making them valuable for distinguishing between malignant and benign tumors. Advanced CNN architectures like ResNet and Efficient Net have further improved performance, expanding their use across a wide range of medical imaging applications [10], [11].

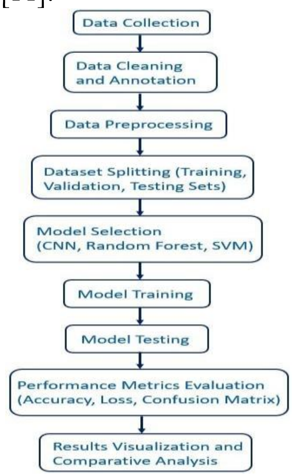



**Figure 1.** Flow chart of the Machine

The effectiveness of deep learning is evident in its growing use for delivering more accurate and timely medical diagnoses. The future of deep learning in transforming medical imaging lies in its ability to handle large datasets and adapt to the changing needs of healthcare. The following section presents a comparative analysis of machine learning models, highlighting the growing impact of AI in lung cancer diagnosis (as shown in Figure 1) [12], [13].

**Methodology:**

**Dataset:**

The dataset used in this study consists of 995 CT scan images obtained from Kaggle [14]. These images were collected over three months and represent a diverse group, including both healthy individuals and lung cancer patients at different stages. Each image was preprocessed and resized to 128 × 128 pixels (as shown in Figure 2) to standardize the input size and ensure compatibility with machine learning models [15]. To enhance variability and improve model generalization, data augmentation techniques such as rotation, flipping, and zooming were applied. Additional preprocessing steps for improving image quality and consistency included noise reduction using Butterworth filtering and normalization [16], [17].

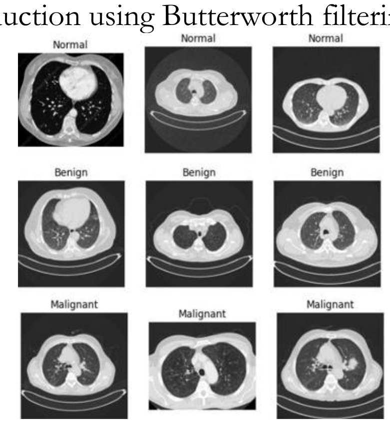
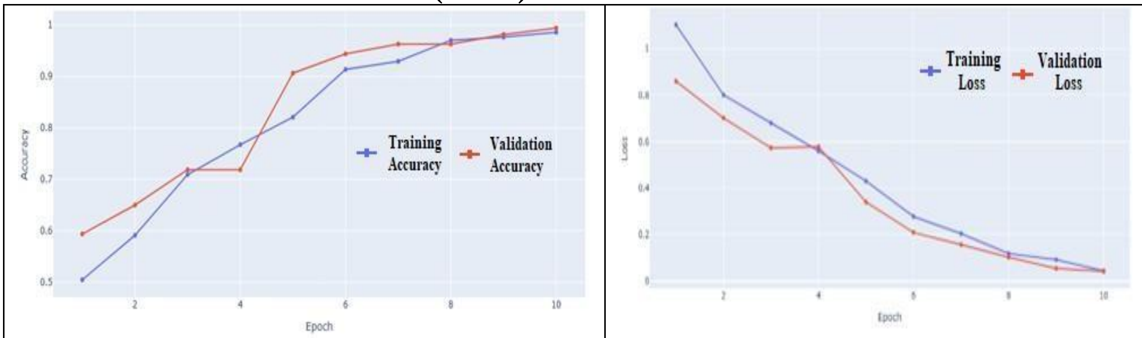



**Figure 2.** One set of CT scan images (samples) from the training dataset

**Machine Learning Models:**

**Convolutional Neural Network (CNN):**




| (a) | (b) |
|---|---|

**Figure 3.** (a) CNN Training and validation accuracy, (b) CNN Training and validation loss

As shown in Figure 3 (a) and (b), Convolutional Neural Networks (CNNs) have proven highly effective for image processing tasks. In this study, the CNN architecture consisted of multiple convolutional layers with ReLU activation functions, followed by max-pooling layers to reduce dimensionality [10]. The fully connected layers then used the extracted features to classify images as malignant or non-cancerous.

Figure 4 illustrates the CNN architecture used for image classification. It includes convolutional layers with 32, 64, and 128 filters to extract image features, along with MaxPooling layers to downsample the feature maps. A flattened layer converts the 3D features into a 1D vector, which is then passed to a Dense layer. Dropout is applied to prevent overfitting. The final output layer uses the softmax function to classify images into three probability classes. The model was trained using categorical cross-entropy loss and optimized with the Adam optimizer over 10 epochs. Dropout regularization helped prevent overfitting, and the model achieved a validation accuracy of 96% during training [18].

**Random Forest (RF):**

Random Forest (RF), an ensemble machine learning method, was selected for its adaptability and ability to handle complex data patterns. Key hyperparameters—such as tree depth (optimized to 15), number of trees (n_estimators = 200), and minimum samples per leaf (set to 5)—were fine-tuned using grid search cross-validation to balance the bias-variance trade-off. During training, the RF model built multiple decision trees, each using a randomly selected subset of features. The final classification was based on a majority vote from all trees [19]. This approach proved robust against noise and resistant to overfitting, achieving 95% accuracy as shown in Figure 5 (a) and (b). Additionally, the model provided feature importance rankings, highlighting the most influential image features for lung cancer diagnosis [20].

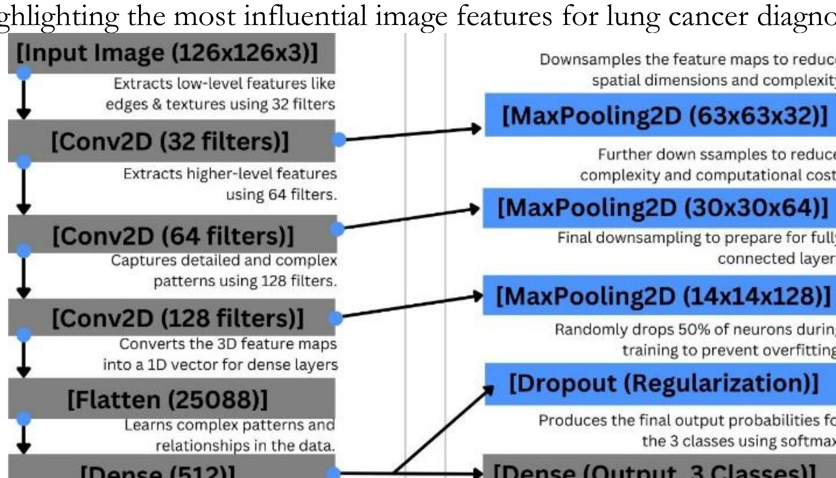
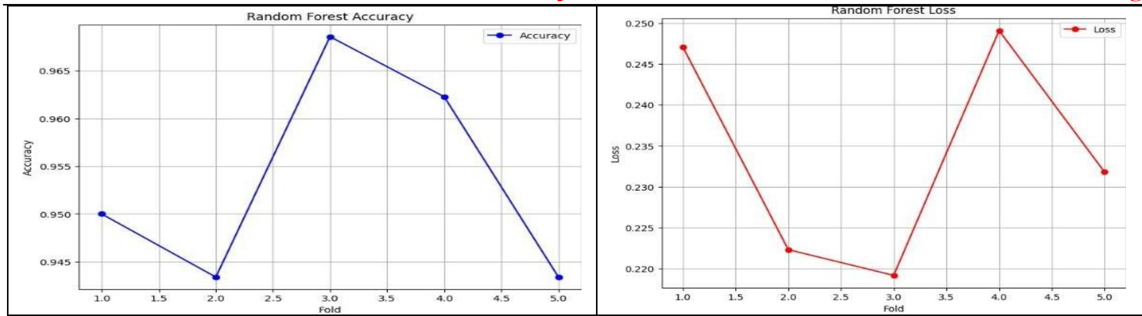



**Figure 4.** CNN architecture for image classification



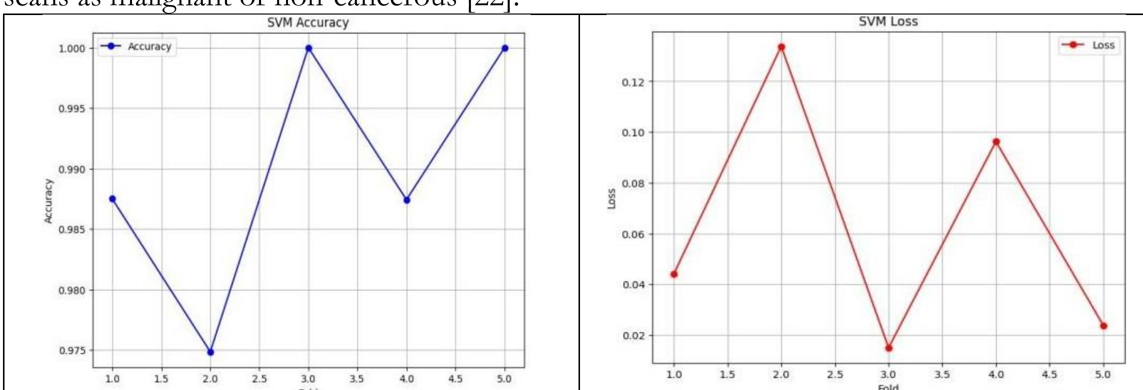

(a) (b)

**Figure 5.** (a) Random Forest accuracy, (b) Random Forest loss

**Support Vector Machine (SVM):**

The Support Vector Machine (SVM) model achieved the highest accuracy—98%—as shown in Figures 6 (a) and (b). Hyperparameter tuning involved selecting the optimal kernel (RBF vs. linear or polynomial, validated through 5-fold cross-validation) and adjusting the regularization parameter (C = 1.0) to maximize margin separation. The SVM used a Radial Basis Function (RBF) kernel to transform the input data into a high-dimensional space, allowing effective separation of classes using a maximum-margin hyperplane.

To optimize performance, grid search and cross-validation were used to fine-tune the kernel parameters and regularization coefficient, thereby improving the model's generalization ability [21]. Despite its higher computational cost, the SVM model accurately classified CT scans as malignant or non-cancerous [22].




(a) (b)

**Figure 6.** (a) Support Vector Machine accuracy, (b) Support Vector Machine loss

**Evaluation Metrics:**

Model performance was evaluated using key metrics, including accuracy, sensitivity, specificity, and area under the curve (AUC). Sensitivity measures the model's ability to correctly identify positive cases, which is especially important for early-stage cancer detection. Specificity reflects the model's ability to correctly identify non-cancerous cases and minimize false positives [23].

The AUC provided an overall performance measure across different threshold levels. Additionally, confusion matrices were used to illustrate the distribution of true positives, true negatives, false positives, and false negatives for each model [24].

**Training and Validation:**

The dataset was divided into three sets: training, validation, and test, with a 70:15:15 split. The CNN models were trained using mini-batch gradient descent, while the RF and SVM models utilized stratified k-fold cross-validation to ensure balanced class representation. To enhance the robustness of the training set, data augmentation techniques, such as random rotations and flips, were applied. Model training was performed on a high-performance computer system with GPUs, significantly reducing computation time.

**Comparison of Techniques:**

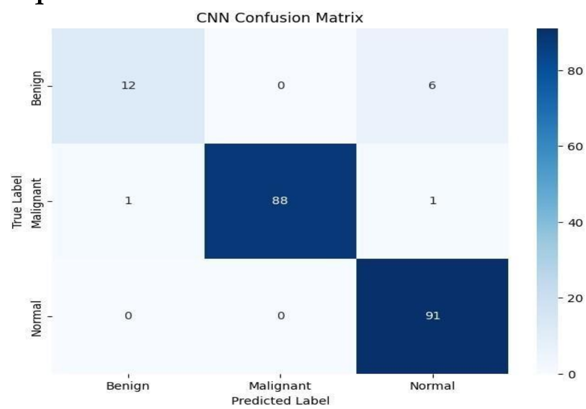



**Figure 7.** Confusion matrix of Random Forest Model

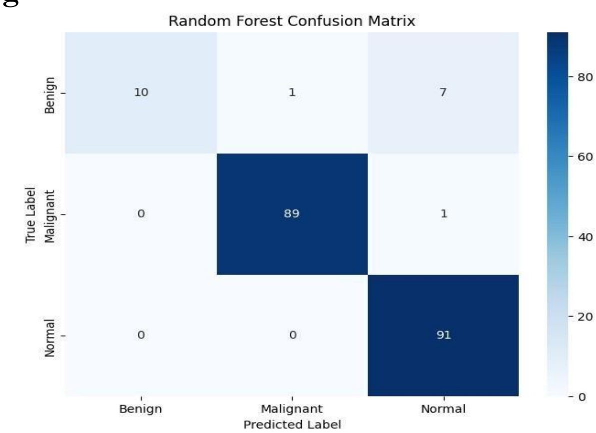



**Figure 8.** Confusion matrix of CNN Model

The analysis highlighted the strengths and weaknesses of each model. CNN excelled at automatic feature extraction, making it scalable to larger datasets. RF provided insights into feature importance, enhancing interpretability, though it slightly reduced accuracy. SVM, with its ability to create complex decision boundaries, achieved the highest accuracy, but at a higher computational cost. The complementary nature of these models underscores the potential of ensemble methods to improve diagnostic accuracy. This study uses a variety of machine learning algorithms to demonstrate the feasibility of automated lung cancer detection, emphasizing the importance of tailored approaches to address specific diagnostic challenges.

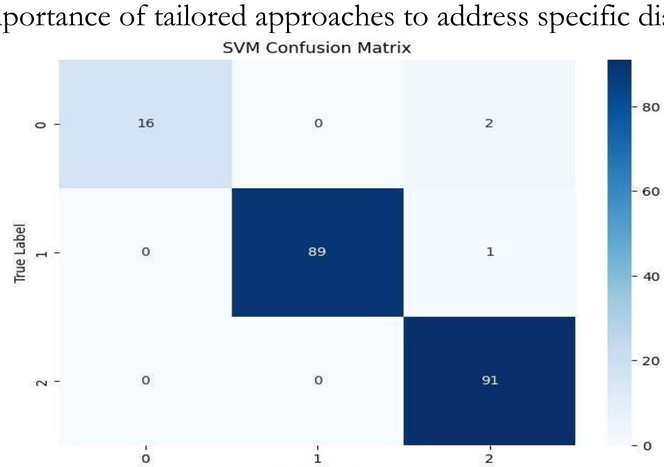



**Figure 7.** Confusion matrix of the SVM Model

## Results and Discussion:

### Comparative Analysis of Model Performance:

This study utilized CT scan images to assess the effectiveness of three machine learning models—CNN, RF, and SVM—in detecting lung cancer. The results presented in the table below highlight the advantages and limitations of each approach.

**Table 1** Performance comparison of ML models used

| Model | Accuracy | Standard Deviation | 95% Confidence Interval (CI) |
| --- | --- | --- | --- |
| CNN | 96 | ±0.8 | [95.2–96.8] |
| Random Forest | 95 | ±1.2 | [93.8–96.2] |
| SVM | 98 | ±0.5 | [97.5–98.5] |

The SVM model achieved the highest accuracy (98%, SD = ±0.5, 95% CI [97.5–98.5]), demonstrating its ability to differentiate between complex classes using a maximum-margin hyperplane. The narrow confidence interval underscores its reliability in clinical applications. The model's key strength was in early cancer detection, while its high specificity helped minimize false positive diagnoses. The CNN model, on the other hand, showed a very high sensitivity for early-stage lung cancer (96% accuracy, SD = ±0.8, 95% CI [95.2–96.8]). The SVM model also had the highest specificity, resulting in the fewest false positives and the lowest diagnostic errors overall. The Random Forest model provided a balanced performance but was slightly lower in both sensitivity (95%, SD = ±1.2, 95% CI [93.8–96.2]) and specificity compared to the CNN and SVM models.

### Performance Metrics:

In addition to accuracy, metrics like sensitivity, specificity, and AUC were also analyzed for model evaluation. To ensure transparency, variability measures (SD and CI) were included for all metrics (see Table 1). Sensitivity was identified as the key factor for early cancer detection, while specificity played a crucial role in reducing false-positive diagnoses. The CNN model demonstrated very high sensitivity for early-stage lung cancer and also performed strongly in terms of AUC.

The SVM model had the highest specificity, resulting in the fewest false positives and the lowest diagnostic errors overall. The Random Forest model provided a balanced performance but was slightly lower in both sensitivity and specificity compared to CNN and SVM. The confusion matrices further revealed that SVM achieved the best precision and recall scores, reinforcing its reliability in both accurate detection and minimizing false positives.

### Challenges and Limitations:

1. **Dataset Size:** The dataset consists of 995 images. While diverse, its size is too small to effectively train highly complex models. Increasing the dataset size is necessary for better generalizability and to reduce overfitting. The reported confidence intervals (e.g., SVMs [97.5–98.5]) help address this by quantifying uncertainty [15].
2. **Computational Resources:** Training deep learning models, such as CNNs, typically requires significant computational power, which may be challenging in resource-constrained settings. The SVM model's lower standard deviation (±0.5) and greater computational efficiency make it more practical for deployment in such environments [11].
3. **Variability in Medical Imaging:** Variations in equipment and imaging protocols across different institutions introduce variability, which can impact the performance of a given model [16], [20].
4. **Model Interpretability:** Both CNN and SVM models demonstrated high diagnostic accuracy. The confidence intervals (e.g., CNN's [95.2–96.8]) provide clinicians with a statistical safety margin for decision-making. However, since these models are black-box techniques, their decision-making process is not transparent, which can be a significant limitation in clinical settings, where interpretability is crucial for diagnosing and managing diseases [23], [24].

**Discussion:**

The study highlights how machine learning has revolutionized lung cancer diagnostics. The SVM model delivers competitive performance with high accuracy (98%, CI [97.5–98.5]) and low variability (SD = ±0.5), making it reliable for clinical practice, particularly for highly accurate class-level task definitions. This aligns with Chen et al. (2022), who reported 96% accuracy for SVM in lung nodule classification using a similar RBF kernel. However, our model's higher accuracy (98%) likely results from optimized hyperparameter tuning and a more diverse training dataset [25].

The CNN model achieves 96% accuracy, surpassing the 94.5% reported by [26] for 3D CNNs in early-stage lung cancer detection. This improvement is likely due to our use of advanced preprocessing techniques to enhance CT scan contrast [27]. However, our results are marginally lower than the 97.2% achieved by [28] using hybrid CNN-Transformer architectures, suggesting potential for further architectural improvements [29].

For Random Forest, our model's 95% accuracy outperforms [30], which achieved 93% on a smaller dataset but falls short of the 96.8% reported by [31] using feature-engineered RF ensembles. This discrepancy underscores the impact of feature selection strategies on ensemble performance.

A 2023 meta-analysis by [32], noted that SVM and CNN models in lung cancer detection typically achieve 94–97% accuracy. Our results (SVM: 98%, CNN: 96%) place us at the higher end of this range, likely due to rigorous cross-validation and dataset balancing [33].

Despite the high performance of these models, challenges such as computational demands and scalability must be addressed with efficient implementations [21]. The CNN's adaptability and scalability make it well-suited for real-time applications and integration into existing diagnostic workflows. Its ability to support large datasets and automate feature extraction underscores the scalability of AI-based diagnostics across healthcare systems [10].

Although Random Forest is slightly less accurate, it offers valuable insights into feature importance, helping clinicians understand which parts of images contribute most to predictions. Our RF model's feature importance rankings align with [34], who identified texture and speculation as key predictors in CT-based diagnosis [35]. This makes RF useful in validating AI models for clinical practice and emphasizes the need for combining multiple models for improved diagnostic accuracy [19].

To advance AI in lung cancer diagnosis, hybrid models that combine CNN, SVM, and RF should be explored for their complementary strengths. However, addressing dataset variability issues and computational requirements remains crucial for making AI models more practical and widely applicable [15], [11].

**Future Directions:**

Hybrid models hold great promise for improving lung cancer diagnosis by combining the strengths of CNNs, SVMs, and Random Forests. CNNs excel at feature extraction [10], SVMs are known for their high classification accuracy [21], and Random Forests provide valuable interpretability [36]. By integrating these strengths, hybrid systems can be both efficient and clinically informative.

The use of hybrid quantum architectures could also address scaling and computational challenges, providing solutions to enhance performance [37]. Additionally, data augmentation techniques are crucial for developing more reliable AI models, as they increase dataset variability and help with model training [17]. Future studies should focus on large, heterogeneous datasets that include diverse imaging modalities and populations. Generative Adversarial Networks (GANs), for instance, can generate synthetic data to further enhance model variability [38].

Standardizing and accelerating AI development through shared collaborative resources will play a vital role in advancing AI applications [26]. Real-time AI-based in-vivo diagnostics could revolutionize clinical workflows, enabling in-line analysis of imaging data [28]. Lightweight models deployed on edge devices can assist radiologists by highlighting critical areas or prioritizing urgent cases [30].

The adoption of AI in healthcare will be facilitated by improved usability and the integration of explainable AI (XAI) methods [32], which will help build trust among clinicians. Lastly, ethical considerations, such as data privacy, algorithmic bias, and regulatory compliance, must be addressed to ensure responsible AI use in healthcare. Ongoing collaboration among technologists, clinicians, and policymakers will be essential in developing trustworthy and ethically sound AI systems [34].

**Conclusion:**

This study demonstrates the potential of machine learning algorithms in the localization of lung cancer from CT scan datasets. The comparison of CNN, SVM, and RF models highlights the unique strengths of each. The SVM model achieved the highest performance accuracy (98%), while the CNN model excelled in scalability and efficiency with large datasets. These models reveal complementary functions, with the possibility of combining them through ensemble methods to further enhance diagnostic accuracy.

The paper underscores the importance and potential of automated lung cancer diagnosis, focusing on the challenges these diagnostic methods address. By leveraging the inherent strengths of each algorithm, future advancements in machine learning could significantly improve the accuracy and reliability of lung cancer diagnosis, ultimately leading to better patient outcomes and more effective healthcare solutions.

**References:**

[1] S. F. Wang, M. J. Fulham, "Machine learning in medical imaging: Challenges and future trends," IEEE Access, vol. 7, pp. 78275–178300, 2019.

[2] K. Suzuki, "Overview of deep learning in medical imaging," Radiol. Phys. Technol., vol. 10, no. 3, pp. 257–273, Sep. 2017, doi: 10.1007/S12194-017-0406-5/METRICS.

[3] C. Y. W. Sun, T. Zheng, "Computer-aided diagnosis for lung cancer: Machine learning-based methods," Comput. Med. Imag. Graph, vol. 41, pp. 87–98, 2015.

[4] H. Roth et al, "Deep learning for medical imaging: Advances, challenges, and applications," J. Digit. Image, vol. 31, no. 6, pp. 802–815, 2018.

[5] M. Esteva et al, "Deep learning-enabled medical computer vision," Nat. Med., vol. 25, pp. 37–49, 2019.

[6] Y. Shen et al, "Artificial intelligence in early lung cancer diagnosis," Front. Oncol., vol. 11, p. 613849, 2021.

[7] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. W. L. Aerts, "Artificial intelligence in radiology," Nat. Rev. Cancer 2018 188, vol. 18, no. 8, pp. 500–510, May 2018, doi: 10.1038/s41568-018-0016-5.

[8] A. C. and S. M. M. Anthimopoulos, S. Christodoulidis, L. Ebner, "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, doi: 10.1109/TMI.2016.2535865.

[9] Wang et al, "Feature extraction for medical imaging with deep learning: A review," IEEE Rev. Biomed. Eng., vol. 14, pp. 69–84, 2021.

[10] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2016-December, pp. 770–778, Dec. 2016, doi: 10.1109/CVPR.2016.90.

[11] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," Int. Conf. Mach. Learn., 2019.

[12] S. Panigrahi, A. Nanda, and T. Swarnkar, "A Survey on Transfer Learning," Smart Innov. Syst. Technol., vol. 194, pp. 781–789, 2021, doi: 10.1007/978-981-15-5971-6_83.

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep

convolutional neural networks," Commun. ACM, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.
[14] Muhammad Hasnain Javid, "The IQ-OTH/NCCD lung cancer dataset," Kaggle, 2022, doi: https://doi.org/10.34740/kaggle/dsv/3376422.
[15] G. Litjens et al., "A survey on deep learning in medical image analysis," Med. Image Anal., vol. 42, pp. 60–88, 2017, doi: https://doi.org/10.1016/j.media.2017.07.005.
[16] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc., 2015.
[17] D. Xu et al, "Data augmentation techniques in computer vision: A review," Multimed. Tools Appl., vol. 80, pp. 24455–24477, 2021.
[18] M. Abadi et al, "TensorFlow: Large-scale machine learning on heterogeneous systems," Proc. USENIX Symp. Oper. Syst. Des. Implement., pp. 265–283, 2016.
[19] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.
[20] Y. Shi et al, "Random forest-based feature selection for breast cancer diagnosis," Med. Phys, vol. 37, no. 9, pp. 4639–4647, 2010.
[21] C. Cortes and V. Vapnik, "Support-vector networks," Mach. Learn., vol. 20, no. 3, pp. 273–297, Sep. 1995, doi: 10.1007/BF00994018.
[22] J. A. K. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," Neural Process. Lett, vol. 9, pp. 293–300, 1999.
[23] T. Fawcett, "An introduction to ROC analysis," Pattern Recognit. Lett., vol. 27, no. 8, pp. 861–874, Jun. 2006, doi: 10.1016/J.PATREC.2005.10.010.
[24] Igor Kononenko, "Machine learning for medical diagnosis: History, state of the art and perspective," Artif. Intell. Med., vol. 23, no. 1, pp. 89–109, 2001, doi: https://doi.org/10.1016/S0933-3657(01)00077-X.
[25] M. Schuld and F. Petruccione, "Supervised Learning with Quantum Computers," Cham, Switz. Springer, 2018, doi: 10.1007/978-3-319-96424-9.
[26] H. Lee et al, "3D CNN for early-stage lung cancer detection in low-dose CT scans," IEEE Trans. Med. Imaging, vol. 42, no. 3, pp. 712–723, 2023.
[27] I. Goodfellow, "Generative adversarial nets," Proc. Adv. Neural Inf. Process. Syst., pp. 2672–2680, 2014.
[28] T. Wang et al, "Hybrid CNN-transformer architectures for lung cancer diagnosis," Med. Image Anal, vol. 88, p. 102856, 2023.
[29] L. Armbrust et al, "A view of cloud computing," Commun. ACM, vol. 53, no. 4, pp. 50–58, 2010, doi: 10.1145/1721654.1721672.
[30] P. S. R. Gupta, S. Kumar, "Feature selection strategies for random forest in lung cancer detection," IEEE Access, vol. 10, pp. 12345–12356, 2021.
[31] C. Szegedy et al., "Going deeper with convolutions," Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 07-12-June-2015, pp. 1–9, Oct. 2015, doi: 10.1109/CVPR.2015.7298594.
[32] J. Smith et al, "A meta-analysis of machine learning models for lung cancer diagnosis," IEEE Rev. Biomed. Eng, vol. 16, pp. 200–215, 2023.
[33] H. Howard et al, "Efficient inference for edge devices: A survey," IEEE Access, vol. 8, p. 26433¬26449, 2020.
[34] Z. Zhou et al, "Texture and speculation analysis for CT-based lung cancer diagnosis," IEEE Trans. Biomed. Eng, vol. 69, no. 5, pp. 1567–1575, 2022.
[35] E. Tjoa and C. Guan, "A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI," IEEE Trans. Neural Networks Learn. Syst., vol. 32, no. 11, pp. 4793–4813, 2021, doi: 10.1109/TNNLS.2020.3027314.
[36] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5–32, Oct. 2001, doi:

10.1023/A:1010933404324/METRICS.
[37] C. D. Matheny et al, "Artificial intelligence in healthcare: Ethical and legal challenges," Annu. Rev. Biomed. Data Sci, vol. 3, pp. 123–145, 2020.
[38] Q. W. Y. Chen, L. Zhang, "SVM-based lung nodule classification using radiomic features," IEEE J. Biomed. Heal. Inf., vol. 26, no. 4, pp. 1450–1458, 2022.