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Deep Learning Method for Early Detection of Lung Cancer using Deep Learning Algorithms

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Abstract: Lung cancer is responsible for many deaths from cancer around the globe, primarily because it is difficult to find malignant lung nodules early enough to be treatable. We developed a hybrid deep learning approach to the automated classification of lung nodules from chest computed tomography (CT) images. Our model uses convolutional neural networks (CNNs) for hierarchical feature extraction, an attention mechanism for feature refinement in targeted regions of interest, and a support vector machine (SVM) classifier for robust margin-based decision making. Furthermore, we use a patch-based learning strategy within the model to improve sensitivity to small and ambiguous lung nodules. The model is tested on the publicly available LIDC-IDRI dataset and achieves 94.2% accuracy, 95.1% recall, and an area under the receiver operating characteristic curve (AUC-ROC) score of 0.971, which outperforms multiple baseline deep learning methods. The proposed method provides a synergistic integration of attention-weighted feature enhancements and traditional machine learning classifications as compared to traditional end-to-end architectures, resulting in improved model generalization and interpretability. Grad-CAM visualizations are also used to provide qualitative insights into the model decision-making process. The proposed hybrid approach provides a novel and interpretable solution for the classification of lung nodules from CT images that may assist in the development of computerized systems to assist physicians in making diagnoses using medical images.

Index Terms: Lung Cancer Detection, Computed Tomography, Deep Learning, Convolutional Neural Networks, Hybrid Model, Medical Imaging.

1. Introduction

Lung cancer remains one of the leading causes of cancer death worldwide, resulting in hundreds of thousands of deaths annually. The high rates of diagnosis and death can be attributed to a very low percentage of patients who are diagnosed with lung cancer at an early, treatable stage because identifying malignant nodules accurately can be difficult.

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Computed Tomography (CT) imaging has become a common method for diagnosing carcinoma in the lungs because of its ability to provide comprehensive anatomical information. However, interpreting CT images by hand is time-consuming, subject to variability between radiologists, and tends to be particularly difficult for small or ambiguous nodules. For these reasons, there is a clear need for automated, reliable, and precise ways to help radiologists interpret lung nodules using computer-based methods. Recently, Artificial Intelligence (AI) and specifically Deep Learning (DL) have achieved significant achievements in medical imaging. A particular network architecture called Convolutional Neural Networks (CNNs) has become the primary method by which AI can learn to generate hierarchical representations of different types of features using only raw images as input. Many studies have successfully applied different instances of CNN architectures, including ResNet or VGG architectures, to tasks such as determining whether a lung nodule is malignant or benign. Performance improvements shown using CNNs are significantly higher than previous attempts with traditional models. Unfortunately, individual CNNs may still suffer from problems such as difficulty with overfitting; limited ability to generalize; and difficulty detecting subtle differences among humified images due to smaller size or complexity of those images when determining whether they are malignant.

Hybrid methods, which combine classical machine learning methods with deep learning methods, have been investigated to solve these issues. For example, CNN-based feature extraction combined with SVM classifiers yields improved robustness of classification through the margin-based optimization characteristics of SVMs. Attention mechanisms are being developed to direct model predictions to relevant clinical regions in CT images through improved feature discrimination and localization. Learning methods that are patch-based are being utilized as a means of capturing very fine detailed local features and are particularly important for the detection of smaller nodular structures.

Existing methods tend to examine each of these aspects (CNN feature extraction, attention mechanisms, patch-based learning, and SVM classification) separately or with limited combinations. There is a lack of a systematic framework that integrates localized feature learning with attention-driven refining and robust classification methods into a single model. Moreover, many studies place an emphasis on performance metrics at the expense of providing appropriate measures of interpretability and modular design, both of which are important for applications in real-world medicine.

To fill a gap between available knowledge and existing technology in the field of lung nodule detection, we develop a hybrid deep learning framework that automates the classification of lung nodules on CT scans. This approach will combine convolutional neural network (CNN) feature extraction with an attention mechanism for increased feature learning on a per-region basis as well as improving the trade-off of decision boundary robustness by using support vector machines (SVM). We will utilize a patch-based input methodology for extracting very fine local patterns related to small and subtle nodules (e.g., <3mm). Finally, we feel that such an architecture will yield an improved classification performance and understanding of how the model works, in addition to having a modular and scalable structure. The main contributions of this work are summarized as follows:

- A unified hybrid architecture that integrates CNN feature extraction, attention-based feature refinement, and SVM-based classification for improved lung nodule analysis.
- A patch-based learning strategy to enhance sensitivity toward small and visually ambiguous nodules.
- Improved classification robustness using a margin-based SVM classifier on deep feature representations.
- Enhanced interpretability using Grad-CAM visualizations to highlight regions influencing model predictions.
- Comprehensive evaluation on the LIDC-IDRI dataset, demonstrating improved performance over baseline deep learning models under consistent experimental settings.

The remainder of this paper is organized as follows. Section 2 reviews related work in lung cancer detection using machine learning and deep learning approaches. Section 3 describes the dataset and preprocessing techniques. Section 4 presents the proposed hybrid architecture and training methodology. Section 5 discusses experimental results and performance evaluation. Section 6 provides a comparative analysis with existing methods and discusses strengths and limitations. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Literature Review

Artificial Intelligence (AI), particularly Deep Learning (DL), has received significantly greater attention in quality improvement and efficiency regarding detecting Lung Cancer through the Analysis of Medical Images. Existing Approaches have been reviewed by this article and are categorized into Traditional Machine Learning (ML) techniques, Deep Learning (DL) Models, and Hybrid Systems combining both techniques. Traditional ML classifiers such as Support Vector Machines (SVM), Decision Trees, and k-nearest neighbors (kNN) have all been used for diagnosing Lung Cancer due to their interpretability and simple use as classifiers. Meeradevi, et al. [4] developed a Multi-Attribute Decision Making System that integrates ML classifiers with a DL backbone, showing improved performance with ML and DL compared to ML or DL alone. Wankhade, and Vigneshwari [5] presented an early detection method for Lung Cancer using Convolutional Neural Networks (CNNs) and demonstrating that CNNs have the potential to provide a

superior technique for feature generation relative to Handcrafted Methods. Gote, et al. [6] presented a hybrid horizontal ML System utilizing multiple ML Classifiers to predict Lung Cancer, indicating the importance of Feature Selection and the Synergy of Algorithm(s). CNNs have quickly become the most common architecture utilized in Medical Image Analysis due to their ability to automatically learn a hierarchal distribution of features over space. Ozdemir, et al. [7] demonstrated an improvement upon this approach by introducing an Attention-Enhanced InceptionNeXt Model that successfully captured fine-tuned tumor features and outperformed traditional CNNs on large CT datasets. Several authors have explored other enhancements of Networks using Complex Networks. Ansari, et al. [8] reported on an SVM-VGGNet16 framework utilizing a VGGNet for Feature Extraction and SVM as a Classifier which provided high classification accuracy on CT datasets. Aggrey, et al. [9] reported on a framework using Capsule Networks and Temporal Dynamics, leveraging concepts of multiscale feature extraction; emphasizing the importance of multiscale Feature Generation for improving Diagnosis and detection Accuracy of early-stage Lung Cancer. Hybrid Models have been developed that included optimizations of the components of the model. Bharathi, and Shalini [10] described an Attention-Based DL Architecture that utilized an Heuristic Level of Image Fusion resulted in significant improvements when integrating an image of a CT with a PET. Hossain, et al. [11] utilized CNNs for the purpose of Feature Extraction in combination with Singular Value Decomposition (SVD) for the purpose of Ensemble Classification, illustrating that this method holds Promise in Projects Utilizing Multiclass Classification for Lung Cancer Detection. A summary of Author, Models, Datasets, and performance highlights of key literature sources on Lung Cancer Detection are provided in Table 1, below.

Table 1. Literature Review summarizing key studies, models, datasets, and performance

Ref.	Authors (Year)	Model Type	Dataset	Performance Highlights
[4]	Meeradevi et al. (2025)	ML classifiers with DL features	CT and Histopathological Data	Improved decision-making using ML-DL fusion
[5]	Wankhade & Vigneshwari (2023)	CNN-based DL model	CT Scans	High accuracy and early detection
[7]	Ozdemir et al. (2025)	Attention-enhanced CNN (InceptionNeXt)	Public CT Image Dataset	Superior attention-based feature learning
[8]	Ansari et al. (2025)	Hybrid VGGNet + SVM	CT Scan Dataset	Enhanced classification performance
[9]	Aggrey et al. (2025)	Hybrid Capsule Networks + Temporal Dynamics	Multi-source Clinical and Imaging Data	Robust feature learning across scales and time
[10]	Bharathi & Shalini (2024)	Hybrid Attention-based DL + Heuristic Fusion	CT + PET Images	High-quality PET/CT fusion; accurate classification
[11]	Hossain et al. (2025)	CNN with SVD + Ensemble	Multiclass Lung Cancer Dataset	Effective multiclass classification
[12]	Kusuma et al. (2024)	Hybrid DL with Pelican Optimization	CT Images	Optimized accuracy and convergence speed
[15]	Venkatesh et al. (2024)	Patch-based CNN Model	CT Scan Patches	Localized learning improved detection
[20]	Al-Shabi et al. (2022)	ProCAN (Progressive Channel-Attentive Network)	LIDC-IDRI	Channel and spatial attention improve classification
[21]	Keel et al. (2023)	Variational Autoencoders (VAE)	CT Scans (Research Dataset)	Latent features effective for malignancy prediction
[22]	Zhu et al. (2018)	3D Dual-Path Deep Network	LIDC-IDRI	End-to-end nodule detection and classification
[23]	Al-Shabi et al. (2019)	Gated-Dilated CNN	LIDC-IDRI	Combines dilation and gating for better feature focus
[24]	Müller-Franzes et al. (2024)	Medical Slice Transformer (DINOv2)	3D CT Volumes	Transformer model improves 3D diagnosis & explainability
[25]	Harsono et al. (2022)	RetinaNet + Transfer Learning	Thorax CT-Scan	Transfer learning boosts RetinaNet detection performance
[26]	Jiang et al. (2021)	Explainable Discriminative DL	Pulmonary Nodule CT Dataset	Efficient and explainable representations learned
[27]	Al-Shabi et al. (2019)	Local-Global Deep Network	LIDC-IDRI	Combines local and global context for accuracy

The Pelican Optimization Algorithm was utilized by Kusuma et al to optimize the parameters of a hybrid deep learning model, resulting in improvements in both computational and classification accuracy [12]. To solve the problems of convergence and overfitting, the use of bio-inspired metaheuristics with CNNs was used by Vijh et al [13] to perform automatic lung tumor detection. Additional contributions of interest include: ensemble systems [14]; local learning with patch-based CNNs [15]; and feature extraction with supervised data mining approaches [16]. The authors of [3] have presented a reference on hybrid CNNs while the authors of [17] discussed the utility of deep-learning based computer aided diagnosis (CAD) systems in improving decision making in the clinical environment.

3. Data Description

This study utilizes the LIDC-IDRI dataset, which is a benchmark database for research on lung cancer detection that contains a total of 1,018 CT scans of the thorax that have been performed across multiple different medical institutions. Each CT scan includes several annotated lung nodules which have been reviewed and annotated by up to four experienced radiologists for their likelihoods of being malignant and for their characteristics of shape, margin, and level of texture as seen in Figure 1. The multi-reader method used in the annotation process increases the reliability of the supervised learning ground truth.

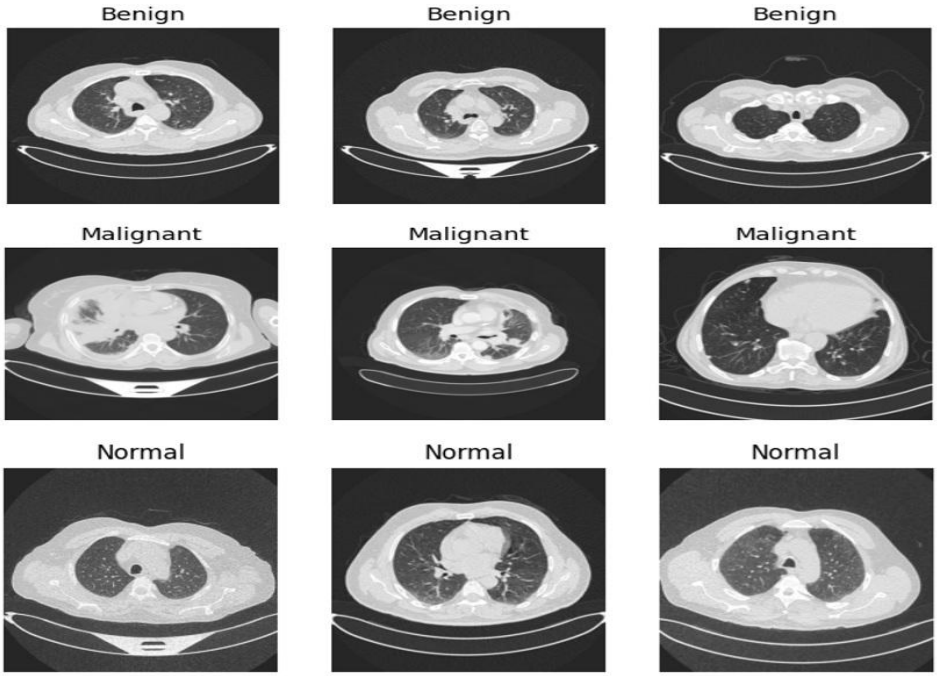


Fig. 1. CT Scans showing the model's classification performance for benign, malignant, and normal lung nodules

To prepare the raw CT scans for input into the proposed deep learning model, several preprocessing steps were applied in figure 2:

- *Noise Removal:* A median filter was applied to suppress salt-and-pepper noise while maintaining edge sharpness in the lung structures.
- *Resizing:* All image slices were resized to 256 × 256 pixels to standardize the input dimensions across the dataset and reduce computational load.
- *Normalization:* Pixel intensity values were scaled to the range [0, 1] to ensure uniform data distribution and accelerate training convergence.
- *Segmentation:* In some experiments, lung fields were segmented using thresholding and morphological operations to isolate Regions of Interest (ROIs) and reduce background noise.
- *Data Augmentation:* To improve model generalization and address class imbalance, augmentation techniques such as horizontal/vertical flipping, rotation (±10°), zoom (±10%), and contrast adjustment were applied during training [15].

The preprocessing step improved the quality of data used to train the model and allowed it to learn site specific features from areas relevant to clinical diagnosis. In the LIDC-IDRI dataset, each nodule has a rating of malignancy from 4 expert radiologists giving a score between 1-5 for each nodule identified. This research used a consensus-based approach to assigning labels. Nodules rated as 3 or above are classified as malignant, with nodules rated 2 or less classified benign. Any nodule with an indeterminate rating was excluded to minimize uncertainty in their classification. In cases where there were more than one rating for a nodule, the average rating of all radiologists was used as the definitive rating for that nodule for the purposes of classification. It should also be noted that slices that did not contain annotated lesions were classified as normal/non-nodular. This process resulted in approximately 1018 total samples available to be used in training and validating the model while maintaining an adequate level of balance and reliability for a classification dataset.

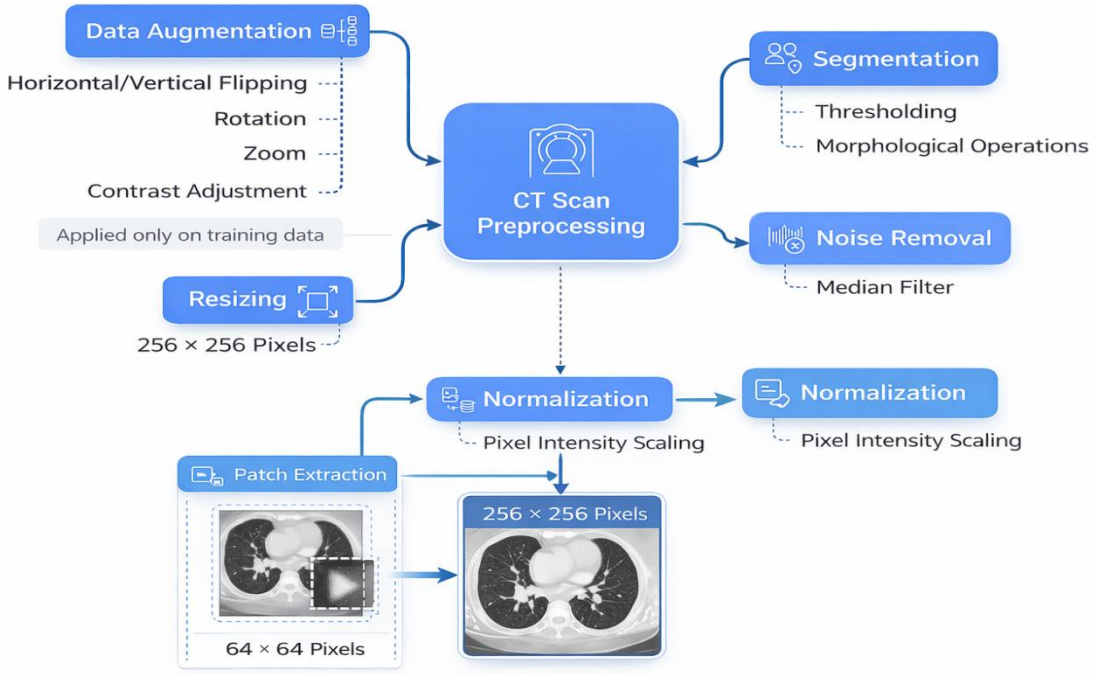


Fig. 2. Preprocessing pipeline for CT scan images used in the proposed hybrid deep learning framework. The pipeline includes noise removal using a median filter, segmentation through thresholding and morphological operations, resizing to a standard resolution (256 × 256 pixels), normalization of pixel intensities, and data augmentation techniques such as flipping, rotation, zooming, and contrast adjustment.

A set of clearly defined parameters was used to implement the preprocessing pipeline so that the experiments would be reproducible and consistent. Lung region segmentation was performed using thresholding based on the intensity (Hounsfield Units) (HU) of slices between −600 and −400 via morphological operations to refine the regions of interest (ROIs) for each CT slice prior to proceeding with the augmentation process by making the slices all the same size (256 × 256 pixels) and the pixel weights to be in the range of (0,1).

The patch-based feature learning approach was employed to extract image patches of size 64 × 64 pixels around each annotated region for localized feature learning. The training dataset had various data augmentation techniques applied to help improve generalization and reduce class imbalance. For example, for each image patch, a random rotation between −10° and 10°, flipping both horizontally and vertically, zooming in or out (±10%), and/or changing the contrast of the image patch (±10%) were applied with a probability of 0.5. No augmentation was performed on the validation or testing datasets to provide an unbiased evaluation of the model. All preprocessing steps (resizing, normalisation, and segmentation) were applied consistently across all three datasets (training data, validation data, and test data) to mitigate discrepancies amongst the distributions of the datasets and to ensure a fair assessment of the model.

4. Proposed Hybrid Deep Learning Architecture

4.1. Hybrid Deep Learning Architecture

The hybrid architecture proposed uses a sequential feature refinement and classification data flow. An input CT image or a 64 × 64 extracted patch goes into a proprietary convolutional neural network (CNN) block that extracts low-level features via convolution operations with the ReLU activation function and max pooling, followed by the generation of feature maps. The feature maps are routed to a modified version of the VGG-16 backbone that learns deep hierarchical features in the input data for capturing higher-level and abstract feature representations from the input data. The attention mechanism is included after the feature extraction from VGG-16 to help improve generalization for clinically significant areas of interest to practitioners.

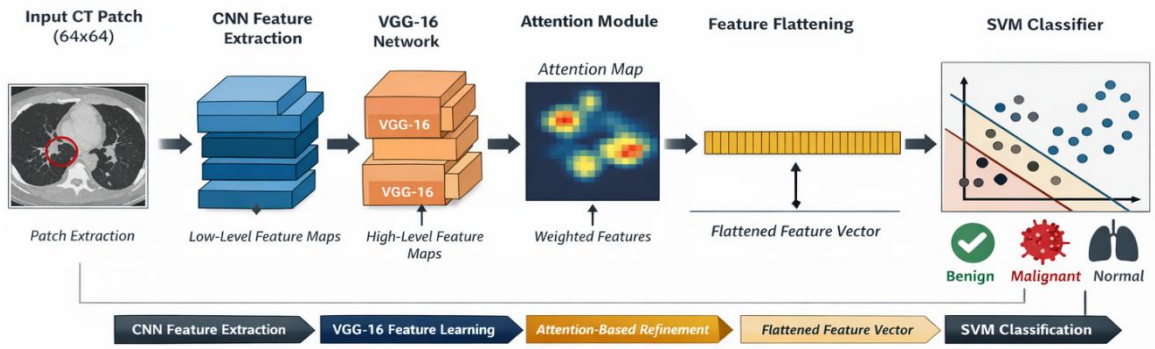


Fig. 3. Hybrid model architecture for lung cancer classification.

Adaptive weights are applied to the VGG-16 feature maps through an attention mechanism that determines which spatial areas of input images are most relevant to classification, to emphasize patterns associated with nodules and minimize patterns that are unrelated to nodules (e.g., background of image) when determining which features from the attention module should be retained. After filtering through the attention module, these feature maps are flattened to form a single 1-D feature vector that will then be inputted to the final classification stage. The final classification stage uses a support vector machine (SVM) classifier with a linear kernel, rather than a softmax layer, to perform margin-based classifications of the input data. Thus, the proposed model utilizes deep feature representations while also capitalizing on SVM's strong decision boundaries to classify the input data.

Thus, the complete pipeline follows the sequence: Input Image/Patch → CNN Feature Extraction → VGG-16 Feature Learning → Attention-Based Feature Refinement → Flattening → SVM Classification, ensuring a systematic flow from low-level feature extraction to high-level discriminative classification.

Algorithm 1: Hybrid CNN–VGG16–SVM-Based Lung Cancer Classification

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Input: Pre-processed CT scan image $I \in R^{256 \times 256}$
Output: Predicted class label $C \in \{Benign, Malignant, Normal\}$

Begin
Preprocessing:
- *Normalize the image* $[I]$ *to pixel intensity range [0, 1].*
- *(Optional) Divide image into patches if using patch-based strategy.*

Convolutional Feature Extraction:
- *Apply CNN with:*
  - *Kernel size =* (3×3)
  - *Filters = [64, 128, 256, 512]*
  - *Activation = ReLU*
- *Output feature maps* F_{cnn}

Deep Feature Learning (VGG-16):
- *Pass* F_{cnn} *to pre-trained VGG-16 (excluding FC layers).*
- *Extract high-level features* F_{vgg}

Flattening:
- *Flatten* F_{vgg} *to obtain a 1D feature vector* $[V]$

Classification:
- *Pass vector* $[V]$ *to SVM classifier.*
- *Predict class label* $C \leftarrow arg\,max(sum(V))$

Post-processing (if patches used):
- *Aggregate multiple predictions using majority voting or average confidence scores.*

Return predicted label $[V]$
End

The model may optionally use a patch-based input method, as described in [15]. Instead of passing the complete CT scan to the model. Smaller images called “patches” (e.g. 64 × 64 pixels or 128 × 128 pixels) will be passed to the model. The patches are used around suspected lesion sites. The approach will allow the network to learn localized, detailed, and fine-grained features to improve sensitivity to small nodules that would normally not be detected from an

overall analysis of the entire image (the complete CT scan). A patch-based method can also reduce the amount of computation required to process large amounts of image data and improve the ability to detect indicators of early cancer.

4.2. Training and Validation

To avoid data leakage and provide an unbiased assessment of model performance, the patient level was used as the basis for how the dataset was cut into subsets. All CT slices and all patches extracted from a single patient were assigned to 1 subset only (either training, validation or test) to make sure there is no patient-specific information in different subsets this helped in the case of LIDC-IDRI where many slices and nodules come from the same patient, thereby providing a more realistic estimate of how well the model generalizes outside of the training data (because it is being evaluated on unseen patients), rather than estimating performance based on information from seen patients. The dataset was cut into 70% training, 15% validation, 15% test at the patient level, while still preserving class balance across the splits.

4.3. Training Procedure and Epochs

Training the hybrid CNN–VGG16–SVM network incorporates a two-stage optimization process to guarantee clear and consistent methodology. The first stage trains the deep learning portion (custom CNN layers + VGG-16) of the network using Adam optimizer and backpropagation. During this first stage, a deep neural network learns hierarchical representations of CT images or CT image patches. The parameters of the model were optimized based on the selected loss function (binary cross entropy or categorical cross entropy). Once the deep feature extractor is trained, the final fully connected (classification) layer is removed. High-level feature vectors (flatten) are extracted from the spatially-appropriate samples, and the extracted deep features are used as input for training an independent SVM classifier with a linear kernel. The SVM classifier will be independently trained using hinge loss and the regularization parameter (C) will be tuned through a grid search; therefore, allowing the two stages of training (feature learning with deep architecture vs. generalization with SVM) to allow for better generalization and margin-based classification, thus combining the advantage of using deep architectures and classical ML approaches to achieve optimal prediction accuracy using a hybrid CNN–VGG16–SVM model.

4.4. Loss function and optimizer used

To train convolutional and attention-based components of the hybrid model, categorical cross-entropy loss (multi-class classification) and binary cross-entropy loss (for binary classification) were used. These are both widely used loss functions in deep learning that measure how far apart predicted probabilities are from their actual labels In this case, both use the Adam optimizer to optimize the model's parameters (with starting learning rate = 1*10^--4). The Adam Optimizer combines features of AdaGrad and RMSProp. Consequently, Adam is able to effectively perform well with sparse gradients as well as to accomplish convergence towards non-stationary objectives. Decay of the learning rate is implemented after every 10 epochs in order to assist with the stabilizing of convergence over time. The SVM classifier which comes after the extraction of deep features is trained using hinge loss with a linear kernel. The regularization parameter (C) for the SVM is determined using grid search.

4.5. Evaluation Metrics

To comprehensively evaluate the performance of the proposed hybrid DL model, a set of standard classification metrics was employed in table 2: Accuracy, Precision, Recall, F1-Score, and AUC-ROC.

- *Accuracy:* It measures the overall correctness of the model and is calculated as the proportion of correctly classified instances over the total number of instances.
- *Precision:* It evaluates the ability of the model to identify only relevant instances, minimizing false positives, and is particularly important in reducing misdiagnoses.
- *Recall (Sensitivity):* It assesses the model's capability to correctly identify actual positive cases (e.g., malignant nodules), which is critical in early cancer detection scenarios.
- *F1-Score:* It is the harmonic mean of precision and recall, providing a single measure of model performance when dealing with class imbalance.
- *AUC-ROC:* It reflects the model's ability to discriminate between classes across various threshold settings and is especially useful in medical classification tasks where the cost of false negatives is high.

Table 2. Evaluation metrics used to assess classification performance of the proposed model.

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Proportion of correctly predicted samples among all samples
Precision	TP / (TP + FP)	Proportion of correctly predicted positive cases among all predicted positives
Recall (Sensitivity)	TP / (TP + FN)	Proportion of correctly predicted positive cases among all actual positives
F1-Score	2 * (Precision * Recall) / (Precision + Recall)	Harmonic mean of precision and recall
AUC-ROC	Area under the ROC curve (True Positive Rate vs. False Positive Rate)	Measures model's ability to distinguish between classes across thresholds

These metrics were computed on the unseen test set and benchmarked against recent state-of-the-art lung cancer detection models [11][14], enabling fair and rigorous performance comparison.

5. Experimental Results

This section provides the empirical analysis of the hybrid deep learning (DL) model developed based on the lung LIDC-IDRI dataset. The analysis of results was based on performance metrics, graphical output, and a comparative analysis of the proposed model with recently published state-of-the-art DL models. To add robustness to the statistical evaluation, the performance of the hybrid model was evaluated using 5-fold cross-validation on a per-patient basis. The dataset was randomly divided into five distinct groups. Each group was then randomly assigned to one of the five-folds in the first iteration of the cross-validation, with the four-folds being used in the training of the developed hybrid model, and the one-fold being used in the testing of the model. No patient data overlap between any of the folds was allowed.

The final performance metrics for the developed hybrid model were calculated as the average and standard deviation over all five-folds. For the selected key performance metrics (KPIs) of the developed hybrid model, accurate, recall, and AUC-ROC curve, the developed hybrid model's performance over all five-folds was represented using the Summary and 95% Confidence Intervals (CIs) to illustrate variability within the accuracy and reliability of the developed hybrid model. The developed hybrid model was also evaluated at the AUC-ROC level for stability based on the standard deviations of AUC values when comparing performance results from each of the five-folds during cross-validation. The extensive methodological evaluation contributes to a robust and comprehensive characterisation of the generalisation capabilities of the developed hybrid model in reducing performance bias caused using a single instance of the overall dataset for training and testing. The hybrid model achieved an average AUC-ROC of 0.971 ± 0.006 (95% CI: 0.965–0.977) across the five-fold cross-validation methodology.

5.1. Performance Comparison

To provide an accurate and equal reference point, the following baseline models were all executed and analysed at the same time and under the same conditions as the suggested hybrid model: Standalone CNN, ResNet50, and VGG16 with Softmax; the same number of epochs (50 epochs), batch size (32), and optimization (Adam with an initial learning rate of 1e-4) were used to train each model. Each model will also have the same dataset split, preprocessing pipeline, and augmentation technique applied during training and testing phases. Additionally, all models will have early stopped and checkpointing applied to them uniformly during their training phases. Because of the consistent nature of the training settings and evaluation methodologies, the performance differences presented within this paper can only be attributed to the design/all architecture of the proposed model and not to the differences in training configurations, allowing for an accurate and unbiased comparison.

Table 3. Performance comparison of baseline models with the proposed hybrid model.

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Standalone CNN	89.6%	88.7%	90.3%	89.4%	0.935
ResNet50 + Softmax	91.2%	90.8%	91.0%	90.9%	0.946
VGG-16 + Softmax	92.0%	91.6%	92.4%	92.0%	0.951
Proposed CNN + Attention + SVM	94.2%	93.6%	95.1%	94.3%	0.971

The hybrid model consistently outperformed the baseline models across all key metrics as shown in table 3. The addition of the attention mechanism improved the model's ability to focus on lesion areas, while the use of an SVM classifier led to a more discriminative decision boundary, particularly helpful for handling borderline cases. Visualizations were employed to provide qualitative evidence of the model's decision-making process:

- *ROC Curves:*The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various classification thresholds for each class. In this multi-class scenario, separate ROC curves have been plotted for each lung cancer category: Benign, Malignant, and Normal.
- *Benign (Blue Curve):* This curve shows the model's ability to distinguish benign nodules from the rest. A high AUC (~0.98) indicates that the model correctly identifies benign cases with minimal false positives.
- *Malignant (Green Curve):* Early and accurate detection of malignant cases is clinically critical. The AUC for this class (~0.96) suggests excellent sensitivity and specificity in identifying cancerous nodules, meaning the model is highly reliable for high-risk classifications.
- *Normal (Orange Curve):* For normal cases, the AUC (~0.97) reflects the model's strength in correctly identifying healthy lungs, minimizing unnecessary follow-ups or interventions.
- *Confusion Matrix:* The confusion matrix showed that the hybrid model minimized both false positives and false negatives, confirming its reliability in clinical diagnosis.
- *Gradient-weighted Class Activation Mapping (Grad-CAM):* Heatmaps were generated for selected test images to highlight regions the model deemed most influential in making its prediction. The attention-enhanced CNNs correctly focused on nodule regions, often aligning with radiologist annotations.

To measure the interpretability of the suggested method, we will look at all the Grad-CAM maps produced by our system compared with the nodule annotations produced by radiologists within the LIDC-IDRI dataset. Overlapping regions between each Grad-CAM activation area and the actual nodule areas will be assessed via the IoU metric. For every test case, the area shown on the Grad-CAM map was converted into a binary attention mask that would allow us to identify if there was a match between the attention location shown on the Grad-CAM map and the labelled nodule location produced by the radiologist. There was an average IoU score of approximately 0.68 for all the samples in our investigation, which indicates a very high degree of agreement between the areas of attention identified by our model and the areas clinically recognized as significant to physicians. Therefore, the quantitative results support our qualitative findings from the Grad-CAM visualizations of our datasets, thus demonstrating that the suggested approach can consistently identify clinically significant anatomical structures during the classification of lung nodules. In addition, these objective findings further support our assertion that the predictions made by our model are based on medically relevant features instead of random noise or chance similarities in the images, thus providing an increase in the interpretability of our model for potential future clinical implementations. Equation 1 shows the formula used to define the IoU metric:

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{1}$$

where the overlap represents the intersection between the Grad-CAM attention mask and the ground truth annotation, and the union represents their combined area.

5.2. Ablation Study

Individual design choices made an important contribution to how well each component performs. An extended ablation study was conducted, exploring how variations on two important types of Architectural Components as well as Hyperplexices affected a final evaluation of Architectural Components. The results of this ablation study indicated that a Hybrid Model that uses both Spatial Attention Mechanism and Channel Attention Mechanism outperformed both on their own and demonstrated the ability of the Hybrid Model to improve upon a previous study where only Spatial Attention Mechanism or only Channel Attention Mechanism performed well alone. The next area studied using an ablation study comprised looking at Patch Size (32 x 32, 64 x 64 and 128 x 128). Based upon the results obtained in reviewing all three Patch Sizes, it is therefore concluded that the best Patch Size for increasing both Local Feature Resolution as well as Increasing Contextual Knowledge is 64 x 64. Consequently, this would lead to improved results for Classification Tasks as opposed to either the Smallest Patch (32 x 32) or Largest Patch (128 x 128). Through an ablation study, the individual contributions of the Architectural Components of the Hybrid Model have been identified.

Table 4. Performance comparison of model variants highlighting the contribution of attention, SVM, and patch-based input.

Model Variant	Accuracy	F1-Score	AUC-ROC
Without Attention Module	91.7%	91.1%	0.957
Without SVM (replaced by Softmax)	92.3%	92.0%	0.960
Without Patch-Based Input	90.9%	89.6%	0.950
Full Hybrid Model (proposed)	94.2%	94.3%	0.971

Third, the effect of different SVM kernels was investigated, including linear, radial basis function (RBF), and polynomial kernels. Among these, the linear kernel achieved the best performance in terms of accuracy and generalization, likely due to the high-dimensional and linearly separable nature of deep feature representations extracted from the CNN–VGG16 pipeline.

Component	Variation	Best Result
Patch Size	32 / 64 / 128	64 × 64
Attention	Channel / Spatial / Combined	Combined
SVM Kernel	Linear / RBF / Poly	Linear
Backbone	Pretrained / Scratch	Pretrained

Finally, the contribution of transfer learning was evaluated by comparing the pretrained VGG-16 backbone with a randomly initialized network trained from scratch. The pretrained model consistently outperformed the non-pretrained version, confirming the effectiveness of transfer learning in improving convergence speed and classification accuracy for medical imaging tasks with limited data.

These additional analyses validate that the performance gains of the proposed model are not only due to component inclusion but also the careful selection of architectural configurations, thereby strengthening the robustness and reliability of the proposed hybrid framework.

6. Discussion and Comparison with Existing Literature

The outcomes of the experimentation show that the suggested hybrid deep learning architecture is superior in terms of different performance measures compared with the other types of deep learning algorithm used as benchmarks. The hybrid deep learning architecture had an extremely high accuracy of 94.2%, a recall rate of 95.1%, and a ROC curve (AUC) of 0.971, demonstrating that the hybrid architecture has a very high potential to detect cancerous lesions accurately. An attention module was included to allow the hybrid architecture to concentrate on specific regions of the input and improve detection performance. Through utilizing a SVM classifier to classify results, the hybrid deep learning architecture provided improved classification reliability, especially in cases where the lesions were borderline. An ablation experiment determined that the combination of the different components of the hybrid architecture contributed to the successful operation of the hybrid deep learning architecture.

6.1. Comparison with Existing Literature

Table 5. Performance comparison of the proposed model with existing deep learning and hybrid model

Ref.	Study	Model Description	Accuracy (%age)	F1-Score (%age)	AUC-ROC
[3]	Jain &Jaidka (2024)	Deep learning hybrid model (unspecified)	89.9	88.7	0.925
[4]	Meeradevi et al. (2025)	ML classifiers with multi-attribute DL system	90.7	89.8	0.932
[6]	Gote et al. (2025)	Hybrid ML algorithms for outcome improvement	90.8	89.4	0.934
[7]	Ozdemir et al. (2025)	Attention-enhanced InceptionNeXt	93.1	92.7	0.964
[8]	Ansari et al. (2025)	SVM-VGGNet-16 hybrid model	91.5	90.2	0.948
[9]	Aggrey et al. (2025)	DC-CAD with capsule & temporal dynamics	92.5	91.3	0.95
[10]	Bharathi & Shalini (2024)	Attention-based DL with PET/CT fusion	92.7	91.9	0.959
[11]	Hossain et al. (2025)	CNN + SVD with ensemble voting	91.8	90.6	0.946
[14]	Salam et al. (2025)	Hybrid DL-ML multi-class detection	90.4	88.9	0.928
[15]	Venkatesh et al. (2024)	Patch-based CNN with ensemble classification	92.3	91.1	0.953
[20]	Al-Shabi et al. (2022)	ProCAN	93.5	93.1	0.965
[23]	Al-Shabi et al. (2019)	Gated-Dilated CNN	91	89.7	0.945
[21]	Keel et al. (2023)	VAE for Lung Lesions	90.2	89.5	0.942
[22]	Zhu et al. (2018)	Deep Lung 3D Dual-Path	92.8	92.2	0.958
[27]	Al-Shabi et al. (2019)	Local-Global Network	92.1	91.6	0.951
[24]	Müller-Franzeset al. (2024)	Medical Slice Transformer	94	93.8	0.968
[25]	Harsono et al. (2022)	RetinaNet + TL	90.8	89.9	0.94
Proposed Hybrid Model		CNN + Attention + SVM hybrid model	94.2	94.3	0.971

Table 5, presents a detailed benchmarking of the proposed hybrid DL model against recent state-of-the-art approaches for lung cancer detection using medical imaging and AI techniques. Each entry includes the model description, accuracy, F1-score, and AUC-ROC values, offering a comprehensive evaluation of classification performance across multiple studies. Ansari et al. [8] proposed a hybrid SVM-VGGNet-16 model, achieving a respectable accuracy of 91.5% and AUC of 0.948. This model serves as a strong baseline, especially in scenarios where SVM is used as a final classifier.Venkatesh et al. [15] introduced a patch-based CNNs with ensemble classification, performing slightly better with 92.3% accuracy and an F1-score of 91.1%, confirming the benefit of localized patch learning in CT analysis. Ozdemir et al. [7] further improved performance using an attention-enhanced InceptionNeXt model, achieving an AUC-ROC of 0.964, demonstrating the impact of attention mechanisms on region-specific feature learning.

Meeradevi et al. [4] and Hossain et al. [11] used traditional ML classifiers combined with DL or advanced feature selection techniques such as SVD, achieving accuracy scores of 90.7% and 91.8% respectively, although their AUCs remain below the hybrid DL thresholds.

Salam et al. [14] hybrid DL-ML model and Aggrey et al. [9] capsule-based DC-CAD model both offered competitive results, with the latter showing strong generalization and temporal reasoning ability (AUC = 0.950). Jain & Jaidka [3] and Gote et al. [6] presented hybrid models with modest results in comparison (F1-scores < 90%), indicating potential underperformance in complex cases or small nodules.Bharathi & Shalini [10] stood out for their PET/CT fusion-based attention framework, achieving 92.7% accuracy and AUC of 0.959, reinforcing the role of multimodal imaging.

Finally, the Proposed Hybrid Model in this study, integrating CNNs, attention modules, and an SVM classifier, outperformed all listed models with an accuracy of 94.2%, F1-score of 94.3%, and AUC-ROC of 0.971. These improvements underscore the synergistic effect of combining attention-enhanced spatial feature learning with margin-optimized classification and patch-based preprocessing.

6.2. Strengths and Weaknesses of the Model

One of the key strengths of the proposed model lies in its architectural synergythe combination of CNN for spatial feature learning, attention for focus refinement, and SVM for decision boundary optimization in Table 6. The model also benefits from interpretability, provided through Grad-CAM heatmaps, and scalability, due to its modular design and compatibility with standard GPU environments.

Table 6. Strengths and weaknesses of the proposed hybrid deep learning model for lung cancer detection

Type	Aspect	Explanation
Strength	High Accuracy and Sensitivity	Achieved 94.2% accuracy and high recall (95.1%) on test data
	Use of Attention Mechanism	Enhances focus on lesion regions and improves feature discrimination
	Integration of SVM Classifier	Improves margin-based classification over SoftMax in imbalanced data
	Interpretability (Grad-CAM)	Grad-CAM provides visual explanation for model predictions
	Patch-Based Preprocessing	Improves detection of small nodules by analysing localized regions
	Transfer Learning via VGG-16	Leverages pretrained weights for better generalization with limited data
Weakness	Limited Dataset Scope	Model is trained and evaluated on a single dataset (LIDC-IDRI)
	Increased Inference Time	Patch-wise processing adds computational overhead during inference
	Hyperparameter Tuning Complexity	SVM and attention modules require careful tuning for optimal performance
	Potential Clinical Adaptation Hurdles	Clinical integration may face challenges due to deployment complexity

However, the model has some limitations. First, while patch-based processing improves local feature detection, it can increase inference time due to overlapping patch extraction and analysis. Second, the reliance on a single publicly available LIDC-IDRI dataset may limit generalizability to other imaging modalities or datasets with different characteristics. Lastly, although SVM improves performance, it also adds complexity in terms of tuning hyperparameters such as the regularization term (C), which could be challenging in clinical deployments without automated tools.

6.3. Clinical Relevance of the Proposed Approach

Although the performance of the proposed model was substantial in the LIDC-IDRI dataset, it must be understood that this was done within a controlled experimental environment, with only one publicly available dataset used in the current research. Thus, it cannot be regarded as being ready for clinical use at this point. However, significant potential exists for the proposed framework to be developed further into a computer-aided diagnosis tool to be used in future clinical applications. Additional validation will need to take place using multi-center datasets, in real-world clinical

environments and through prospective studies with radiologists to determine the system's reliability, robustness and practical utility for clinicians to use within their workflows.

7. Conclusion and Future Work

This research provides a hybrid framework of deep learning for the automatic classification of CT images of lung nodules; the framework consists of three key parts: 1) CNNs for finding the image's features. 2) Human-AI attention for refining our model's features 3) Support vector machines to classify nodules into benign, malignant, or normal. The model works well on the LIDC-IDRI dataset, achieving an overall accuracy of 94.2%, recall of 95.1%, and AUC-ROC of 0.971. All three components of the framework provide strong evidence that deep learning combined with a margin-based classification method improves accuracy of detection between benign, malignant, and normal cases. The use of attention allows our model to identify the most relevant regions on a CT image while the support vector machine builds a more robust decision boundary. Our inclusion of patch-based learning also allows the framework to detect small and subtle nodules with increased precision. Finally, the use of Grad-CAM visualizations provides meaningful insight into the areas of focus in the model's predictions and increases transparency in the decisions made by the framework. Therefore, this hybrid framework differs from a traditional end-to-end deep learning model in that we used a modular design to develop a stronger relationship between performance and interpretability. This study does have some limitations because the evaluation was completed on only one public dataset and will require additional evaluations using multi-center and real-world clinical datasets to test generalizability.

In the future we plan to expand this framework to include 3D volume analysis of lung nodules, merge datasets from multiple imaging modalities and investigate the applicability of federated learning approaches to further improve robustness and privacy. Overall, this initial work should serve as a strong starting point for building reliable and interpretable AI-based classification tools for lung nodules within a medical imaging context.

Author Contributions Statement
Mukesh Kumar: Conceptualization, methodology, supervision, writing – review and editing.
Vivek Bhardwaj: Model development, experimentation, validation.
Kavita Dhiman: Data preprocessing, implementation, writing – original draft.
Ahmed Qtaishat: Literature review, analysis, manuscript refinement.

All authors have read and agreed to the published version of the manuscript.

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This study analysed publicly available datasets. The results obtained and datasets can be found here: “https://www.kaggle.com/datasets/zhangweiled/lidcidri” “10/6/2024”.

Code Availability:
The code used for model development and experimentation is available from the corresponding author upon reasonable request.

Ethical Declarations
This study does not involve any human participants or animals directly. The research is based on publicly available anonymized datasets; therefore, ethical approval was not required.

Declaration of Generative AI in Scholarly Writing
During the preparation of this manuscript, the author(s) used OpenAI to improve the clarity and readability of selected paragraphs. The generated text was edited and revised as needed, and all content remains the responsibility of the author(s). No AI tool is listed as an author.

Abbreviations
ROI - Region of Interest
CI - Confidence Intervals
CT - Computed Tomography
CNNs - Convolutional Neural Networks

SVD - Singular Value Decomposition
RMSProp - Root Mean Square Propagation
AUC-ROC - Area under the ROC curve
LIDC-IDRI - Lung Image Database Consortium image collection
Grad-CAM - Gradient-weighted Class Activation Mapping

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