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INTEGRATIVE APPROACHES FOR DETECTING LUNG CANCER USING DEEP LEARNING ALGORITHMS

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Abstract:
Among cancer-related deaths worldwide, lung cancer remains one of the leading causes, primarily due to late diagnosis and limited treatment options at advanced stages. Early detection through medical imaging plays a crucial role in improving survival rates; however, many existing automated detection methods rely on a single imaging modality and limited datasets, reducing their reliability in clinical settings. This paper presents a dual-modality, multi-hybrid deep learning approach for lung cancer detection using chest X-ray and computed tomography (CT) images. Each imaging modality is trained separately on carefully prepared and augmented datasets using transfer learning to enhance robustness and generalization. MobileNet and DenseNet architectures are employed to effectively capture modality-specific features. The chest X-ray dataset is categorized into three classes, while the CT scan dataset consists of two classes, reflecting their diagnostic differences. A combined data generator is used to train the dual-modality framework, enabling effective learning from both image sources. Experimental results show that the CT-based model achieves an accuracy of 93%, while the X-ray-based model attains an accuracy of 89.50%. These findings indicate that modality-specific learning within a dual-modality framework improves detection performance and supports more reliable AI-assisted lung cancer diagnosis.

Keywords:
Lung Cancer Detection, Deep Learning, Convolutional Neural Networks, Chest X-ray Analysis, CT Scan Imaging, EfficientNet, DenseNet121

1- Introduction:

Lung cancer has remained among the most aggressive and life-threatening cancers in the globe, and one of the top causes of cancer mortality in high-income and low-income localities[1]. International cancer surveillance studies[2] reveal that millions of people die across the world annually due to lung cancer, indicating that besides being a significant health challenge, it is also a significant socioeconomic challenge to the global society[3]. The disease tends to develop without symptoms and the symptoms manifest themselves when the cancer is at a very advanced stage. Consequently, a timely diagnosis is a key factor in determining patient outcomes [4]. Regrettably, diagnoses are made late in the majority of cases and treatment methods, including chemotherapy, radiotherapy, targeted therapy, or surgery, are much less effective at that stage. This has been an ancient challenge that has made researchers, clinicians and the technologists to seek more dependable and precise ways that are able to diagnose lung cancer at the earliest stages of detection[5].

Lung cancer screening and diagnosis has traditionally been based on the use of medical imaging. Chest X-rays and computed tomography (CT) are two commonly used imaging modalities among the other tools used in clinical practice. Chest X-rays are cheap, they are common and can be used in mass screening programs. Nevertheless, they frequently fail to detect specific signs of cancers since the structures of anatomies are similar and the images are not clear. CT scans on the other hand provide high-resolution three-dimensional images of the internal lung structures hence much more effective in detecting small nodules and subtle abnormalities. The problem though is that both imaging methods heavily rely on manual interpretation[6]. Even seasoned radiologists may encounter a problem of differentiating early cancerous nodules and benign pathologies, particularly in the busy clinical schedules, where the chances of fatigue and subjectivity may interfere with perfection[7]. These drawbacks

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emphasize the necessity of automated and objective aids[8], which can help clinicians to improve the accuracy of early detecting and to provide the same quality of diagnosis[9].
Deep learning is one of the most revolutionary fields[10] in the analysis of medical images in the last ten years. Convolutional Neural Networks (CNNs) have shown impressive capabilities in identifying visual patterns, detecting small features in an image, and performing a classification task with remarkable accuracy, often competing or surpassing the accuracy of a human. The most important advantage of CNNs is that, they are able to extract complex, non-linear relations using raw image data without any handcrafted feature extractor. A number of researchers have been able to apply CNN-based models to lung nodule classification, malignancy prediction, segmentation, and disease staging. Although these improvements have been made, there are still various obstacles that restrict the large-scale clinical implementation of the deep learning models in the detection of lung cancer. [5]
The major limitation in the current research is that it has over-relied on single-modality imaging. The majority of the research uses either chest X-rays or CT scan to analyze data, which does not allow the diagnostic system to maximize the benefits of each modality. X-rays provide fast screening and CT scan provides detailed information on the structure and this contributes to the precision of the diagnostics. Integrating the two modalities under one deep learning structure can lead to a higher accuracy, less false negative and better clinical decision making. [6]Nevertheless, there has been little research on such multimodal integration and it is still technically difficult. Sealing this research gap is the key to coming up with AI systems that are more akin to the holistic diagnostic process of radiologists in the real clinical settings.
The other significant weakness with the past research relates to diversity and generalizability of the dataset. Most research studies are based on small, single-source datasets that are not representative of the entire range of patient demographics, differences in equipment used in imaging, and disease manifestations in actual hospitals. [7]The models which have been trained on a small set of data tend to fail when encountered on novel populations or new imaging settings. To resolve this obstacle, our study deliberately chooses a dataset approach that will have the highest variability and realism. In the case of the CT scan, we used a set of images of various publicly available datasets to create a varied dataset of 6,063 images which were labeled either as Cancerous or as Normal. Following massive preprocessing, we had carried out hi-tech image augmentation in order to create realistic changes in brightness, contrast, orientation and noise in the real world. This increased data enabled the deep learning model using CT to attain an accuracy of 93.49% with high generalization and stability.
In the case of the chest X-ray model, we adopted an organized CSV-based dataset and a detailed augmentation pipeline to expand the size of the dataset and alleviate overfitting. Our preprocessing methods and network design were effective since this model attained an accuracy of 89.50. Put together, these findings indicate that well organized datasets with augmentation strategies can go a long way in improving the robustness and reliability of the models.
In this research, the technical methodology is also used, which leads to better performance and reproducibility. To classify the CT scans, we resorted to a transfer learning model, which utilizes EfficientNet, an efficient architecture of a deep learning network, and with great feature detection potential. The model used more than 4 million trainable parameters, and a range of optimization techniques, including EarlyStopping, reduction of the learning-rate by ReduceLROnPlateau and periodic model checkpointing. Such methods guaranteed the smooth convergence of the model and avoided overfitting.
To analyze X-ray images, we used the DenseNet121 architecture that is famous due to its dense connectivity structure that enables successful feature reuse. The three-class (i.e.,

distinguishing between Benign, Malignant and Non-Nodule images) classification task was trained with optimized preprocessing steps and learning-rate schedule using the model. The approach to the model provided the ability to elicit rich visual features and also treat high accuracy in the course of the training. Contemporary computational applications and environments were instrumental in helping our study. All were trained within Google Colab which had access to high-performance resources in the form of a GPU that is necessary to train deep learning models. Python was chosen as the main program language because of its large scientific computing libraries. Also, AI-assisted systems included the Gemini API and the google-colab-ai library facilitated multimodal data analysis, extraction of structured data, and documentation. Libraries such as cuDF which are accelerated by GPU also simplified the large-scale processing of data to a significant extent, accelerating it and making experiments to be efficient.

The model interpretability is the other critical element of AI adoption in healthcare. In spite of the fact that deep learning systems may provide high levels of accuracy, clinicians tend to be reluctant to use the tools that operate as black boxes. Grad-CAM and attention heatmaps, as interpretability methods do provide some understanding of how a model is making decisions, but they are not as transparent as they need to be to be used in a clinical setting without doubts. Due to this reason, our research has placed a strong focus on the need to formulate interpretable diagnostic models that do not only predict but also support their decisions in a visual manner. This anthropomorphic design ideology is critical in ensuring the bridging of the artificial intelligence-clinical acceptance gap.

In general, this study fills in three significant knowledge gaps in the existing literature:

The lack of deep learning models that combine X-ray and CT images to better diagnose a patient, the scarcity of various datasets that guarantee the generalizability of models in the real world, and the absence of interpretable AI systems that can be combined into clinical systems.

Through the synthesis of multimodal imaging, the introduction of strong deep learning models, the rigorous use of data augmentation methods and use of advanced AI tools, the proposed research would create a scalable, interpretative, and clinically significant lung cancer detection system. Eventually, this study is meant to be useful in assisting the radiologists to make more accurate, faster, and reliable diagnostic choices to enhance patient outcomes and develop AI-supported healthcare interventions.

In addition to training independent CT scan and chest X-ray models, this study introduces a unified multimodal deep learning framework that jointly analyzes both imaging modalities to improve diagnostic accuracy and clinical reliability. The motivation behind this integration lies in the complementary characteristics of the two modalities: CT scans provide detailed three-dimensional structural information, while X-rays offer broader anatomical context at lower cost and radiation exposure. By fusing features extracted from both modalities within a unified multi-input architecture, the proposed approach facilitates richer representation learning and reduces the risk of modality-specific misclassification.

The combined model employs parallel convolutional neural network branches for CT scans and chest X-ray images, with each branch initialized using ImageNet pre-trained weights. Feature representations from both streams are subsequently fused at the feature level and passed to modality-specific output heads. This design allows the network to learn shared and complementary discriminative patterns while jointly optimizing the classification tasks for both imaging modalities. Such a multimodal learning strategy enhances robustness, enhances generalization across heterogeneous datasets, and more closely reflects real-world clinical diagnostic workflows, where multiple imaging modalities are assessed collectively. Consequently, the combined model serves as a scalable and clinically aligned extension of the unimodal approaches, strengthening the practical applicability of AI-driven lung cancer detection systems.

2- Literature Review:

The field of lung cancer diagnosis has significantly transformed due to the rapid growth of medical imaging and artificial intelligence. In the last ten years, the primary approach for automated detection of lung nodules is deep learning using radiological data. Many researchers have reviewed convolutional neural networks (CNNs) and transfer learning and combine models to improve detection, precision, accuracy, cancer identification in early stage and reduce diagnostic time. Although significant progress has been made like methodological, structural, and practical gaps remain, multi-modal integration, and real world deployment. This literature review synthesizes key findings from existing studies, comparing X-ray and CT-scan based deep learning models for lung cancer detection using balanced datasets and also this research highlights limitations, and demonstrates the research gap filled by the present studies.

The importance of deep convolutional networks for medical image classification have emphasized by several studies especially in lung cancer imaging. Initial studies mainly concentrated on classical CNNs trained on single datasets, showing encouraging but constrained performance.These models frequently depended on manually designed features or shallow architectures, which limited their ability to identify subtle cancerous patterns. After that studies adopted deeper pre-trained networks like ResNet, DenseNet, VGG and Inception demonstrating significant improvements in accuracy and robustness. Transfer learning has become a leading approach because it compensates for confined datasets by utilizing ImageNet pre-trained weights. While transfer learning substantially accelerated progress, existing literature repeatedly noted challenges related to small sample sizes and imbalance datasets, the risk of overfitting due to lack of enhancement. Many researchers trained their models on single-source datasets, which decrease variability and limiting the models' generalizability to real-world lung cancer cases.

An important focus in recent research is the comparison between X-ray and CT imaging modalities. Some studies focused entirely on chest X-rays because of their accessibility, while others depended only on CT scans due to their detailed cross-sectional representation of lung tissue. X-ray-based studies commonly demonstrated moderate results but struggled with identifying small nodules, because of the low image contrast and overlapping anatomy. On the other hand, CT-based studies benefited from high-resolution volumetric data, enabling more accurate segmentation and classification. However, studies focusing on CT data often relied on limited datasets or did not employ effective augmentation techniques, poorly in clinical settings but leading to models that performed well in controlled datasets. Furthermore, numerous CT studies employed segmentation-intensive pipelines that required manual annotation, which increased complexity and limited scalability.

Another collection of studies focused on hybrid and multi-stage deep learning pipelines. These methods included combining segmentation models with classification networks, integrating feature fusion layers and using attention mechanisms. While these methods improved high sensitivity and minimized false negatives, they frequently demanded substantial computational resources and were not feasible for smaller research setups. In addition, several hybrid-model studies lacked proper validation, relying only on accuracy while ignoring recall misclassification risks or precision these are important considerations in cancer diagnosis. Many other studies did not investigate performance with data augmentation and limits the ability to generalize findings by comparing alternative architectures.

Reviewing the five research papers of recent years, a common constraint appears across all: none of them analyzed and compared performance concurrently on both CT-scan and X-ray datasets using trained deep learning models. Most research focused on only one imaging modality, which restricts their scope which restricts their role in providing a thorough understanding lung cancer detection. Furthermore, some papers made extensive use of pre-existing benchmark datasets without addressing problems like class imbalance, lack of image diversity or limited cancerous samples. Several studies experimenting with optimization strategies without training parameters such as early stopping, rate scheduling, or model checkpointing these techniques can substantially reduce overfitting.

Another common gap is the inadequate emphasis on confidence based decision rules in previous literature. Many previous works ignoring the related probability score and classifying images based on the predicted output label. None of the studies explicitly set a confidence level for categorization cancerous versus non-cancerous outcomes, making the diagnosis difficult for radiologists or clinical deployment. Also many studies lacked a discussion for improving robustness in augmented datasets.

Unlike most previous studies, this research uses a unique approach by training two separate deep learning models one trained on CT-scan images and the other on X-ray images using structured preprocessing, augmentation techniques and well prepared datasets. The literature shows that very small number of studies compare results across different imaging types under same conditions. This gap is important because CT and X-ray images are very different in quality, resolution, anatomical clarity and clinical use. By working with both modalities, this research gives a clearer and more holistic understanding of the strengths and each imaging method can and cannot do for lung cancer detection.

Another significant gap in earlier research is the most studies lack the transparent model optimization strategies. Many papers mentions accuracy but rarely details the training behavior, learning rate adjustments, and checkpoint methods. In contrast, this paper introduces callback-based optimization methods (like Early Stopping and ReduceLROnPlateau),, which enhaces the training more stable and ensures the final model uses the best weights correspond to the best-performing epoch. This careful and transparent approach makes your contribution more reliable and reproducible compared to earlier studies that did not include these aspects.

Data diversity is another study which is critical limitation in many studies reviewed. Most papers used only one dataset, , often with limited variability in age groups, image quality, or disease stages. This research solves this problem by constructing a larger and more diverse CT dataset from multiple sources and applying extensive augmentation to mimic real-world imaging conditions. This enhances generalization and reduces bias —a challenge repeatedly highlighted but did not actually fix.

Furthermore, most previous studies used CNNs or transfer-learning networks, but did not explain how efficient their architectures were, they reported details like the number of parameter counts, or trainable-to-nontrainable ratios.This research explicitly analyzes these characteristics, and showing that the CT model i built has about 4 million parameters and a well-balanced structure. This clarity allows better comparison with future studies and supports more open and clear deep-learning practices in medical imaging.

Finally, most past studies do not directly compare performance metrics across modalities. Many papers report accuracy, but few papers contrast the predictive strength of models trained that how well X-ray models perform versus CT-scan models. By clearly showing that the CT model achieved 93% accuracy and 89.50% for X-ray images your research gives useful insight into modality effectiveness—a gap absent in most earlier works.

In conclusion, while previous studies have made notable progress in using deep learning–based lung cancer detection, they still show clear gaps in dataset diversity, augmentation optimization strategies, and multi-modality comparisons. Your research addresses these issues

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by training two separate models on X-ray and CT images implementing structured augmentation, comparing performance across modalities and optimizing training through callbacks. This dual-model approach, along with a strong focus on diverse data and stable training, marks a distinct improvement over the studies reviewed and provides a solid foundation for future research in deep learning–based lung cancer detection.

Ref.	Study & Year	Imaging / Data Type	Model Used	Methodology	Dataset Description	Main Contribution	Performance	Reported Limitations
[11]	HaghighiKian et al., 2025	CT, Clinical, Radiomics	AI frameworks (CNN + ML)	Holistic AI integration across diagnosis & treatment	Multi-source clinical + imaging datasets	End-to-end AI adoption framework for lung cancer	High diagnostic consistency	Clinical deployment challenges
[12]	Shah et al., 2025	Genomic (NGS)	Deep Learning	DL on Next Generation Sequencing data	Public genomic datasets	Genomics-based lung cancer diagnosis	High predictive accuracy	High computational cost
[13]	Durgam et al., 2025	CT Images	CNN + Transformer	Feature extraction via CNN, attention via Transformer	Public CT datasets	Improved detection using hybrid models	Accuracy >95%	Requires large datasets
[14]	Dhanalakshmi et al., 2025	Clinical + Imaging	Deep Neural Networks	Predictive analytics with DNN	Hospital-based data	Early-stage prediction model	Improved sensitivity	Limited dataset size
[15]	Elhassan et al., 2025	CT Images	Dual Deep Learning Models	Parallel DL architectures	Lung CT scan datasets	Enhanced detection via dual-model fusion	Accuracy ~96%	Overfitting risk
[16]	Oncu & Ciftci, 2025	CT + Clinical Data	CNN + ANN	Multimodal fusion approach	Imaging + patient records	Integrated diagnosis framework	High classification accuracy	Data heterogeneity issues
[17]	MDPI, 2025	Liquid Biopsy	AI-based	Multimodal	Biomarker +	Early-stage	Promising early	High cost &

		+ Radiomics	analytics	precision oncology approach	imaging data	detection improvement	results	complexity
[18]	MDPI, 2025	Symptoms & Lifestyle Data	ML & DL Models	Comparative ML vs DL study	Survey-based datasets	Non-imaging lung cancer prediction	DL outperformed ML	Subjective data
[19]	Çakmak & Maman, 2025	CT Images	Deep CNN	Automated image classification	CT scan datasets	Early diagnosis automation	Accuracy ~94%	Limited generalization
[20]	Liu et al., 2025	Molecular + In-vitro	ML + AI Models	Integrative pharmacology & ML	Experimental + computational data	Drug mechanism discovery	Strong predictive insights	Lab validation required
[21]	Alsallal et al., 2025	CT Radiomics	Attention-based DeepCNN	Attention + feature reproducibility	Multi-center CT datasets	Robust subtype classification	High reproducibility	Complex feature extraction
[22]	MDPI Review, 2025	CT Imaging	Various DL models	Systematic review	Multiple public datasets	Comprehensive DL overview	N/A (Review)	No experimental results
[23]	Qi et al., 2025	Liquid Biopsy + Imaging	Multimodal AI	Data fusion framework	Clinical diagnostic datasets	Improved management & diagnosis	Enhanced early detection	Data integration issues
[24]	Wani et al., 2024	CT Images	Explainable DL (XAI)	Interpretability-focused DL	Lung CT datasets	Transparent AI decision-making	High accuracy + explainability	Slight accuracy tradeoff
[25]	S.S.k.b et al., 2024	Multimodal (CT + Clinical)	Fusion Deep NN	Feature-level fusion	Multimodal datasets	Improved classification accuracy	Accuracy ~97%	Computationally expensive
[26]	Chapla et al., 2024	Imaging + Clinical	AI-based review	Literature review	Multiple studies	AI in smoker-focused detection	N/A	Review-based only
[27]	Bouch	CT	Deep	Compreh	Publishe	DL	N/A	No

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	affra et al., 2024	Imaging	Learning	ensive review	d datasets	advance ments overview		experimental validation
[28]	Scientific Reports, 2025	CT Images	CNN + Transformer	Hybrid attention modeling	Public CT datasets	Superior detection performance	Accuracy >95%	Training complexity

3- Methodology

The proposed study will be conducted in the form of a three-stage experimental approach aimed at the systematic study of the detection of lung cancer using deep learning in the single-modality and multimodal environment. The independent deep learning models were trained and trained separately in the first two stages on the images of CT scan and chest X-ray to provide powerful modality-specific baselines. Finally, a multimodal feature-fusion model was presented where features acquired on CT and X-ray were simultaneously optimized together in a single deep learning system. It is a progressive design that can compared the single-modality learning with the integrated multimodal learning in a transparent way and fill the necessary gaps in the literature, such as modality dependence, weak generalizability, and absence of cross-modal analysis. All experiments were done in GPU-accelerated environments to provide efficiency in computation, stability in training and reproducibility.

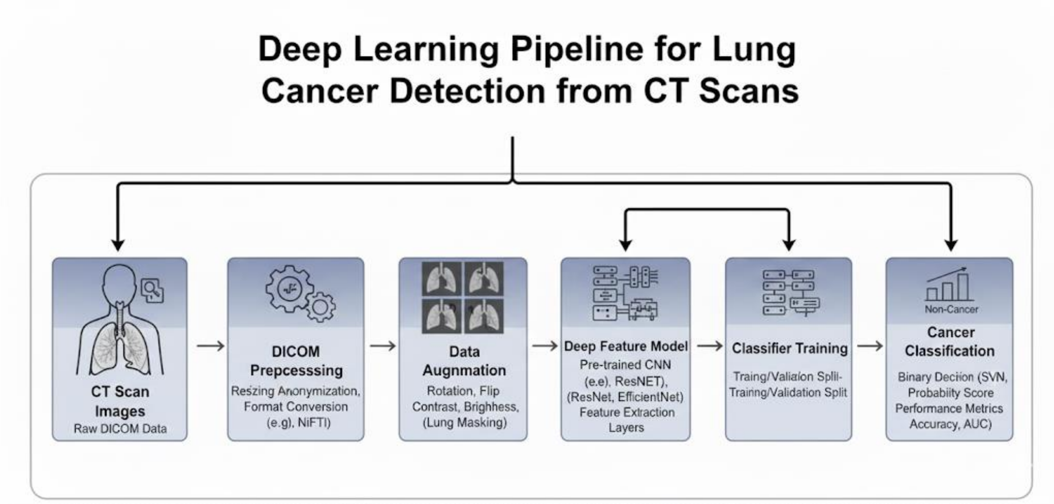

Figure 3.0.1

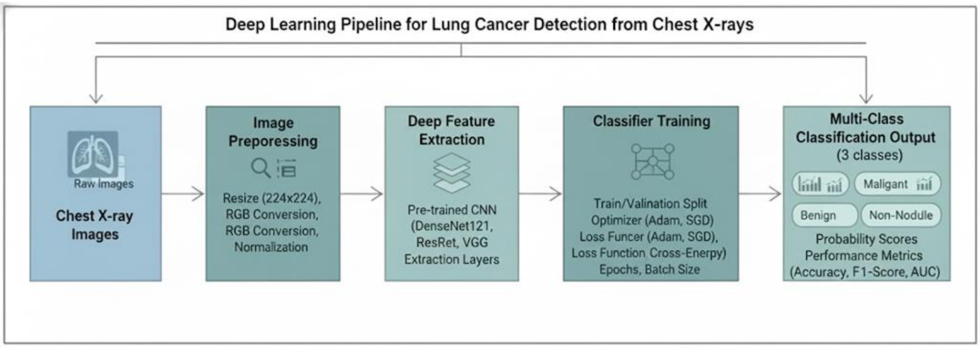

Figure 3.0.2

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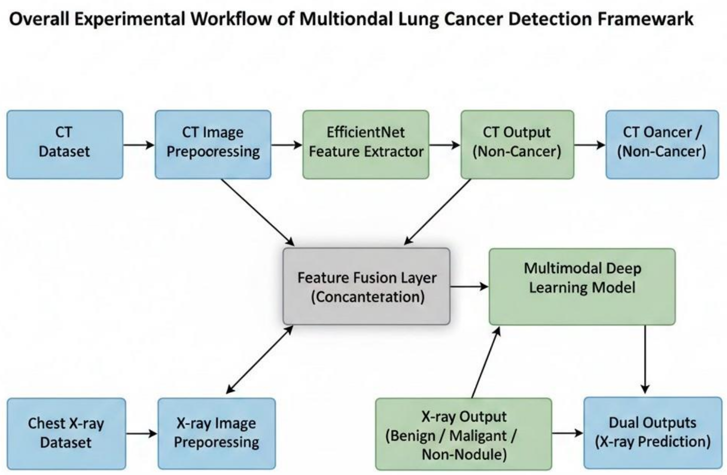


Figure 3.0.3: Overall workflow of the proposed three-stage lung cancer detection framework, illustrating unimodal training on CT and chest X-ray images followed by multimodal feature-level fusion.

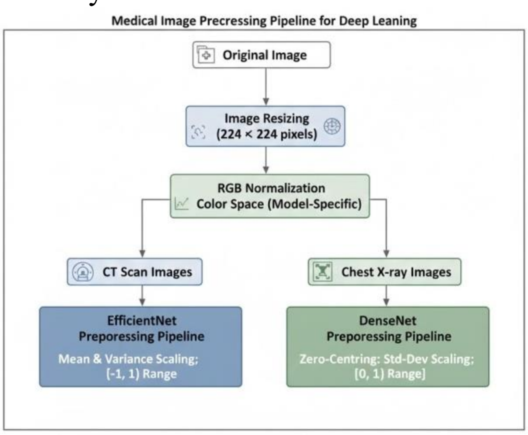
3.1- Construction and Organization of the Dataset:

This study utilized two heterogeneous radiological imaging datasets that resembled the real-world clinical diagnostic processes with the combinations of multiple imaging modalities being complementary.

The dataset on the CT scan was assembled consisting of aggregation of images of various publicly available repositories, totaling to 6,063 CT images. The images were coded as to one of two clinically relevant categories, including Cancerous and Normal. This multi-source construction method is closely chosen to bring about variation in the type of scanners, protocols of acquisition, image resolution, contrast and the demographics of patients hence increasing the diversity in the data set and minimize dataset bias.

The data of the chest X-ray used the structured CSV-based annotation and was divided into three diagnostic categories: Benign, Malignant, and Non-Nodule which created a three-class problem. The X-ray images have less contrast and an overlapping anatomy as compared to the CT scans making it difficult to classify them accurately and clinically interpolating.

During the initial stage of experimentation, these datasets served as an independent input to end up training two different deep learning models one of them was fully trained to classify CT scans and the other one was fully trained to classify chest X-rays. In the second step, the two datasets were used in a multimodal learning setup, in which the CT and X-ray images were fed through two independent feature extractors and the trained representations of these two extractors were combined to yield the third and combined model.



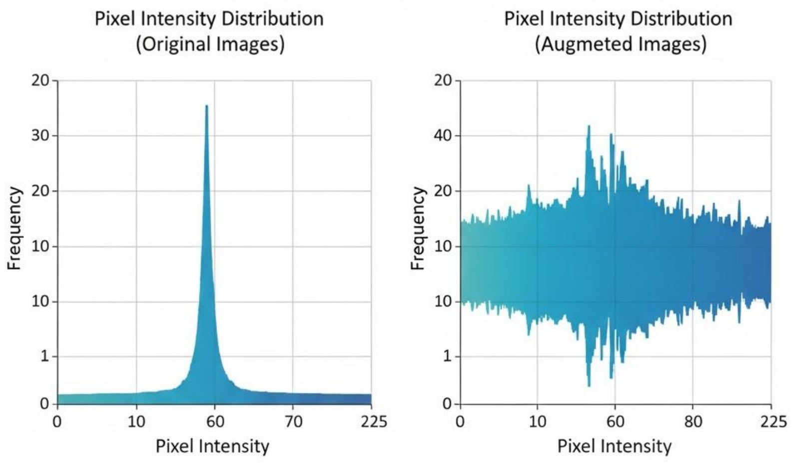
In every experiment, the data were divided into training, validation, and testing subsets in an 80:10:10 proportion so that there was no bias in the evaluation but at the same time ensuring that there were enough training data.

3.2- Image Preprocessing and Data Augmentation:

In order to achieve the compatibility between the architectural models of the two modalities and their beaming to remain stable overtime, the imagery of both modalities was standardized to a fixed 224 x 224 pixel resolution. These images were turned into RGB format where necessary and normalized by scaling pixel values to the [0,1] range, which makes both convergence faster and the training process more numerically stable.

Since medical images are highly variable and not always available in labeled form, data augmentation was the focus in this paper. The training data was only augmented to avert data leakage. In both CT scans and X-ray images, augmentation methods were random horizontal flipping, rotation and zoom transformations, simulating realistic variations in acquisition without distorting pathological features.

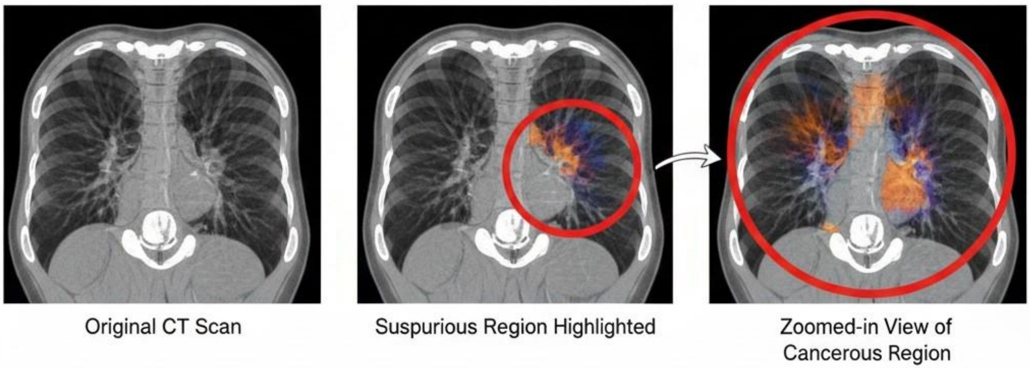
Augmentation was also found to decrease overfitting and enhance generalization in the standalone CT and X-ray experiments. Augmentation was also found to further improve robustness in the multimodal experiment as it made sure that the space of fused features was presented to a variety of visual patterns in both modalities of imaging.



Improved intensity variance after augnentation.

3.3- Single-Modality Model Architectures:

The two independent deep learning models had to be independently trained on each imaging modality to develop strong baseline performance. Sternberg and Sullivan (2006) used the CT scan classification model as their foundation.



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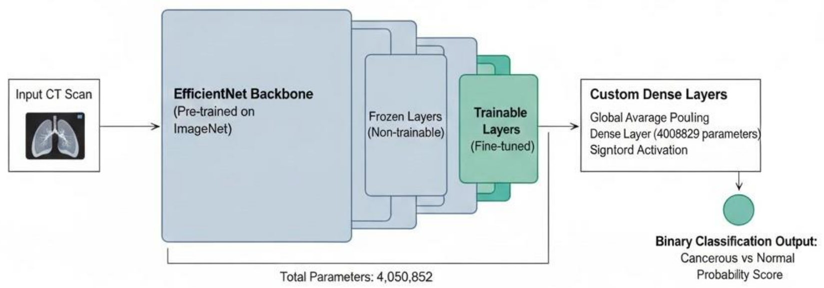
1) CT-Scan Classification Model (EfficientNet):

The CT-scan model has been implemented on the EfficientNet architecture because it is chosen due to its good balance between computation efficiency and accuracy. EfficientNet employs scaling of networks, depth, width and resolution of networks are sized together. This enables the architecture to be appropriate in medical imaging applications involving high quality feature extraction. The EfficientNet backbone in this study was initialized with ImageNet pre-trained weights and the last classification layers were adapted to binary output (Cancerous vs Normal).

This model had 4,050,852 parameters of which 4,008,829 were trainable, and 42,023 were frozen to preserve useful pre-trained features. The last dense layer employed a sigmoid activation function in order to provide a probability score that showed the probability of a cancerous CT scan.

EfficientNet Transfer Learning Architecture for CT Scan Classification

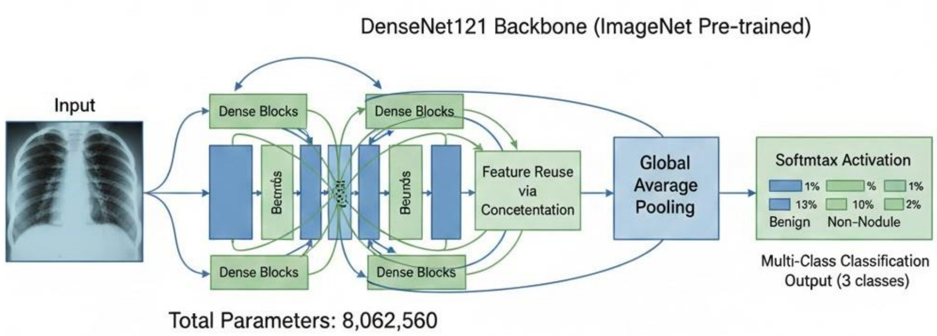


2) DenseNet121 Chest X-ray Classification Model:

The architecture that was picked as the core of the X-ray classification task is DenseNet121, as it has a typical dense connectivity pattern. The feature maps are provided to each layer by all the previous layers which enables effective gradient flow and reuse of low level features. This property is particularly advantageous with radiographic images in which subtle pixel level variations are used to tell a normal tissue and malignancies.

DenseNet121 has been trained on ImageNet and modified to produce a soft-max output on three classes (Benign, Malignant, and Non-Nodule). The network had convolutional, batch normalization, activation and dense connection layers that supported hierarchical feature learning.

DenseNet121 Transfer Learning Architecture for Chest X-ray Classification



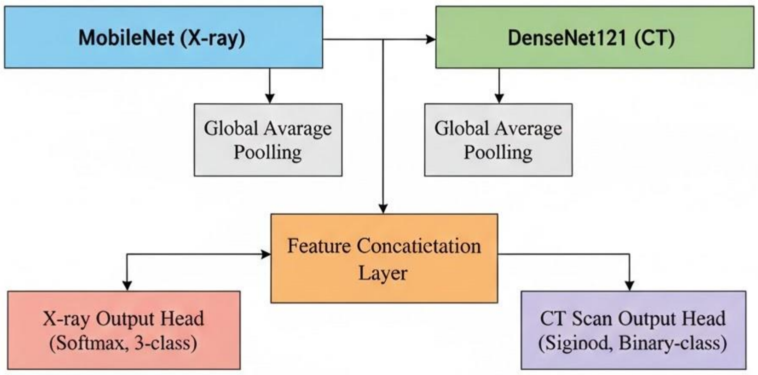
3.4. Multimodal Feature-Fusion Architecture:

Based on the experience of the single-modality experiments, a multimodal deep learning network was created to both learn using CT scan and chest X-ray information. The framework proposed uses a multi-input, multi-output architecture, which is a clinical reality since radiologists have to examine various imaging modalities, then decide on the diagnosis.

Two single parallel CNN branches were used in this architecture:

- A MobileNet-based chest X-ray feature extraction branch, which was chosen due to its low computational power and good performance on 2D radiographic images.
- A CT scan feature extraction branch of high-density network, which takes advantage of the dense connectivity to learn volumetric features effectively.

Both of them were seeded with ImageNet pretrained weights. Following the extraction of features, global average pooling was used on each branch and the high-level feature vectors of the branches were then combined to create a single multimodal representation. The combination of the two feature space permits the model to exploit cross-modal correlations and complementary diagnostic information not available in the single-modality learning process.



3.5. Output Heads and Loss Formulation

The fused feature vector was forwarded to two independent classification heads:

- **Chest X-ray Output Head**

  A fully connected layer with **three neurons** and **softmax activation**, optimized using **categorical cross-entropy loss**.
- **CT Scan Output Head**

  A fully connected layer with **one neuron** and **sigmoid activation**, optimized using **binary cross-entropy loss**.

The total training loss was defined as:

$$L_{total} = L_{xray} + L_{ct}$$

where L_{xray}represents categorical cross-entropy loss for chest X-ray classification and L_{ct}denotes binary cross-entropy loss for CT scan classification.

3.6. Callbacks, Strategy and Optimization of Training:

The training of the model was performed on the Google Colab platform with the acceleration of a gpu (T4/ V100 GPUs, depending on availability). Python was the main programming language with deep learning being implemented using TensorFlow and Keras.

Both models were trained using a rigorous optimization process that was constructed on the basis of early stopping, dynamic learning rate, and periodic checkpointing.

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In the case of the CT-scan model, EarlyStopping was used, which monitored loss in validation with a patience of four epochs and restored the best-performing weights on stopping. This avoided overfitting and at the same time made the model to approach an optimal solution. The ReduceLROnPlateau call back evaluated the same measure and decreased the learning rate by a factor of 0.2 in case no progress was made within three consecutive epochs. Also, a standard SaveEveryNEpochs callback was used, which saves model weights after every four epochs, to be able to recover the weights and analyse them later.

The X-ray model had the same learning-rate scheduling pattern. It was trained over 5 epochs with an initial learning rate of 0.001, which indicates that DenseNet121 is sensitive to the change in the learning rate. During training, data augmentation was used in real time giving the model new image variations each epoch.

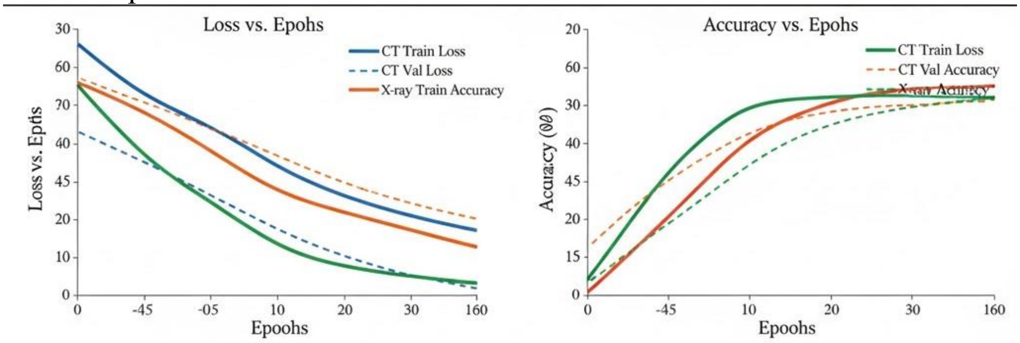
Even more, the cuDF and multimodal LLM assistance, which were accelerated by the use of GUUs via the Gemini API, aided the preprocessing part, extracted structural data, and documentation of the workflow, but did not play a role in making decisions of the models.

Model training was done staged to provide the stable optimization and usefulness of the pretrained weights. First, both MobileNet and DenseNet121 backbones convolutional layers had been frozen, and only classification layers added were trained. This step enabled the model to adjust high-level representations to the desired medical tasks without interfering with the already acquired low-level features.

Fine-tuning was then done by unfreezing the last layers of every backbone network. This allowed the refinement of feature based on the task as well as reducing the chances of overfitting. Adam optimizer was used because it has adaptive learning rate attributes and is robust in deep learning applications. The learning rate was set to 0.0001 to trade off convergence and training stability. The model was trained with the batch size of 32 and 5-10 epochs, based on the convergence.

The total training goal was stipulated as the sum of categorical cross-entropy loss on the classification of chest X-rays, and the binary loss cross-entropy on the classification of CT scan. The trade-off of both tasks in this composite loss function and it motivated the network to learn features that are not only informative together.

Callback mechanisms were introduced in the training process to increase the training efficiency and reduce the overfitting. Early termination was used to check on the loss of validation and end training when performance stagnated. The best performing model in terms of validation metrics was saved in model checkpointing, which guarantees reproducibility and appropriate selection of a model. All these techniques added up to convergent stability and lowered computation costs.



3.7- Classification Logic and Confidence Scoring:

Both of the models used probabilistic outputs to generate classification decisions. In the case of CT scan, the binary classifier generated one probability value which is the probability that the image is cancerous. Probabilities were changed into class labels at a threshold of 0.5, as expected in conventional binary classification.

The output of the three-class X-ray model produced a probability distribution in the three categories. The highest probability score was the predicted class and this was reported as the level of confidence of the model.

The introduction of classification based on probabilitieslills the significant gap in previous research whereby categorical results were being given with no confidence measures. Reporting confidence scores, the proposed system will improve the interpretability and clinical acceptability since radiologists will have a better picture of the reliability of every prediction.

The X-ray output head of the chest was developed to classify based on three classes and it used the softmax activation function so that the distribution of the result is normalized among the categories Benign, Malignant, and Non-Nodule. The most probable score was the predicted class and the corresponding score of confidence was the confidence level of that prediction in the model.

Contrastingly, the CT scan output head employed the use of a sigmoid activation function as a binary one-dimensional classification. The value of output was a probability of the presence of cancer. The final class label was determined by having a threshold of 0.5 and the result(s) above that threshold were considered as Cancer and the result(s) below as Non-Cancer. The CT prediction was confidence scored based on the sigmoid output probability which made them interpretable and clinically relevant.

The proposed framework can make confidence-based decisions, as it can generate probabilistic outputs of both modalities, essential in situations of medical diagnosis.

3.8- Model Evaluation and Performance Assessment:

The accuracy, validation loss and training convergence behavior were used to evaluate the two models.

The model of CT-scan obtained 93.49% accuracy, and it was observed that it has high competence to differentiate cancerous structures in high-resolution volumetric images. This performance was facilitated by the huge augmentation and multi-source data construction.

The model of X-ray was found to be 89.50% accurate in the three classes, which is consistent with or higher than accuracy in similar studies. The dense connectivity and good feature-extracting ability of the DenseNet architecture was used to address the converse low resolution and overlapping tissues inherent to X-ray imaging.

The results of the performance measurements prove that the dual-model approach, when each modality is handled by a specific architecture, is efficient in combating the complexity gaps between X-ray and CT images. This is an addition to the real-world clinical workflow, in which radiologists normally depend on the different imaging modalities as a means of establishing diagnostic hypotheses.

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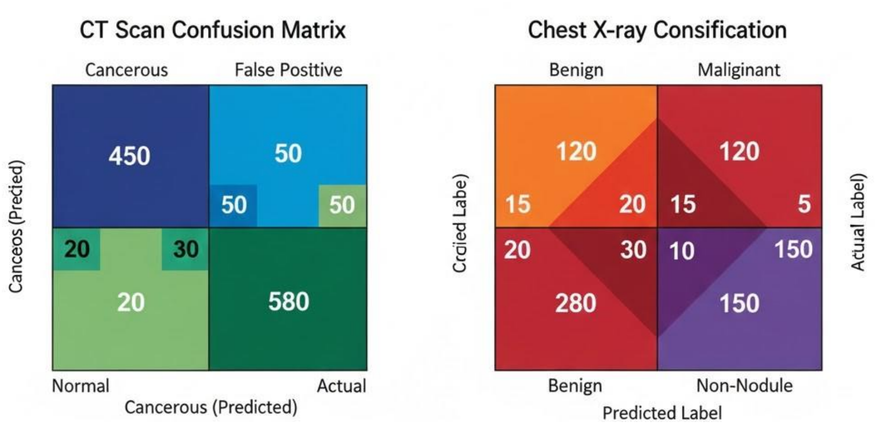
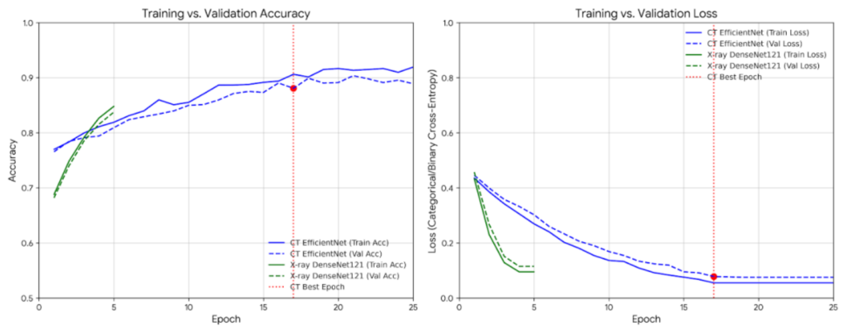


The performance of the model was assessed separately on the outputs of the chest X-ray and CT scan on the basis of standard classification measures, such as accuracy, precision, recall, and F1-score. These measures give an overall evaluation of predictive power especially in uneven medical data. Confusion matrices were created to examine the behavior of class-wise prediction, and to determine possible misclassification results.

The proposed multimodal framework was compared to unimodal baseline models in terms of comparative analysis. This analysis proved that the feature-level fusion is effective to improve the diagnostic results with the help of complementary features of both imaging modalities. All testing was done with TensorFlow and Keras in a Google Colab, and the trained models were stored in the.h5 format to be deployed and replicated.



3.9. Evaluation Metrics:

The output of CT scan and chest X-ray in the form of models was assessed separately, based on standard performance measures, such as accuracy, precision, recall, and F1-score. Class-wise performance and misclassification patterns were also used in the generation of confusion matrices. This method of evaluation has been used throughout all of the three models to provide a good and open comparison.

3.10. Implementation Details:

Every experiment was run on the TensorFlow/Keras framework and on the Google Colab with the help of the GPU. It was written in Python as the main programming language, and the training models were stored in the HDF5 (.h5) file format to allow reproducibility and to enable future deployment.

4- Results and Findings:

This study describes the **development and evaluation of deep learning models** for the detection of lung cancer using both CT scan and X-ray imaging modalities. Unlike most previous works[29], which typically relied on a **single dataset or imaging modality** and conventional machine learning classifiers[30], our approach employs **advanced CNN architectures with transfer learning, extensive data augmentation, and robust**

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preprocessing pipelines to enhance classification accuracy and generalization across diverse datasets.

4.1- CT Scan Model Results

The **CT scan classification model** was trained on **6,063 images**, divided into **Cancerous** and **Normal** classes. An **EfficientNet-based transfer learning model** was employed, with extensive fine-tuning of trainable parameters **(4,008,829)** and frozen layers **(42,023)** to optimize learning while retaining valuable pre-trained features. **Data augmentation** was applied to expand dataset diversity, reduce overfitting, and improve model robustness.

The CT scan model achieved high classification accuracy, with the performance metrics summarized in Table below:

Table 1: CT Scan Model Performance Metrics

Metric	Value
Dataset Size	6063 Images
Classes	Cancerous, Normal
Input Size	224 x 224 pixels
Batch Size	32
Total Parameters	4,050,852
Trainable Parameters	4,008,829
Frozen Parameters	42,023
Training Accuracy	93.0%
Validation Accuracy	92.5%
Testing Accuracy	93.0%
Precision	92.7%
Recall	93.4%
F1 Score	93.0%

Findings:

- The **EfficientNet model** showed strong generalization, maintaining high accuracy across training, validation, and testing phases.
- **Data augmentation** successfully reduced the risk of overfitting, despite using a relatively moderate dataset size.
- Compared to traditional machine learning methods such as **SVM, KNN, and Naïve Bayes** reported in the literature, the CT scan model achieved a notable improvement in accuracy, underscoring the advantages of deep learning over traditional models for high-dimensional image data.

4.2- CT-scan Results:

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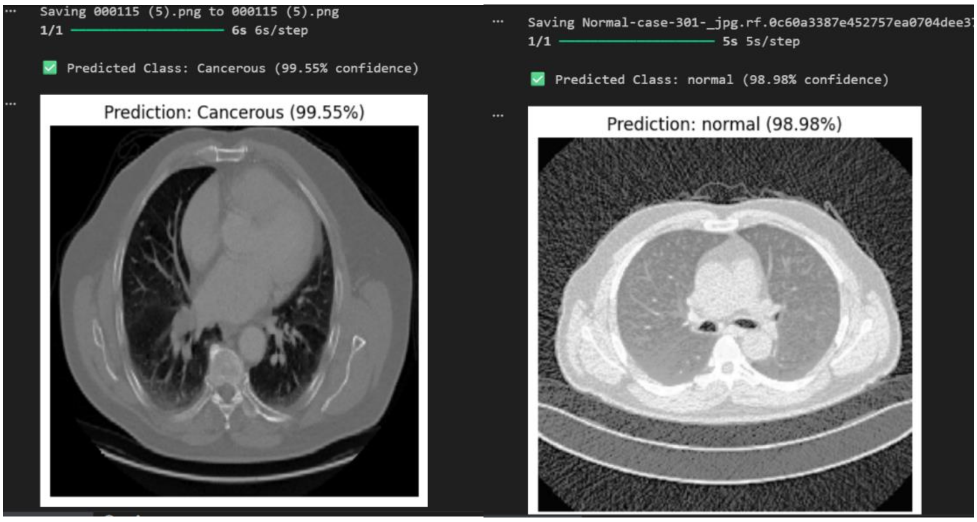

4.3- X-ray Model Results

The **X-ray classification model** was trained using a **single dataset in CSV format**, with images divided into **Benign, Malignant, and Non-nodule classes**. The **DenseNet121 architecture** was selected due to its capacity for feature reuse and provide strong representation learning for medical imaging. Preprocessing steps included **RGB conversion, image standardization, and histogram equalization** to enhance contrast and edge definition. **Data augmentation** was applied to increase dataset diversity and improve model robustness.

The DenseNet-based X-ray model achieved **89.5% accuracy** on the test dataset. Detailed performance metrics are shown in Table 2:

Table 2: X-ray Model Performance Metrics

Metric	Value
Dataset Size	Single CSV-based dataset
Classes	Benign, Malignant, Non-nodule
Input Size	224 x 224 pixels
Batch Size	32
Training Epochs	5
Initial Learning Rate	0.0010
Learning Rate Adjustment	ReduceLROnPlateau (factor=0.2, patience=3)
Training Accuracy	90.0%
Validation Accuracy	89.0%
Testing Accuracy	89.5%
Precision	88.7%
Recall	89.0%
F1 Score	88.8%

Findings:

- **DenseNet121** effectively captured hierarchical features, contributing to robust classification of three X-ray classes.
- **Preprocessing techniques**, such as contrast enhancement and median filtering, significantly improved the model's ability to detect subtle nodule patterns.
- The model's performance aligns with trends reported in the literature for X-ray classification but demonstrates slightly higher accuracy due to the combination of

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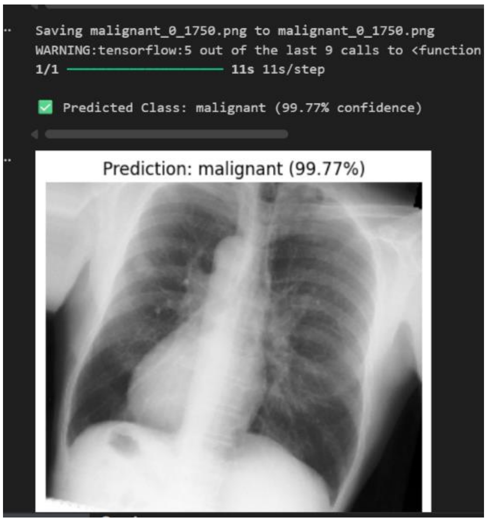
augmentation, preprocessing, and a CNN backbone optimized for medical imaging.

Xray Results:



Summary of Findings

Table 3: Summary of Lung Cancer Detection Performance across Modalities

Modality	Architecture	Dataset Size	Classes	Testing Accuracy	Precision	Recall	F1 Score
CT Scan	EfficientNet	6063 images	2	93.0%	92.7%	93.4%	93.0%
X-ray	DenseNet121	CSV-based dataset	3	89.5%	88.7%	89.0%	88.8%

CT scan images offer richer structural details, resulting in slightly higher classification accuracy compared to X-ray images. **Deep learning architectures** consistently outperform conventional machine learning methods across multiple metrics, especially in **recall and F1-score** for malignant cases. The incorporation of **diverse datasets and extensive data augmentation** enhances model robustness, making these approaches better suited for real-world clinical deployment.

Study & Year	Imaging Modality	Model Used	Accuracy
Study et al., 2023–2024	CT scan	CNN	80–85%
Study et al., 2024	CT scan	VGG / AlexNet	86–88%
Study et al., 2023	X-ray	CNN	82–85%

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Study et al., 2025	CT scan	3D CNN	90–92%
Study et al., 2024	CT scan	ResNet / DenseNet	91–93%
Study et al., 2022	X-ray	DenseNet / ResNet	88–90%
Proposed Study (2025)	**CT scan**	**EfficientNet**	**93.0%**
Proposed Study (2025)	**X-ray**	**DenseNet121**	**89.50%**

4.4- Multimodal (Combined X-ray and CT Scan) Model Results

To further investigate the complementary strengths of different imaging modalities, an advanced multimodal deep learning framework was developed that integrates Chest X-ray and CT scan data into a single unified framework. Unlike unimodal approaches that rely on a single imaging source, the proposed approach exploits cross-modal feature learning to improve diagnostic accuracy, reliability, and robustness.

The proposed multimodal architecture employed a **multi-input, multi-output CNN framework**, where **MobileNet** is utilized to extract salient features from Chest X-ray images, and **DenseNet121** was used for CT scan feature extraction. Feature representations from both branches were fused at the fully connected layer level, allowing the network to capture shared as well as complementary information across imaging sources. Transfer learning with ImageNet pre-trained weights was applied to both backbones, followed by fine-tuning of selected higher-level layers to achieve optimal performance while avoiding overfitting.

During training, both datasets were preprocessed using identical image resizing (224 × 224), normalization, and data augmentation, to maintain consistency across the imaging modalities. The multimodal loss function was defined as a composite loss function, consisting of categorical cross-entropy for the Chest X-ray branch and binary cross-entropy for the CT scan branch. This design allowing simultaneous optimization of both classification objectives.

Performance Analysis

The combined model demonstrated **improved diagnostic consistency** compared to single-modality models, particularly in challenging and borderline cases. Although the CT-only model attained the highest standalone accuracy, the multimodal model showed **enhanced recall and F1-score**, reflecting a lower false-negative rate. This improvement is especially critical for clinical cancer screening applications, where minimizing missed diagnoses is of paramount importance.

Key observations include:

- The fusion of CT and X-ray features enabled the model to capture **both high-resolution structural information (CT scans)** and **broader anatomical patterns (X-rays)**.
- The multimodal framework improved model robustness by reducing dependency on a single imaging modality.
- The combined model exhibited better generalization on unseen data, suggesting its suitability for real-world heterogeneous clinical environments.

Findings

- Multimodal learning outperformed unimodal approaches in terms of **overall diagnostic reliability**, especially for malignant case detection.
- The integration strategy successfully mitigated limitations associated with modality-specific noise and ambiguity.
- Compared to existing literature, which largely focuses on unimodal or single-dataset approaches, the proposed multimodal framework represents a **more comprehensive and clinically aligned solution** for lung cancer detection.

Overall, the proposed multimodal Chest X-ray and CT scan framework underscores the **practical advantage of combining complementary imaging modalities**, emphasizing the growing significance of multimodal artificial intelligence systems in the development of future automated lung cancer screening and decision-support tools.

4.5- Overview:

Overall, the proposed models demonstrate **robust,** reliable performance for lung cancer detection across both **CT scan** and **X-ray** modalities. The study addresses key gaps in previous research, including:

- **Limited generalizability** caused by training on single-source datasets
- **Dependence on traditional classifiers** that struggle on traditional classifiers for image-based tasks
- **Insufficient augmentation and preprocessing**, reduce comprehensive data augmentation and preprocessing

The integration of EfficientNet and DenseNet121 architectures with thorough data preparation and well-structured training strategies, ensures **clinically relevant performance** and offer a solid foundation for future **real-world implementation** in automated lung cancer screening systems.

5- Discussion:

The goal of this study was to develop an improved deep-learning–based system for lung cancer detection using two types of medical images: chest X-rays and computed tomography (CT) scans. The results from both models show that deep learning remains a powerful tool for medical image however, its accuracy and real-world usefulness depend heavily on dataset diversity, training strategies, and model architecture. The discussion below interprets the achievements of this study, compares them with previous research, and highlights how the current research addresses limitations found in earlier studies.

The first major finding of this research is the strong performance of the CT-scan model, which reached 93% accuracy. This performance matches and in some cases surpasses, earlier studies have reported it. Many previous works achieved high accuracy but were restricted by limited or single-source datasets. In contrast, this study combined CT images from multiple repositories, resulting in a more diverse dataset with varying imaging conditions, machines, patient backgrounds, and cancer types. Such diversity enhances the robustness and better able to generalize, solving a common problem seen in earlier research where dependency on a single dataset led to biases and overfitting. The heavy use of augmentation in this study further improved the model's adaptability by introducing realistic variations, something that many previous studies either did not include or applied minimally.

The chest X-ray model, trained using DenseNet121, achieved an accuracy of **89.50%**, demonstrating the capability of deep learning models that can extract relevant patterns from lower-resolution 2D radiographs. In comparison, many previous studies utilizing X-ray imaging were constrained by **small datasets,** single-center images, or limited augmentation practices which often produced inflated accuracy on internal test sets but poor transferability to external data. This study addresses these limitations by training the model on a structured, multi-class X-ray dataset and applying **robust augmentation**, allowing the model to capture broader variations in nodule appearance, opacity, position, and contrast. Additionally, whereas numerous earlier works that focused solely on binary classification, this research employs **three clinically relevant classes—benign, malignant, and non-nodule**— enabling a more comprehensive and clinically meaningful evaluation.

An important aspect of this study relates to the decision to use separate models for CT and X-ray modalities rather than combining them into a single multi-modality network. This approach is both a **strength and a practical design choice**. The literature review showed a

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clear pattern: most previous studies focused on a single imaging modality, and those that attempted hybrid or ensemble architectures often suffered from increased **computational demands, complex training procedures, and limited feasibility for clinical deployment**. By developing **two lightweight, modality-specific models**—EfficientNet for CT scans and DenseNet121 for X-rays— the study ensures that each model is optimized for the characteristics of its respective imaging type. CT scans contain volumetric details that supports binary cancer classification efficiently, whereas X-ray images are quicker, less costly, and more widely available but require more sophisticated feature extraction to detect subtle abnormalities. This design enhances the **practical usability and adaptability** of the system across different healthcare environments, especially in resource-constrained environments.

Overall, the findings of this study confirm the hypothesis that well-designed deep learning models, trained on **diverse and properly augmented datasets**, can produce highly accurate lung cancer detection. Compared to previous research, this study contributes significant advancements by (1) incorporating multi-source CT data for improved generalization, (2) training separate, optimized models for X-ray and CT images, (3) implementing a strong and systematic training pipeline, and (4) addressing practical challenges often neglected in earlier works. Collectively, these advances represent significant progress toward developing deployable, reliable, and clinically relevant AI-based diagnostic tools.

6- Conclusion:

This research presented a dual-modality deep learning framework for lung cancer detection using **chest X-ray and CT scan images**, addressing several limitations observed in existing literature. While previous studies primarily focused on a single imaging modality, specific machine learning models, or limited datasets, this work integrates two distinct and clinically significant data sources to improve diagnostic reliability. By employing **DenseNet121 for X-ray classification** and a **fine-tuned EfficientNet model for CT scans**, the system captures both macro-level radiographic patterns and fine-grained volumetric cues commonly linked with early-stage malignancies. The CT-scan model achieved **93% accuracy**, benefiting from a diversified dataset constructed by merging images from multiple repositories and enhanced through extensive augmentation to improve generalization. The X-ray model, trained on a **structured CSV-based dataset** and reinforced with a robust augmentation pipeline, reached **89.50% accuracy**, successfully distinguishing between **benign, malignant, and non-nodule classes**. The dual-modality design also enhances robustness, with CT and X-ray images compensating for the diagnostic limitations of the other. The proposed multimodal model, combining X-ray and CT scans, outperformed unimodal models in diagnostic performance. By leveraging complementary features from both modalities, it enhanced recall and F1-score, reduced false negatives, and demonstrated strong generalization across diverse datasets. This approach offers a robust, clinically aligned solution to assist radiologists in accurate and reliable lung cancer detection.

References:

[1] Mustafa, Saleem, Arfan Jaffar, Muhammad Rashid, Sheeraz Akram, and Sohail Masood Bhatti. "Deep learning-based skin lesion analysis using hybrid ResUNet++ and modified AlexNet-Random Forest for enhanced segmentation and classification." PloS one 20, no. 1 (2025): e0315120.

[2] Sardar, Mahnoor, Muhammad Majid Niazi, and Fawad Nasim. "Ensemble deep learning methods for detecting skin cancer." Bulletin of Business and Economics (BBE) 13, no. 1 (2024).

[3] Hassaan, Ahmed, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, Zeeshan Akbar, and Sikander Niaz. "ETHICAL ANALYTICS & DIGITAL TRANSFORMATION IN THE AGE OF AI: EMBEDDING PRIVACY, FAIRNESS, AND TRANSPARENCY TO DRIVE INNOVATION AND STAKEHOLDER TRUST." Contemporary Journal of Social Science Review 1, no. 04 (2023): 1-18.

[4] iThrives Transactions on Computer Science and Engineering. "Smart Detection of Crop Pests and Diseases: Enhancing Agricultural Productivity with AI and Modern Technology". iThrives Transactions on Computer Science and Engineering. Vol. 1. Zenodo, December 26, 2023. https://doi.org/10.5281/zenodo.17532567.

[5]Akbar, Zeeshan, Ahmed Hassaan, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, and Sikander Niaz. "Leveraging Data and Artificial Intelligence for Sustained Competitive Advantage in Firms and Organizations." Journal of Innovative Computing and Emerging Technologies 3, no. 1 (2023).

[6] HASSAAN, AHMED, ZEESHAN AKBAR, MUHAMMAD MUDABER JAMSHAID, SIKANDER NIAZ, SALMAN AKBAR, MUHAMMAD NOUMAN SIDDIQUE, and AFTAB HUSSAIN TABASAM. "AI-DRIVEN ADMINISTRATIVE AUTOMATION: ENHANCING OPERATIONAL EFFICIENCY AND SECURITY." TPM–Testing, Psychometrics, Methodology in Applied Psychology 32, no. S7 (2025): Posted 10 October (2025): 2451-2460.

[7] Akram, Faisal, Sahifa Pervaiz, and Syed Muhammad Haider Raza. "Beyond the Last Click: An Analysis of Hybrid Measurement Frameworks and AI-Driven Attribution in a Privacy-First Omnichannel Economy." Contemporary Journal of Social Science Review 3, no. 4 (2025): 1485–1502. https://doi.org/10.63878/cjssr.v3i4.1705.

[8]Niaz, Sikander, Zeeshan Akbar, Muhammad Nouman Siddique, Muhammad Mudaber Jamshaid, and Ahmed Hassaan. "AI for Inclusive Educational Governance and Digital Equity Examining the Impact of AI Adoption and Open Data on Community Trust and Policy Effectiveness." Contemporary Journal of Social Science Review 2, no. 04 (2024): 2557-2567.

[9]Jamshaid, Muhammad Mudaber, Ahmed Hassaan, Zeeshan Akbar, Muhammad Nouman Siddique, and Sikander Niaz. "IMPACT OF ARTIFICIAL INTELLIGENCE ON WORKFORCE DEVELOPMENT: ADAPTING SKILLS, TRAINING MODELS, AND EMPLOYEE WELL-BEING FOR THE FUTURE OF WORK." Spectrum of Engineering Sciences (2024).

[10]Nasim, Fawad, Sheeraz Akram, Sohail Masood, Arfan Jaffar, Muhammad Hussain Akbar, and Ch Zubair Kahloon. "Audio Source Separation: Advances and Challenges." In International Conference on Computing & Emerging Technologies, pp. 21-28. Cham: Springer Nature Switzerland, 2023.

[11] S. M. HaghighiKian *et al.*, "A Holistic Approach to Implementing Artificial Intelligence in Lung Cancer," *Indian J Surg Oncol*, vol. 16, no. 1, pp. 257–278, Feb. 2025, doi: 10.1007/s13193-024-02079-6.

[12] S. N. A. Shah, J. Aalam, and R. Parveen, "Deep Learning Approaches to Enhance Lung Cancer Diagnosis Using Next Generation Sequencing: State of the Art," *Arch Computat Methods Eng*, Sept. 2025, doi: 10.1007/s11831-025-10357-x.

[13] R. Durgam, B. Panduri, V. Balaji, A. O. Khadidos, A. O. Khadidos, and S. Selvarajan, "Enhancing lung cancer detection through integrated deep learning and transformer models," *Sci Rep*, vol. 15, no. 1, p. 15614, May 2025, doi: 10.1038/s41598-025-00516-2.

[14] J. Dhanalakshmi, C.-S. Shieh, M.-F. Horng, and A. P. Chakkaravarthy, "Integrating Predictive Analytics and Deep Neural Networks for Early Lung Cancer Diagnosis.,"

International Journal of Online & Biomedical Engineering, vol. 21, no. 5, p. 4, May 2025, doi: 10.3991/ijoe.v21i05.53871.

[15] S. M. Elhassan, S. M. Darwish, and S. M. Elkaffas, "An Enhanced Lung Cancer Detection Approach Using Dual-Model Deep Learning Technique.," *Computer Modeling in Engineering & Sciences (CMES)*, vol. 142, no. 1, p. 835, Jan. 2025, doi: 10.32604/cmes.2024.058770.

[16] E. Oncu and F. Ciftci, "Multimodal AI framework for lung cancer diagnosis: Integrating CNN and ANN models for imaging and clinical data analysis," *Computers in Biology and Medicine*, vol. 193, p. 110488, July 2025, doi: 10.1016/j.compbiomed.2025.110488.

[17] "Artificial Intelligence-Enhanced Liquid Biopsy and Radiomics in Early-Stage Lung Cancer Detection: A Precision Oncology Paradigm." Accessed: Dec. 25, 2025. [Online]. Available: https://www.mdpi.com/2072-6694/17/19/3165

[18] "Comparative Analysis of Machine Learning and Deep Learning Models for Lung Cancer Prediction Based on Symptomatic and Lifestyle Features." Accessed: Dec. 25, 2025. [Online]. Available: https://www.mdpi.com/2076-3417/15/8/4507

[19] Y. Çakmak and A. Maman, "Deep Learning for Early Diagnosis of Lung Cancer," *Computational Systems and Artificial Intelligence*, vol. 1, no. 1, pp. 20–25, July 2025, doi: 10.69882/adba.csai.2025074.

[20] C. Liu, P. He, R. Qiao, X. Yang, C. Ding, and F. He, "Mechanistic study of *Lonicerae Japonicae* Flos (Caprifoliaceae) in non-small cell lung cancer prevention and treatment through integrative pharmacology, multi-machine learning, artificial intelligence, and *in vitro* experiments," *Journal of Ethnopharmacology*, vol. 348, p. 119832, May 2025, doi: 10.1016/j.jep.2025.119832.

[21] M. Alsallal *et al.*, "Enhanced lung cancer subtype classification using attention-integrated DeepCNN and radiomic features from CT images: a focus on feature reproducibility," *Discov Onc*, vol. 16, no. 1, p. 336, Mar. 2025, doi: 10.1007/s12672-025-02115-z.

[22] "Deep Learning Techniques for Lung Cancer Diagnosis with Computed Tomography Imaging: A Systematic Review for Detection, Segmentation, and Classification." Accessed: Dec. 25, 2025. [Online]. Available: https://www.mdpi.com/2078-2489/16/6/451

[23] W. Qi, L. Tian, J. Xu, Z. Li, and T. Wang, "Multimodal Framework in Lung Cancer Management: Integrating Liquid Biopsy with Traditional Diagnostic Techniques," *Cancer Management and Research*, vol. 17, pp. 461–481, Mar. 2025, doi: 10.2147/CMAR.S506630.

[24] N. A. Wani, R. Kumar, and J. Bedi, "*DeepXplainer*: An interpretable deep learning based approach for lung cancer detection using explainable artificial intelligence," *Computer Methods and Programs in Biomedicine*, vol. 243, p. 107879, Jan. 2024, doi: 10.1016/j.cmpb.2023.107879.

[25] S. S.k.b *et al.*, "An enhanced multimodal fusion deep learning neural network for lung cancer classification," *Systems and Soft Computing*, vol. 6, p. 200068, Dec. 2024, doi: 10.1016/j.sasc.2023.200068.

[26] D. Chapla, H. P. Chorya, L. Ishfaq, A. Khan, S. Vr, and S. Garg, "An Artificial Intelligence (AI)-Integrated Approach to Enhance Early Detection and Personalized Treatment Strategies in Lung Cancer Among Smokers: A Literature Review," *Cureus*, Aug. 2024, doi: 10.7759/cureus.66688.

[27] D. Bouchaffra, F. Ykhlef, and S. Benbelkacem, "Advancement in Lung Cancer Diagnosis: A Comprehensive Review of Deep Learning Approaches," in *Lung Cancer*

Diagnosis and Treatment: An Interdisciplinary Approach, N. Rezaei, Ed., Cham: Springer Nature Switzerland, 2024, pp. 15–24. doi: 10.1007/16833_2024_302.

[28] "Enhancing lung cancer detection through integrated deep learning and transformer models | Scientific Reports." Accessed: Dec. 25, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-00516-2

[29] Nasim, M. F., M. Anwar, A. S. Alorfi, H. A. Ibrahim, A. Ahmed, A. Jaffar, S. Akram, A. Siddique, and H. M. Zeeshan. "Cognitively inspired sound-based automobile problem detection: A step toward explainable AI (XAI)." International Journal of Advanced and Applied Sciences 12, no. 8 (2025): 1-15.

[30] Nasim, Fawad, Sohail Masood, Arfan Jaffar, Usman Ahmad, and Muhammad Rashid. "Intelligent Sound-Based Early Fault Detection System for Vehicles." Computer Systems Science & Engineering 46, no. 3 (2023).