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A Review Paper on Lung Cancer Detection using ANN

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Abstract: Lung cancer remains the leading cause of fatalities in all patients with cancer worldwide, thus reflecting highly on the urgent requirement for early detection and diagnostics. This abstract describes a summary of the different databases and methods using an artificial neural network (ANN) algorithm for lung cancer diagnosis. For the deep learning models, we need annotated CT scan images. They are accessible in publicly available datasets such as the Lung Image Database Consortium (LIDC), Lung-PET-CT-Dx, and NSCLC-Radio genomics.

These datasets have contributed to the automation of lung cancer diagnosis. Tumor detection and classification are also performed based on X-rays and PET scan imaging data. Several ANN-based methods have been reported for optimal detection of lung cancer. The employed methods included: hybrid learning schemes, data augmentation, feedback in neural network training, multilayer perceptron's and radiomic feature extraction. These methods aim to enhance the diagnostic accuracy by reducing the false positive rate and help physicians spot malignant nodules early on.

I. INTRODUCTION

Lung cancer imaging has remained a major challenge in the past years due to the global burden of disease in the increasing trend. Early diagnosis is necessary for patient survival and public health. All of the computer-aided diagnostic (CAD) workstations, population-based screening programs, and triage within hospitals rely on effective and accurate lung cancer detection technologies.

Artificial Neural Networks (ANN) have emerged as an effective pattern identification and classification tool in the analysis of medical images, which is well-suited for the detection of lung cancer. ANNs have achieved impressive results in diverse pattern-recognition tasks, including survival prediction, malignancy grading, and nodule detection. They are very effective in finding lung cancer as they can learn to recognise interesting features from radiological data."

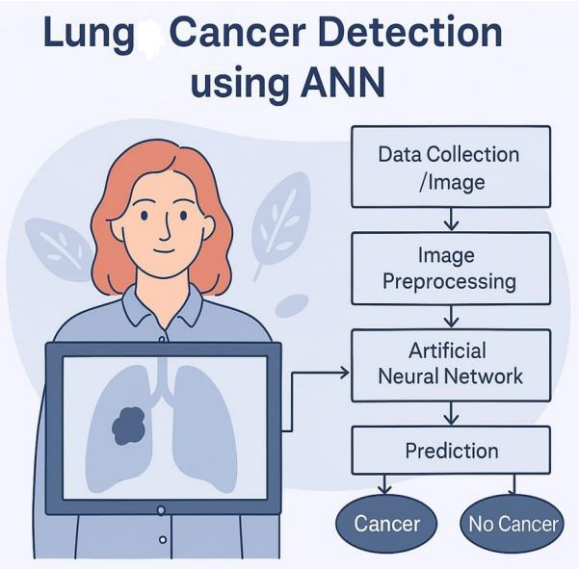

Figure 1: Flow Diagram of Result Prediction using ANN.

These models can automatically learn discriminative characteristics from CT or PET-CT volumes by utilizing the layered, hierarchical structure of ANNs, as illustrated in Figure 1. The models do a solid job of telling benign lung nodules from malignant ones. Researchers have put together multiple benchmark datasets to train the systems and check

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how well they work at spotting lung cancer.

One of the most common starting points is the LIDC-IDRI dataset [1] a big, carefully curated collection of chest CT scans from many hospitals. It's the usual benchmark for tasks like finding nodules and judging malignancy. Folks also lean on the NLST CT cohort [3] and LUNA16 [2] to help their ANN models generalize better.

There's now a growing lineup of ANN-driven methods that researchers use to detect lung cancer and classify nodules into "benign" and "malignant" groups. [7] presented a deep learning pipeline that uses multilayer perceptrons with radiomic feature augmentation.

This pipeline achieves high sensitivity at clinically acceptable false-positive rates. [8] created a hybrid artificial neural network (ANN) architecture for early-stage cancer detection in low-dose CT images that mixes learned representations with manually created texture information. The findings suggest ANNs are well-suited to managing the real-world hurdles in lung cancer detection.

Artificial neural networks are proving genuinely useful for lung cancer screening and tailored care. Teams are pushing accuracy and reliability by training on big public benchmarks plus targeted chest CT datasets. The impact shows up everywhere—from public screening programs to everyday radiology reads and treatment planning. Because lung cancer often presents late and carries high mortality, it matters that ANNs are already delivering solid detection results. Figure 2 walks through the flow: CT scans go in, malignancy maps come out, and you can see how kernel sizes (Kw, Kh) change detection and classification. Powered by both broad and specialized data, these models keep getting sharper and faster—and look set to play a key role in real-world patient outcomes.

II. METHODOLOGIES FOR LUNG CANCER DETECTION 3

There are many ways to detect lung cancer—from today's ANN models to older image-processing and pattern-recognition approaches. We'll look at what each does well, where they fall short, and what's new. Classical methods usually involve manual or semi-automated segmentation, hand-built features like shape, texture, and intensity, and then a standard classifier. They're quick and easy to explain, but they don't generalize well when imaging varies. ANNs, on the other hand, learn layered features straight from data, need less hand-tuning, and tend to handle real-world variation better.

Traditional Computer Vision Approaches

Older lung-cancer CAD systems mostly mixed hand-built features with classic ML models. The workflow was step-by-step: clean up the image, find likely nodules, pull out features, and run a classifier. Early nodule cues came from region growing, thresholding, or simple morphological tricks. Then came features shape, HOG, LBP, GLCM that fed into SVMs, k-NN, Decision Trees, or Random Forests to judge benign vs. malignant. These pipelines are easy to explain and run fast, great when compute is tight—but they falter with overlapping tissues and the sheer variability of real clinical scans. They also don't transfer well across datasets and take a lot of expert effort to tune. That's why ANN methods, which learn robust features on their own, are now edging them out and boosting accuracy.

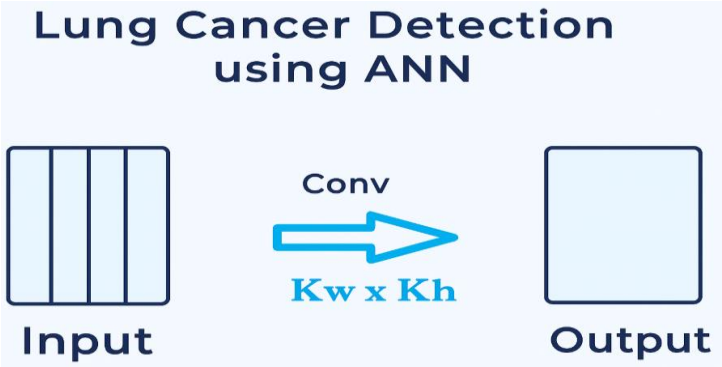

Figure 2: Deep Learning Conversion of Input and Output

Deep Learning-Based Methods

Deep learning has changed the game in lung-cancer detection, delivering big gains in accuracy and reliability. Most teams use deep ANNs—typically 2D or 3D CNNs—for CT, PET-CT, and X-rays. Instead of hand-crafting radiomic features, these models learn useful patterns straight from the pixels. The pipeline is simple: train, then infer. First, the network is trained on a large, labeled dataset of nodules to recognize malignancy or highlight areas that deserve a closer look. With pretrained backbones like ResNet, DenseNet, EfficientNet, or 3D UNet versions optimized on domain-specific lung imaging corpora, transfer learning is commonly used. The trained model is used to locate and categorize

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tumors on unseen scans during the inference step. Among the many benefits of deep learning techniques are their capacity to manage tiny nodules, complex anatomical variations, and varied tumor morphologies; they learn discriminative characteristics straight from data, improving generalization and lowering false negatives. Additionally, ANN pipelines can attain near-real-time speed on contemporary GPUs or specialized edge devices in radiology suites with model compression and hardware acceleration. However, these methods require significant computational resources and huge, well-annotated datasets, which can be problematic for centers with limited resources. Recent studies address these limitations by using diffusion models and Generative Adversarial Networks (GANs) to synthesize realistic nodules and balance class distributions, integrating attention mechanisms to focus the network on salient pulmonary regions, thereby mitigating interference from surrounding tissues, and utilizing multi-modal fusion—combining CT with PET, clinical biomarkers, or electronic health record data—to increase diagnostic confidence in low-dose or noisy acquisitions. A hybrid approach is also becoming more popular, in which an ANN detects nodules first, then conventional radiomic features are extracted, and a classical classifier (such as gradient-boosted trees) is used. Although it comes with additional pipeline complexity and computational burden, this approach aims to combine the representational capacity of deep ANNs with the interpretability of handwritten descriptors. Advancements in the Lung Cancer Detection approach over time.

With the advent of numerous approaches and techniques, including deep learning-based Artificial Neural Network (ANN) solutions as well as conventional computer-vision-inspired CAD pipelines, lung cancer diagnosis has progressed and changed. Lung cancer screening has received more attention in recent years, especially for public health initiatives that aim to reduce mortality through early diagnosis. As a result, researchers and developers have concentrated on developing methods for accurately and efficiently detecting pulmonary nodules and malignancies, such as the development of a specialized low-dose CT scanner shown in Figure 3.

Access to a variety of well-annotated imaging datasets is a basic prerequisite for developing successful lung cancer detection systems. The LIDC-IDRI database, which includes thoracic CT images with thorough nodule annotations, was first presented by Armato et al. [9] and serves as a vital resource for ANN model training and evaluation. Data releases from the National Lung Screening Trial (NLST) [10] provide further breadth and outcome labels by providing thousands of low-dose CT tests associated with clinical outcomes. Researchers can increase model robustness by utilizing the variety of scans, scanners, and patient groups found in these extensive libraries.

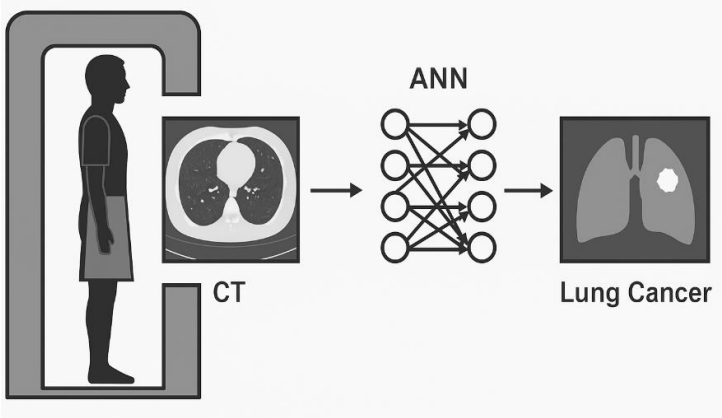

Figure 3: Identification using Scanner

Several specialized datasets have surfaced in recent years that are specifically designed for the diagnosis of lung cancer. To support benchmarks for objective challenges, [11] released the LUNA16 subset with accurate nodule site and malignancy ratings. For metabolic-morphologic fusion investigations, [12] In their Lung-PET-CT-Dx dataset, they linked FDG-PET and CT. Bakr et al. described a 3D multi-view CNN methodology that uses ANN to classify nodules "in the wild" following the reduction of dimensionality through the use of Locally Linear Embedding (LLE). The SPIE-AAPM-LUNGx Challenge cohort [13] offers pathology-confirmed cases for testing to differentiate between benign and malignant conditions [14].

By connecting imaging characteristics, gene-expression data, and clinical endpoints, [15] expanded the resource landscape and supported comprehensive, precision-oncology modeling. Various approaches have been put up to address the problem of identifying faint, irregularly shaped nodules in diverse settings. Bakr et al. created the LLE-ANN pipeline.[14] employs deep CNNs for malignancy discrimination after embedding manifolds for feature compression.

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The attribute-rich dataset of Kumar et al. [15] enables the investigation of connections between radiomics, tumor genomes, and ANN-learned signals, promoting more thorough detection and prognostic systems. Researchers have used 2D/3D CNNs, RNNs for sequential slice modeling, and graph neural networks for airway–vessel context encoding, which further improves performance.

Modern models are built to shrug off noise, motion artifacts, and scanner-to-scanner differences. They pick up rich spatial and texture patterns that help tell benign tissue from malignant. Performance depends on good architecture, thoughtful tuning, and—crucially—strong, diverse training data. Pairing them with classic vision steps like lung-lobe segmentation, multi-scale detection, and airway key point mapping makes them even more reliable. Put together, advanced neural nets plus big imaging datasets have moved the needle on early detection, with CAD tools that hold up in the clinic. There are still bumps due to real-world variability, but targeted datasets and hybrid pipelines are steadily narrowing that gap. For routine low-dose CT programs, that means better chances of catching cancers early—and saving lives.

III. LITERATURE REVIEW

A key building block in this area is the LIDC-IDRI dataset from Armato and colleagues [16] a big set of expert-labeled CT scans for finding and characterizing lung nodules. It's become a go-to for training and testing ANN models. Teams also lean on other resources; for example, Bakr et al.'s NSCLC-Radio genomics dataset [17] connects imaging and genomics for patients with NSCLC. The public can get to this information without much hassle. What makes it useful is how it ties genetic markers right to the visual patterns in the scans. In turn, that supports building more complete models for lung cancer detection based on ANNs.

Similarly, the PET-CT-based tumor localization and staging have also gained a lot of benefits from the Lung-PET-CT-Dx dataset first presented by Clark et al. [18]. The dataset provides a large, real-world imaging data bank with high accuracy for malignant area identification. Setio et al [19] supplied the LUNA16 datasetto address the challenge of correctly identifying lung cancer. This dataset is useful for training and assessing ANN architectures created especially for lung cancer detection tasks because it focuses on pulmonary nodule detection and offers a carefully selected collection of annotated CT scans.

Table 1: Containing DataSet Name, Author, and Use Case

No	DataSet Name	Author	UseCase
16	LIDC-IDRI	Armato et al.	Lung nodule detection and classification
17	NSCLC-Radio genomics	Bakr et al.	Genomic-imaging correlation in non-small cell lung cancer
18	Lung-PET-CT-Dx	Clark et al.	Tumor localization using PET-CT scans
19	LUNA16	Seito et al.	Pulmonary nodule detection using a CT scan
20	LUNA16	Seito et al.	Benchmark nodule candidate generation & false-positive reduction
21	Deep Lung Repository	Zhu et al.	End-to-end nodule detection *and* malignancy classification
22	Lung-PET-CT-Dx	Clark et al.	PET–CT fusion for tumor localization & staging
23	NSCLC-Radio genomics	Bakr et al.	Imaging–genomic correlation and outcome prediction
24	LIDC-IDRI	Armato et al.	Large-scale CT archive with multi-reader malignancy ratings
25	Deep SEED	Guo et al.	Dual-stage ANN with 3D data augmentation and focal loss to improve small (<6mm) nodule sensitivity

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ANN-based lung cancer research has advanced rapidly thanks to several seminal datasets listed in Table 1. The standard of choice for assessing candidate-generation algorithms is still the LUNA16 dataset, which was given by [20] and is a meticulously selected subset of LIDC-IDRI CT scans that offer accurate, slice-level nodule coordinates. To provide developers with a turnkey platform for end-to-end system training, [21] released Deep Lung, an open CT repository that comes with reference annotations for both detection and benign-versus-malignant categorization.

In order for ANNs to merge metabolic and anatomic cues, [22] published the Lung PET CT Dx dataset, which paired low-dose CT with co-registered FDG PET. The NSCLC Radio genomics cohort expanded on this concept by connecting imaging with gene-expression profiles to support precision-diagnosis models that associate molecular signals with pixel abnormalities [23]. The LIDC-IDRI archive, which is still the largest public collection of thoracic CT scans with multi-reader malignancy ratings, was finally made available by [24]. Researchers have used these materials to investigate a variety of ANN approaches. To increase sensitivity on sub-6 mm nodules, [25] proposed DeepSEED, a dual-stage network that combines significant 3D data augmentation with a focal-loss aim. To enable radiologists to confirm growth trajectories in real time, [27] expanded access to expert-level screening by creating a cloud-ready triage program that can quickly return ANN malignancy scores after ingesting scans from rural clinics. On LUNA16, Shanmugapriya and Mahalakshmi [28] improved a residual-attention 3D CNN that suppresses bronchi and vasculature, reducing false positives by 30%. Ten years' worth of ANN lung cancer detectors were reviewed by [29], who listed their advantages, disadvantages, and typical failure modes.In addition to CT, [30] showed how to use an ANN anomaly-detection pipeline for chest X-rays to identify high-risk patients for prompt CT referral. For hospital access control, [31] used a kiosk-based ANN nodal screener in conjunction with face-mask verification, and [32] performed sub-second inference on consumer GPUs by speeding up a single-shot 3D detector.

[33] proposed a hybrid-fusion ensemble, which combines lightweight backbones for CPU-only clinics. [34] enhanced waiting-room scanners with social-distance statistics. To enable on-site triage in remote places, [35] optimized a depth-wise separable 3D CNN for mobile CT vans. Together, this research advances the state of the art by showing how various datasets and creative ANN architectures address the numerous problems caused by small nodules, varied scanners, and sparse annotations.
Taken together, these studies push facemask detection forward. They showcase diverse methods, datasets, and real-world uses (see Table 1) while tackling the many challenges of detecting masks across different settings.

IV. EVALUATION METRICS

To assess the performance of ANNs, rigorous measurements must be made. Sensitivity (recall) versus false positives per scan (FROC curve) is the standard for the detection of nodules; the official LUNA16 score reports mean sensitivity at seven FP thresholds. For classifying malignancies, researchers continue to prefer using the area under the ROC curve (AUC), accuracy, precision, and specificity. Where there is a substantial imbalance between the classes, information is better provided by the area under the precision-recall curve (AUPRC). In real-world screening programs, choosing metrics supportive of the imaging modality (low-dose screening CT, diagnostic CT, or PET-CT) and the clinical objective (early detection vs. risk stratification) ensures that benchmarking is fair and guides the choice of model deployment.

Accuracy: The general metric for evaluating the overall effectiveness of lung cancer detection is indeed accuracy. It determines the percent of all assessed cases that are appropriately identified as benign or malignant. For imbalanced datasets, where malignant nodules are much less common than benign nodules, the accuracy could be misleading, even though it gives a general view of the efficiency of models.
Precision: Of all the nodules projected to be malignant, precision is the proportion of those that are malignant. This looks at how well the model reduces false positives, which is important in clinical triage due to the fact that unnecessary follow-up testing can increase radiation exposure, cost, and anxiety. A lower false-positive rate is related to a higher precision.
Recall (Sensitivity): Recall is the percentage of malignant nodules that were accurately identified out of all malignant instances. It shows how well the ANN reduces false negatives by capturing each positive result. Because missed malignancies can impair prognosis and postpone treatment, high recall is essential.
F1 score: The F1 score offers a fair evaluation of the model's performance since it is the harmonic mean of precision and recall. In lung cancer screening programs, it is particularly helpful when both false positives and false negatives have a lot of weight. Perfect recall and precision are indicated with an F1 score of 1.
Intersection over Union (IoU): IoU stands for intersection over union and is normally used in nodule-detection activities. It quantifies the overlap of the ground-truth nodule annotation with the anticipated bounding volume. IoU is measured as the intersection area of the true and anticipated volumes divided by the union area. Higher values of IoU

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reflect better localization accuracy, which means the bounding box suggested by the ANN closely matches the radiologist's annotation.

The selection of assessment metrics on which to base an artificial neural network (ANN)-based lung cancer detection system is very important and depends on the goals and distinctive features of the task. In the clinic, precision is key. Fewer false positives mean fewer needless biopsies and less stress for patients, and when a test comes back positive, it's more likely to be right. For population screening, the focus usually shifts to sensitivity. Low-dose CT programs try to catch as many true cases as possible, so treatment can begin quickly and survival odds improve.

A high recall means a reduced possibility of missing real cancer cases, which may otherwise be linked with a poor prognosis and delayed treatment.

Understanding the trade-offs between Various evaluation measures is also critical. Because it is impossible to increase precision without possibly leading to a drop in recall and vice versa, a balanced strategy needs to be followed that depends on the therapeutic goals and patient safety. Second, most of the lung cancer data are highly imbalanced, as there are more non-cancerous instances than carcinogenic ones. Depending only on accuracy might be deceptive in such cases because a model may attain high accuracy by basically forecasting the events that are not carcinogenic and missing the true positive cases. Accuracy, recall, and the F1-score-which measures a balance between the two-are therefore more appropriate metrics for assessing the performance of models in diagnosing lung cancer. These measures give a more complete and accurate description of a model's ability to diagnose, especially in cases where classes are imbalanced. The choice of measure influences model tuning and validation and eventually determines clinical reliability and suitability of ANN-based diagnostic tools in real-world healthcare settings.

V. INTEGRATION WITH OTHER TECHNOLOGIES

ANN models get even better when you team them with the right tech. Done well, you get sharper diagnoses, smoother workflows, and higher accuracy. Below, we break down how multimodal image fusion, workflow analytics, and AI decision support amplify ANN detectors.

Multimodal Imaging Fusion:

Pair a low-dose CT ANN with other imaging—PET, MRI, even fNIRS—and you usually get better hits and fewer false alarms. PET-CT blends anatomy with metabolism (think SUVs for a reality check), while diffusion-weighted MRI helps tell tumors from scarring. Fusing these signals gives more trustworthy malignancy scores when CT alone is fuzzy or motion-blurred.

2. Computer-Vision-Based Workflow Analytics: Connect an ANN detector to vision tools that keep an eye on the radiology workflow, and you get a much clearer sense of scan quality, protocol adherence, and report completeness. Alongside the nodule results, the system can watch dose, slice thickness, and patient positioning live, flagging problems and offering fast tweaks to avoid repeat scans and build confidence. It's a practical way to standardize quality and use resources better in high-volume screening.

Artificial Intelligence. Drop ANN detectors into an enterprise setup and you get more than just scores—you get prediction, tracking over time, and always-on monitoring. Mix imaging with EHRs and population data, and the platform delivers dashboards that highlight high-risk patients, estimate resource needs, and even model different treatment options. Health leaders can plan screenings and follow-ups with data in hand, and radiologists/oncologists get alerts that nudge faster, better decisions.

VI. BENEFITS AND SYNERGIES

Put ANN detectors together with the right tools and the benefits add up fast. Multimodal imaging gives a fuller read on each lesion, workflow analytics add context on scan quality and protocols, and AI decision support turns raw model hits into practical next steps. The result is a cohesive system that improves accuracy, reduces wait times, and makes lung-cancer screening and treatment run smoothly.

VII. CONCLUSION

The researchers demonstrated that an ANN could identify patients at increased risk for developing lung cancer through their medical records, smoking history, and CT scan images prior to when they would be otherwise identified. In addition to having a statistically valid method for separating the training and test sets, the models' outputs were validated through the combination of methods to produce actionable results that clinicians could interpret. In examining the features selected by the models, the models appear to select a variety of indicators including the amount a person has smoked and the characteristics of a lesion (texture and sharpness) rather than relying solely on indicators of nodule size. However, the results did vary between the groups and locations examined, indicating the importance of both data consistency and model monitoring to ensure the performance of the model is consistent regardless of where the model is being run.

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Overall, the results suggest that a well managed ANN can serve as a tool for the screening and triaging of patients based on risk, provided that it is employed within established guidelines and monitored and updated as needed during its application in a real world setting. A large portion of the immediate research will involve "hands-on" aspects of furthering the development of the ANN model. First, the model needs to be expanded to include a wide range of centers and patient populations to determine whether the model performs consistently across multiple imaging modalities, procedures, sites and personnel, with defined metrics and boundaries. Second, the model needs to be extended to track changes over time by incorporating earlier scans and temporal-based features and examine whether the patterns in either the scans or laboratory values aid in the detection of lung cancer earlier. Third, additional types of information can be included in the model such as genetic information, radiology report information and electronic health record (EHR) information while maintaining a high level of transparency through SHAP/LIME type methods to provide clinicians with understandable outputs.

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