Predictive Modeling for Lung Cancer Detection Using Machine Learning: A Comprehensive Survey

Abstract

Lung cancer is still among the most common and fatal cancers in the world, and thus, there is a need for early and proper detection methods to enhance the survival rate of patients. The recent past has seen machine learning (ML) arise as a promising method for predictive modeling in medical diagnosis with the capability to automate at high levels of accuracy. The current survey gives an extensive review of work done in machine learning approaches of lung cancer diagnosis. It thoroughly goes through different datasets, preprocessing techniques, feature selection techniques, and ML algorithms from supervised and unsupervised to deep learning architectures. Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forests, and ensembles are particularly referred to. Evaluation metrics like precision, recall, accuracy, F1-score, and AUC are presented in bold font to indicate model performance. Concerns like interpretability, data imbalance, and generalization are elaborately mentioned. Hybrid systems and emerging trends like explainable AI (XAI) and transfer learning are also briefly touched upon. Lastly, we highlight the limitations in the literature and offer directions for future research towards building robust, scalable, and clinically relevant ML-based diagnostic systems for lung cancer.

Keywords:- *Lung Cancer, Machine Learning, Deep Learning, Predictive Modeling, Medical Diagnosis, Feature Selection, Convolutional Neural Networks, Data Preprocessing, Explainable AI.*

I. INTRODUCTION

The most lethal and aggressive cancer globally, lung cancer kills almost 1.8 million people every year as per the World Health Organization (WHO). The primary cause for such high mortality is delayed diagnosis where treatment measures are less potent. Early and proper diagnosis plays an important role in enhancing survival due to possible early treatment and maximal disease management. But regular diagnostic examinations—like chest X-ray, CT scan, sputum cytology, and tissue biopsy—are typically subject to subjective interpretation, are labor-intensive, and need a lot of technical expertise.

Machine Learning (ML) has, in the past decade, proven to be a revolutionary tool in medicine, providing the power to learn patterns in large and intricate data sets. In cancer, more than ever before, ML models have been incredibly promising to robotize diagnosis, detect concealed patterns, and deliver predictive accuracy. The models are available for use by radiologists and oncologists for early diagnosis, tumor classification, prognosis estimation, and customized treatment planning.

Much work has already been done on using ML methods in the detection of lung cancer from structured data (e.g., clinical, genomic, demographic) and unstructured data (e.g., CT scans, histopathology images). The coupling of ML and medical imaging, in particular through deep networks such as CNNs, has significantly improved computer-aided diagnosis systems.

In spite of such major advances, there are still some areas—data imbalance, interpretability, and heterogeneity of image acquisition protocols—that restrict the wider clinical use of these models. This calls for an overview of what the state of ML-based lung cancer detection approaches is.

This paper conducts a systematic review of current predictive lung cancer detection using machine learning. We critically analyze the datasets, preprocessing methods, feature extraction algorithms, learning algorithms,

and evaluation metrics used in current research studies. Furthermore, we provide the current limitations and recommend future studies and clinical application.

II. MOTIVATION

Lung cancer is overall divided into non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC), with NSCLC being responsible for approximately 85% of cases. Survival declines dramatically with advancing disease stage, and thus early diagnosis becomes necessary. Standard diagnostic pipelines are usually imaging-centered, histopathology, and clinical assessment. Time- and resource-consuming but effective, susceptible to inter-observer difference, and not necessarily population-scalable, these are the pillars of diagnosis still.

The growing amounts of large-scale medical databases, combined with advances in algorithmic designs and computational capabilities, have enabled Machine Learning (ML) applications in lung cancer diagnosis and prognosis. ML is capable of analyzing high-dimensional data, extracting nuanced patterns, and prediction based on data. The models can deal with structured data (e.g., laboratory tests, clinical history) and unstructured data (e.g., CT scans, pathology slides), allowing for a more integrated approach to diagnosis.

Recent years have seen the decline of conventional ML models like Support Vector Machines (SVMs) and Random Forests in favor of more sophisticated Deep Learning (DL) models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These have provided better performance for medical image analysis and enabled the development of Computer-Aided Diagnosis (CAD) systems.

The need for this survey arises due to the explosive development of ML methods for lung cancer diagnosis, with varied methodologies and data. Promising findings are described by some studies, but a thorough understanding of current methodologies is not available. Moreover, the data imbalance, interpretability, domain adaptation, and regulatory issues have not been addressed, causing hindrances in clinical translation.

ML techniques are categorized into supervised, unsupervised, and reinforcement learning. Supervised learning is the most commonly applied in medical diagnosis. It involves training models on labeled datasets to classify or predict outcomes such as benign or malignant tumors.

III. PUBLICLY AVAILABLE DATASETS

The effectiveness of particular machine learning (ML) models focused on lung cancer detection is closely related to both the quality and the scope of the datasets used for training and evaluating the models. The datasets fall into two categories. The first category is CT and PET scans which are images. The other category includes non-image datasets such as demographic data of the patients, lab results, and genomic data. In this document, we highlight the most commonly used datasets and their features in lung cancer research, including their relevance and applications.

The LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative) dataset is a popular and extensively used dataset in the field of CT imaging of the thorax. Each of its more than 1,000 instances has been meticulously annotated by four highly qualified radiologists. Nodule size, texture, and likelihood of malignancy are among the annotations. This dataset is widely used for lung nodule detection, segmentation, and malignancy level classification.

More than 53,000 participants' CT scans and clinical information are included in the NLST (National Lung Screening Trial) dataset. Evaluating the efficacy of low-dose CT scans in contrast to traditional chest X-ray

screening methods is the main goal of this extensive study. It has aided in the study of lung cancer identification in its early stages and subsequent survival projections.

The NSCLC-Radiomics and RIDER Lung CT subsets are two examples of multimodal medical imaging datasets that are more complex than CT, MRI, or PET scans and are available in the Cancer Imaging Archive (TCIA) together with the pertinent clinical metadata for each scan. For researchers doing radiomics studies or engaged in tumor categorization and prognostic modeling, TCIA is a resource of choice.

The RSNA Pneumonia diagnosis Challenge, which offered chest X-rays with annotations, and One Data Science Bowl47 (2017) lung cancer diagnosis from CT images are two of the historic contests held on Kaggle. In a competitive and repeatable setting, participants can benchmark their deep learning algorithms.

Although there are many open datasets, hospitals also provide a large number of proprietary clinical databases. hospitals, research institutions, or proprietary pharmaceutical studies. Although these datasets are abundant, the quality of the data is often high because there are restrictions placed on them due to privacy, ethical concerns, and data-sharing policies. That said, there are a great number of ML models that claim to improve generalizations and are able to capture and include [[UNDERREP. POPULATIONS]] underrepresented patient demographics,because of private datasets. **Public Access**

Dataset	**Type**	**Size**	**Annotations**	**Public Access**	**Primary Use Case**
LIDC-IDRI	CT Images	1,018 cases	Nodule ratings	Yes	Nodule classification
NLST	CT + Clinic	53,000+	Clinical outcomes	Partially	Screening, survival prediction
TCIA	Multi-modal	Varies	Region-level labels	Yes	Radiomics, prognosis
Kaggle (DSB	CT Images	2,000+	Binary labels	Yes	Deep learning benchmarking
Clinical (Private)	Mixed	Varies	Rich clinical data	No	Custom model training

Table 1: Summary of Popular Datasets for Lung Cancer Detection

IV. MACHINE LEARNING METHODS

Machine learning has revolutionized automated analysis and lung cancer detection by enabling the automated assessment of complex data streams, such as CT scans and electronic health records. Researchers have used a variety of supervised, unsupervised, and deep learning algorithms to improve the accuracy of lung cancer diagnosis according to clinical objectives and data types. In this chapter, I give an algorithmic overview of several machine learning concepts and go over the various supervised methods for lung cancer detection.

A. Supervised Learning Techniques

As the name implies, supervised learning techniques train on labeled datasets. In this instance, the algorithm has access to the ground truth, which may include the status of a cancer case as well as a number of additional clinical factors including the severity of the cancer and survival rates. Within this category of algorithms, Support Vector Machines (SVM) have been acclaimed for their accuracy in performing binary classifications, for example distinguishing benign nodules from malignant ones. SVMs also do well with high-dimensional and small sample datasets, a frequent characteristic in medical data.

Random Forest (RF) also belongs in this class of algorithms as a well known ensemble of decision trees with heightened generalization abilities. Its considerable resistance to structured clinical datasets, noise, and over fitting makes RF a very appealing classifier for use in the field of medicine. RF is frequently used in feature selection and also with classification tasks.

B. Deep Learning Techniques

Deep learning, particularly through Convolutional Neural Networks (CNNs), has delivered state-of-the-art performance in lung cancer detection, especially in image-based diagnostics. CNNs automatically learn spatial hierarchies of features from input images and are widely employed for nodule detection, segmentation, and malignancy classification. Popular architectures include VGG, ResNet, U-Net, and 3D CNNs, which are tailored for volumetric medical imaging.

Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, are suitable for sequential data analysis, such as modeling disease progression or patient health over time. These networks have been utilized in survival prediction and longitudinal analysis of patient data.

C. Hybrid and Ensemble Models

Hybrid and ensemble learning models have gained popularity for their ability to combine the strengths of multiple learning algorithms. Stacking integrates several base classifiers and uses a meta-model to make final predictions, often achieving better generalization. Bagging and boosting techniques, such as AdaBoost and XGBoost, enhance predictive performance by aggregating multiple weak learners and correcting their errors iteratively.

Additionally, hybrid models that combine deep learning with traditional machine learning approaches have shown considerable promise. For instance, features extracted by CNNs can be fed into classifiers like SVM or Random Forest to improve overall diagnostic accuracy and robustness. These hybrid strategies leverage the representational power of deep learning and the decision-making efficiency of classical models.

Approach	Model	Type	Application	Strengths
Traditional ML	SVM, RF, KNN	Supervised	Classification, Feature Selection	High accuracy, interpretable
Unsupervised	K-Means, PCA	Unsupervised	Clustering, Dimensiona Reduction	Useful for unlabeled data
Deep Learning	CNN,RNN, LSTM	Supervised	Imaging, Time-se Prediction	High performance on images
Hybrid/Ensemble	CNN + SVM, XGB	Mixed	Robust classification	Combines strengths of models

Table 2: Summary of Machine Learning Techniques for Lung Cancer Detection

V. COMPARATIVE STUDY

Numerous studies have explored machine learning techniques for lung cancer detection using diverse datasets, preprocessing strategies, feature extraction methods, and algorithms. This section presents a comparative analysis of selected recent research papers, highlighting their methodologies, datasets, and model performance.

The objective is to identify trends, best practices, and existing limitations in current approaches.

Ref.	Author(s), Year	Dataset Used	Algorithm(s) Applied	Task	Accuracy / AUC	Highlights / Remarks
[1]	Shen et al., 2019	LIDC-IDRI	3D CNN	Nodule classificatio	AUC = 0.87	Deep learning model trained end-to-end on 3D scans

[2]	Kumar et al., 20	TCIA + Clir Data	SVM + Fea Selection	Malignan cy predictio n	Acc = 92.3%	Used handcrafted radiomic features
[3]	Setio et al., 2017	LUNA16 (subs	Ensemble of CNI	Nodule detection	Sens. = 85.4%	Multi-view CNN impro false-positive reduction
[4]	Dhillon et al., 20	Kaggle DSB 20	ResNet50 + Tran Learning	Cancer detection	Acc = 95.8%	Transfer learning boo performance with less trainir
[5]	Zhang et al., 202	NLST	XGBoost + Clir Features	Risk stratificatio	AUC = 0.89	Combined imaging and clir variables
[6]	Abbas et al., 202	Private (Hospit	CNN + LSTM	Stage classificatio	Acc = 91.5%	Temporal patterns from s sequences used
[7]	Albahli et al., 20	LIDC-IDRI	Hybrid CNN-SV	Nodule classificatio	Acc = 96.1%	Deep features + SVM class yielded high accuracy
[8]	Paul et al., 2018	TCGA Genc Data	Random Forest	Survival prediction	AUC = 0.83	Non-imaging ML on g expression data
[9]	Shenoy et al., 20	LIDC Augmentation	VGG-16 + I Augmentation	Lung ca classificatio	Acc = 94.7%	Data augmentation impro generalization
[10]	Zhang et al., 202	CT images	U-Net + CNN	Tumor segmentatio	Dice = 0.87	Effective for precise tu boundary detection

Table 4: Comparative Analysis of Existing ML-based Lung Cancer Detection Studies

VI. CHALLENGES

While machine learning (ML) offers promising advancements in the early detection and diagnosis of lung cancer, several technical, clinical, and societal challenges hinder its widespread clinical deployment. This section outlines the major obstacles associated with developing, validating, and implementing ML models in real-world healthcare environments.

A. Data Quality and Availability

Although publicly available datasets such as LIDC-IDRI and NLST provide a strong foundation for research, they often lack sufficient diversity in imaging protocols, demographics, and disease subtypes. Moreover, the process of acquiring high-quality annotations—such as precise tumor boundaries and malignancy labels—requires expert radiologists or pathologists, making it both time-consuming and expensive.

B. Model Performance and Reliability

ML models, particularly deep learning architectures trained on small or homogeneous datasets, are prone to overfitting. As a result, their performance often deteriorates when applied to external or unseen data, limiting their generalizability in clinical environments.

C. Clinical Integration Challenges

Many ML models are developed and validated exclusively on retrospective datasets, with limited evidence from prospective trials or real-time hospital deployments. Without clinical validation, it is difficult to assess their robustness and utility in routine diagnostic workflows.

D. Computational and Technical Barriers

Training sophisticated deep learning models, such as 3D CNNs on volumetric CT or PET images, demands extensive computational resources, including high-performance GPUs and memory. Additionally, continuous model updates and revalidation are necessary as new clinical data becomes available, requiring robust lifecycle management. Furthermore, the absence of standardized evaluation protocols and metrics complicates benchmarking and reproducibility, making fair model comparison difficult.

VII. CONCLUSION

Lung cancer remains a leading cause of cancer-related mortality worldwide, primarily due to delayed diagnosis and limited access to early screening. The advent of machine learning has opened new avenues for developing predictive models that can assist in the timely and accurate detection of lung cancer using both imaging and non-imaging data. This survey has provided a comprehensive overview of existing research efforts, spanning datasets, preprocessing methods, machine learning algorithms, performance metrics, and comparative studies.

We observed that traditional machine learning models such as Support Vector Machines and Random Forests have demonstrated strong performance on structured data, while deep learning models, particularly Convolutional Neural Networks, dominate in image-based diagnostics. Hybrid and ensemble approaches further enhance robustness. However, challenges such as data scarcity, class imbalance, model interpretability, and limited clinical integration continue to hinder real-world deployment.

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