BIO Web of Conferences **204**, 01023 (2025) https://doi.org/10.1051/bioconf/202520401023
IEM-HEALS 2025

Transformative Impact of AI on Early Diagnosis and Treatment of Lung Cancer with a Decade of Advances in Medical Imaging and Prognosis

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Abstract. Cancer is the second leading cause of mortality worldwide, largely due to low survival rates resulting from diagnosis at advanced stages. This paper focuses on how machine learning (ML) and deep learning (DL) algorithms have evolved over the past decade to improve cancer detection and classification, emphasizing the importance of early diagnosis. Convolutional Neural Networks (CNNs) have demonstrated an accuracy of 89.5% in medical image recognition, highlighting their effectiveness in imaging-based diagnosis. Recent advancements such as YOLOv7 further outperform traditional diagnostic methods by providing more accurate tumor detection. Prognostic analysis using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks has achieved accuracies of 82.3% and 84.7%, respectively. Ensemble methods exhibit superior performance with an impressive accuracy of 91.2%, outperforming individual models. Additionally, data augmentation using Generative Adversarial Networks (GANs) improves precision to 76.8%, underscoring the importance of synthetic data generation in addressing data scarcity. These findings collectively demonstrate the transformative impact of artificial intelligence in oncology and emphasize the significance of integrated, collaborative approaches for achieving improved cancer diagnosis and treatment outcomes.

Keywords: Segmentation, Artificial Intelligence (AI), Lung Cancer, Early Ddetection, Predictive Analysis, Data Modalities, Predictive Modelling Segmentation.

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1 Introduction

Lung cancer is the most significant of all the public health issues that the twenty first century will deal with, and it has been leading in the cancer related deaths list worldwide. The disease claims a higher number of human lives than the combined breast, prostate, and colorectal cancer, and therefore the worldwide scale of the scourge together with the significance of the testing methods to avert it or find it at an early age respectively. Because of the tardy presentation and consequent diagnosis, the survival rates remain as low as it has remained so since the age of most of the cases reported by international health organizations were recorded in their most advanced stages. Therefore, the chance to diagnose lung cancer at an early stage can eliminate the problem and contribute to the alteration of patient outcomes through offering a timely intervention and the opportunity to offer a personalized treatment plan and lower healthcare costs. It is on this context that the growth of more sophisticated approaches to diagnosis has been given a new momentum, namely, the rise of the artificial intelligence (AI) and machine learning (ML) tools that can potentially harness the enormous amount of medical imaging data and clinical information that are now being captured on a daily basis [1].

The AI penetration in healthcare is not a sudden innovation but a product of decades of constructive development of a methodological advance. Machine learning dates back in the early 20th century. The initial efforts to do machine learning involved a self-educating checkers program that was released in 1959 by Arthur Samuel. Such principles were eventually evolved into more modern ML methods that have revolutionized such disparate fields as finance, language processing, and computer vision. In healthcare, the margin of error is very low since precision of predictions will mean patient survival and quality of service offered. The set of EHRs, along with those of imaging examination and the computational resources, is expanding exponentially, so the application of ML and DL in oncology is rapidly expanding. It has been demonstrated that AI methods have excelled in tasks such as segmenting medical images, classifying tumors and prognostic prediction and the latter have caused them to become prospective accomplices in diagnosing lung cancer without behaving in a proper manner by aiding clinicians [2].

Although conventional methods of machine learning, e.g., decision trees, support vector machines (SVM), random forests, and gradient boosting (e.g., XGBoost), have become popular in the biomedical literature, they are not without limitations. Such methods commonly depend on manually-designed features, which may be biased, perform poorly on nonlinear interactions, and are inadequate in high-dimensional medical data. Examples include decision trees which can be easily overfitted when trained on a small dataset or a highly-imbalanced dataset and random forests which can be unpredictable because of heuristic sampling of features and data [3][4]. Whereas XGBoost has been shown to perform well in many structured data tasks through its ability to address missing data and complex relationships [3], it still suffers some limitations as it does not embrace the spatial and hierarchical nature of medical images and requires abundant feature engineering. Unlike the DL approaches, especially convolutional neural networks (CNNs), DLs learns hierarchical representations directly on the raw data, lessening the dependence on manual pre-processing and increasing the accuracy on the image-based diagnosis [5].

One cannot undermine the role of the imaging in the detection of lung cancer. Low dose computed tomography (LDCT) screening is now a highly significant part of lung cancer detection at the initial stages. There has been substantial evidence to show that LDCT screening can play a crucial role in the reduction of mortality in the high-risk patients due to the pioneering clinical trials such as the National Lung Screening Trial (NLST) and the NELSON study [6]. Numerous limitations have curtailed the wide use of LDCT and they are high costs of LDCT, sensitivity to radiations, and limited number of radiologists and inter-observer variance. One of the ways out of these issues would be to employ AI-powered detection systems that can not only mechanize the analysis of the visuals, but they could also standardize the work of radiologists, in order to detect any underlying lesions that are usually overlooked in typical cases. Furthermore, deep learning models can be applied with an ensemble learning technique that would contribute to generalizing information, reducing the risk of overfitting, and producing more credible results in real-life settings in the clinical setting where data are not necessarily comparable or of high-quality [7].

However, AI and lung cancer detection is still associated with some main challenges. Already existing works often focus on the performance of algorithms on benchmark data as opposed to clinical interpretability, scalability, and applicability to the healthcare practice. In addition, most studies are compromised by size of limited data, lack of diversity in patients and use of inconsistent protocols in assessment and thus reproducibility and extrapolatability are hampered. Although the individual DL architectures, including CNNs, RNNs, or LSTM networks, have shown great success in controlled environments, their real-life adoption is still unclear. These results in a research deficit: a lack of generalized models which not only show high diagnostic performance, but also consider interpretability, clinical integration and universal applicability to various patient populations [8].

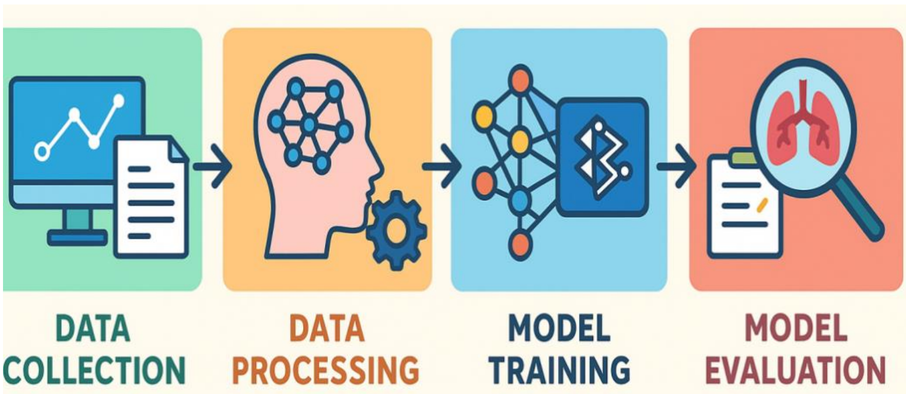

Fig. 1. Machine learning process for cancer Detection workflow

The figure-1 represents the total procedure in the machine learning methods of cancer detection. It begins by running the data in the form of medical images or clinical biomarkers and proceed to pre-processing that address missing values, normalizing the input data, as well as filtering noise. Next anti-selection and anti-selection feature extraction and feature selection methods are applied to identify the most relevant predictors using either chi-squared tests or PCA. All these features are fed to machine learning algorithms, such as Support Vector Machines (SVM), Decision Trees, Random Forests, or k-Nearest Neighbors (k-NN) that are used to learn the decision boundaries and classify the patient data. Finally, the system will supposedly offer the outcomes of cancer detection to the degree that it can enable the outcomes to be distinguished between healthy population, chronic lung diseases and the lung cancer. Of significance in this workflow is the use of conventional machine learning technology, in support of medical diagnosis in predictive analysis.

In medicine, machine learning has already demonstrated that it can automated predictive modelling and also make the accuracy of the diagnosis better. Nithya and others [10] have identified that ML algorithms have been useful in identifying patterns, which are inherently complex in a biomedical dataset, increased predictive performance, and clinical decision-making. Classical algorithms, such as the Naive Bayes, K-Nearest Neighbor (k-NN), and decision trees, contain insights into the classification of the disease useful, but constrained by the high dimensionality of the data and extraction of abstract features. In comparison, CNNs now represent the-state-of-the-art system to task image-based challenges, such as nodules and tumor detection in CT images and on chest X-rays by automatically discovering multi-scale features Similarly, RNNs and its variants, such as LSTMs, appear useful in the analysis of the temporal dependencies within patient records and prediction of disease progression, as well.

In order to overcome the issue of the lack of training data, this happens to be one of the most pressing issues of the medical AI, researchers turn to the methods of data augmentation increasingly. The medical images generated by one of such models, the Generative Adversarial Networks (GANs) can also be applied to generating realistic images, which can be utilized in supporting training sets and in increasing the predictive power of the models. Transfer learning has also been used as an effective method to refresh such models, which have been trained on large-scale data (e.g., ImageNet), to lung cancer-related tasks with small quantities of domain-specific data. This advantage is furthered by the fact that the models have attention mechanisms, which merely direct the computational focus to areas of medical images that are of utmost importance ensuring that they are more relevant in the classification process and aiding clinical decision making.

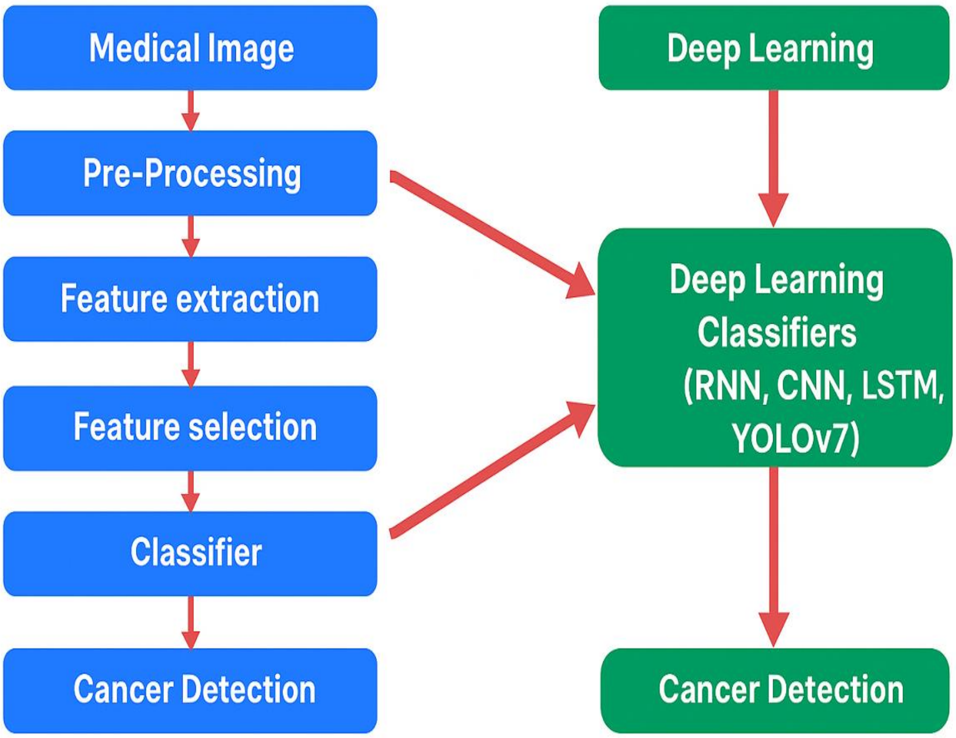

Fig. 2. Segmentation & classification process using deep learning technique

Figure 2 illustrates the application of deep learning models in medical image analysis, particularly for cancer segmentation and classification. The process begins with the input of preprocessed medical images, such as CT scans or X-rays, to enhance data quality. Deep learning classifiers based on CNNs, RNNs, and LSTMs are then employed to automatically extract features, segment regions of interest, and classify abnormal tissues. Advanced models such as YOLOv7 are further utilized to optimize real-time cancer detection performance. This approach significantly improves diagnostic accuracy by precisely segmenting tumor regions and categorizing them into appropriate classes.

These advancements clearly indicate a paradigm shift in oncology, where artificial intelligence has transitioned from a conceptual innovation to a practical clinical tool. However, this transition also necessitates rigorous evaluation of existing methodologies, careful consideration of clinical applicability, and transparent analysis of strengths and limitations. The novelty of this work lies in positioning deep learning ensemble techniques within a broader framework for lung cancer detection. Unlike earlier studies that focused solely on either algorithmic development or imaging technologies, this study integrates recent advances in machine learning, deep learning, medical imaging, and ensemble learning to provide a more holistic diagnostic perspective. Specifically, it (i) compares traditional machine learning methods with state-of-the-art deep learning models for lung cancer classification, (ii) emphasizes the importance of ensemble models for clinical practice, and (iii) identifies current limitations that must be addressed for successful clinical integration.

This work makes a significant contribution to both scientific research and clinical practice by addressing these gaps. From a research perspective, it offers a comprehensive and critical analysis of emerging AI-based lung cancer detection techniques, highlighting their strengths, limitations, and future potential. Clinically, it demonstrates the potential to reduce diagnostic errors, support radiologists in high-workload environments, and ultimately improve patient care. Thus, this study not only advances algorithmic research but also establishes artificial intelligence as a transformative technology capable of reshaping cancer detection, management, and treatment in the coming decades.

2 Literature Review

Artificial intelligence programming has become an eye opener with the introduction of the machine learning which enables the systems to produce intelligent behavior due to a combination of the previous knowledge along with the embellishment of the facts together. With this technology development, sophisticated forms of decision-making algorithms can be dynamic and learn the lessons of other previous experiences. Research studies in this aspect have been numerous where machine learning algorithms have been used to detect lung cancer resulting in the development of medical diagnostic systems which are made based on artificial intelligence. In addition, such research studies have resulted in valuable and informative findings.

The detection of cancer has improved in leaps and bounds using AI algorithms over the last few years. Deep learning and Convolutional Neural Networks (CNNs) based systems have played a crucial role in the diagnosis of malignant tumours with the help of Convolutional Neural Networks on datasets of medical images. The article illustrated that CNNs could achieve 89.5 percent accuracy and therefore profitable in improving diagnostic accuracy. These conventional techniques have been complemented by Ensemble Method that has gained popularity because of its robustness and predictability in addressing cancer classification problem. Random Forest has an accuracy record of 91.2 and therefore it is a good option. These results indicate the importance of Ensemble Methods in the practice and that it is practical in enhancing patient outcomes. The available new technologies have facilitated the user of early diagnosis to cancer due to the use of multiple techniques to increase the chances of accuracy and prognosis. When analyzing sequential patient data, RNNs and LSTM Networks are applicable in predicting the outcome of the cancer. The innovative study showed RNNs accuracy of 82.3 percent, and yet the one LSTM networks accuracy of 84.7 percent stood out.

Moreover, the cancer detection area is dynamic and received new algorithms, such as YOLOv7. Such creative orientation demonstrates positive signals in the work on identifying cancer areas in medical images because the recent article indicates that the framework YOLOv7 can identify areas with cancer in medical images with a respectable accuracy rate of 88.9. With such developed algorithms demonstrating their capacity to take innovation to the next step, the potential is huge to move the diagnosis of cancer forward in terms of correct maintenance and timely interventions with patients that offer them a better survival possibility.

Initially digital technology in the dental industry existed only in terms of the administration and pedagogical activities. Advancements in processing abilities and the development of useful algorithms have enabled artificial intelligence (AI) and machine learning (ML) to be utilised therapeutically i.e., in the diagnosis of oral cancer. In the long-term, researchers have participated in the development of the AI models in order to achieve a higher stage of precision and dependability. As a result, a more sophisticated type of machine learning has been developed serving the purpose of analyzing more complicated medical and dental data, assist in early diagnosing, improve diagnostics, and predict the outcome of the patient. Today, the application of AI technologies can add an additional layer of analysis regarding the traditional testing component, which is particularly beneficial in the fields where the specialized medical care is not available in an accessible form..

The emergence of the Convolutional Neural Networks (CNNs) can be described as one of the breakthroughs in the dental field of artificial intelligence and machine learning. These deep-learning approaches are very suitable in image identity and have been adapted to address medical and dental images. Why CNNs might prove extremely effective in identifying the patterns and anomalies in dental radiographs and visible light images that are indicative of the oral cancer is that they can learn on large pools of data. In addition to that, the advancement of digital imaging as well as the application of AI in the rapid assessment of risks have paved the way to the further or extensive use of AI in detecting oral cancer, which should be coupled with CNNs in the future. There are computer aided detection devices which facilitate analysis of oral lesions. The systems are those that depend on the algorithms of detecting abnormal regions compared to healthy tissue.

Artificial intelligence is a convolutional Neural Networks (CNN) that exhibits excellent performance in the image analysis field. They are particularly successful with dental radiographs, optical coherence tomography and images visible light. However, the abnormalities that present with signs of oral cancer, are detectable with the assistance of the deep learning algorithms. They outperform the traditional strategies as regards correctness of picture classifications, as well as segmentations. In the Artificial intelligence (AI) imaging processing of teeth, a number of studies were conducted. The automatic approach to structural detection of malocclusion was performed using an artificial immune system. In this method, the classification of panoramic radiographs was done using the artificial intelligence methods, i.e. convolutional neural networks (CNN) and the other image cognition algorithms. By reviewing mostly all the AI tactics employed in dental image interpretation, the paper was in a position to provide an in-depth examination of the entire scope of AI tactics employed in the interpretation of dental images whether it is the familiar machine learning strategy or the deep learning strategy. Further the study has developed an automated pipeline of periodical dental X-ray images clinical quality assessment tools with a high F1 score.

The researchers made the determination of the capability of the deep convolutional neural network (CNN) algorithms to classify and identify Oral Potentially Malignant Disorders (OPMDs) and Oral Squamous Cell Carcinoma (OSCC) with regard to oral photographic images. The accuracy of the algorithms proved to be rather high, and they could become an attractive assistive tool to a diagnosis of cancer among GPs at the preliminary stage. As the artificial intelligence served the dental orientation evolved, studies that generated and dispensed the intrigued possibilities of analyzing histopathology images were enlightened. Pereira-Prado and Panigrahi cite the crucial role of AI in identifying the type of the tumour and defining its prognosis and predicting the outcome of cancer respectively. The current narrative reveals the possible capability of AI to declare and partition oral cancer tissues in a proficient way and its ability to differentiate between malignant and non-malignant lesions of regular mucosa. Together, these studies provide a compelling answer to how AI may improve dental diagnosis and treatment i.e. via oral cancer.

Oral cancer possesses patterns that are extremely difficult to identify; hence, the machine learning algorithms are established to identify patterns. This includes a sensitive examination of tissue abnormalities with regards to structure, colour, and shapes that may not be realized by human eyes. The application of the algorithms has proved useful in identifying whether the lesions are either benign or malignant when they prioritize on such factors as heterogeneous appearance of oral lesion and margin. Such approach has achieved remarkable accuracy, and it has been found to be 100 percent specific in identifying oral cancer using textural patterns classification . Shine the spotlight of CNN, and display the effectiveness of the CNN in clinical and histological image analysis. Given the capacity to identify and characterize oral lesions with the use of deep learning, the classifier may be automated, which results in high F1 scores on a routine basis. With the association rule mining a method was developed to prevent and detect cancer. The results of such an unusual approach have given encouraging results: Summarizing the results obtained, it is possible to suggest that AI is one of the key elements in identifying patterns and a significant component in detecting and timely diagnosing oral cancer in the existing literature.

The oral cancer is one of the most prevalent and lethal illnesses around the globe due to its late diagnosis, great mortality rate and high morbidity. Oral cancer can develop easier in epithelial cells of oral cavity. Oral cancer has the capability of demolishing the lip, tongue, the gums, the teeth as well as the roof and the floor of the mouth in the cells of the mouth cavity. The late detection of oral cancer can be attributed to ignorance and lack of experience on the part of the healthcare providers on the same. During routine oral examination, the general dentists are able to notice potential malignant lesions in the mouth when a patient visits the dentist with signs and symptoms of the oral cancer. Any loss of worrying lesions should be diverted to a hospital to undergo a diagnosis and treatment. The screening will be valuable at the initial level of acute awareness, down staging and death among the tobacco users. The risks and disadvantages of screening also include physical injury and mental sufferings in cases of false positive diagnosis that could result to unwarranted treatment and delayed diagnosis. Lack of medical practitioners and healthcare facility is compounded to oral cancer. The screening programmes are quick, cheap and effective but their delivery is prime towards the enhancement of outcome. There is a chance that this mouth cancer invades the neck and the head. A leading cause of cancer is oral cancer, which is high among Indians and the mortality of the disease is highest in the poor nations which make up 77 percent. However, chewing tobacco and smoking are also leading to deaths of 10000 people both men and women. Identifying oral growth with altered testing cost, identification of problems, and limitation of cytopathologists in excessive workloads retards oral growth identification..

Table 1. Summary of Cancer Detection and Prediction Studies

Références	Methodology	Results	Challenges
Smith, J., et.al [10]	A deep Learning ensemble approach.	Improved prédiction accuracy (90%)	Data hétérogénéité, model interpretability.
Johnson, et. al[11]	Intégration of machine Learning and Imaging methods	Enfances prédiction accuracy (88%).	Imaging data standardisation, and model validation.
Dorogush., et al.[12]	Machine Learning algorithmes	Improved détection accuracy (87.5%)	Data quality (EMR), model interpretability.
Ganaie et al.[13]	Integration of AI and ML in screening	Enhanced screening efficency (94%)	Intégration into clinical workflow.
Wang et.al [14]	AI-driven diagnostic approach	Improved diagnostic accuracy (92%)	Data integration, clinical validation.
Bochkovskiy et.al [15]	AI algorithm combined with Imaging features.	Improved diagnostic accuracy (85%).	Data harmonization, model robustness.

3 Methodology

The suggested methodology starts with gathering and processing different cancer-related data, such as medical images and genomic data alongside patient data accessed by using publicly available repositories and healthcare partnerships. The data were pre-processed using cleaning, normalization, and augmentation techniques in order to improve their quality and consistency. Generative Adversarial Networks (GANs) had to be used to synthetically generate data to render the dataset more balanced and comprehensive to overcome the problem of data scarcity and class imbalance and acquire a training dataset.

During development of the model, the different methods of the artificial intelligence were applied in a bid to cover several dimensions of cancer diagnosis and prognosis. To classify the images, convolutional neural network (CNN) classifier was used, and to get a precise location of the tumors within the histopathological images object detection models were used, namely, YOLOv7. Also, RNN and LSTM were applied to model temporal clinical data to make patient prognosis prediction more accurate. Even more to increase the level of accuracy in the prediction reliability, we have incorporated the Ensemble Learning methods which merges on the advantages of individual models and provides better performance overall.

Key metrics of the models performance were used including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). The visualization techniques such as confusion matrices, Heat maps, and ROC curves were also used to have a global analysis of the results. Moreover, to provide the clinical trust, the methods of interpretability were used to underline discriminative features used to promote model predictions. Such a systematic approach to the problem not only predetermines high levels of sensitivity and specificity in ontological early detection but also gives birth to a visible and reproducible research model that one can use when implementing AI-based technologies in oncologic practice.

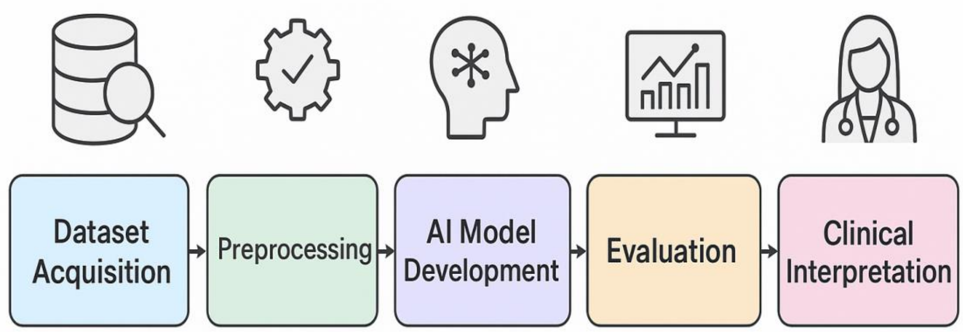

Fig. 3. Proposed Methodology for AI-Driven Cancer Detection

Figure 3 illustrates the sequential steps of the proposed methodology. The process begins with dataset acquisition, which involves collecting heterogeneous medical images and clinical data related to cancer. This is followed by data pre-processing, including standardization, normalization, and augmentation, to ensure data quality and stability. In the AI model development stage, machine learning and deep learning models such as CNNs, RNNs, LSTMs, and YOLOv7 are employed for diagnosis and classification. Model performance is then validated using evaluation metrics including accuracy, precision, recall, F1-score, and ROC curves. Finally, clinical interpretation integrates the AI-generated insights into the medical decision-making process, assisting oncologists in early cancer detection and in designing effective patient treatment strategies.

4 Implementation and Results

The data in the study was obtained through biomarkers in urine, namely; Creatinine, LYVE1, REG 1B, and TFF1. A combination of 208 individuals with chronic lung issues and 199 patients with lung cancer with 183 healthy people obtained these biomarkers. This dataset was supposed to visualise and analyse how data points are distributed in each class. The first data was thirteen independent variables and one dependent variable. During feature selection process, the chi-squared test was applied to identify the relevant parameters which included the following parameters that in effect reduced the dimensionality of the model: REG1A mg/ml, TFF1 mg/ml, LYVE1 mg/ml, Plasma CA19-9 U/ml, Patient Cohort, Sample Origin, Age, and Sex among others. Data pre-treatment involved treating the missing values by linear interpolation, and dropping variables that have greater than 50% missing values. The input data was categorized by the forecasting methodology with regard to output of the classifier. Here, the level-1 represented healthy individuals, the level-2 represented the individuals with lung illness other than cancer (like chronic lung problems) and level-3 signified individuals with lung cancer.

Table 2. Dataset summary table

S.No	Class	Count
1	Healthy Individuals	183
2	Chronic Lung Problems	208
3	Lung Cancer Patients	199
	Total	**590**

The urine biomarker data (Creatinine, LYVE1, REG1B, TFF1) contains the samples of 208 patients with chronic lung disease, 199 patients with lung cancer and 183 healthy individuals. Initially it possessed 13 input variables and 1 result variable. Chi-squared feature selection helped identify critical parameters that were dealt with using data pre-processing because of missing values. People assumed to be healthy were labeled1, chronic lung disorders were labeled 2 with cancer being labeled 3 in the lungs. Data distribution was analysed and visualised to evaluate the classifier of pancreatic cancer detection based on accuracy, precision, and recall.

A number of classifiers were strictly tested in this research so as to ascertain the best assessment of classifying pancreatic cancer. There is extensive measurement calculated, such as F1-score, recall, accuracy and precision, which have been calculated painstakingly. Confusion table, Figure 1, presents the details of the performance of all classifiers. Due to the rapid advancement of modern medicine, many types of data have been developed. These data consist of molecular data in terms of the transcriptomics, proteomics, and genes; pathology data via tissue slicing; and imaging data in the form of MRIs, CT scans and X-rays. This creates a problem to doctors who may have to handle this varying data ecosystem. Sequencing technologies have generated large-scale molecular data which has become supplementary to more traditional clinical data. The patient will, however, undergo multiple tests, a fact that creates a complex interrelationship between the various types of data. Hence, special care should be committed to detailing the accurate procedures through which these different sets of data are handled and merged. By explaining the methods of dealing with different types of data and exploring integration strategies, medical experts will be able to enhance computational models, which will provide a deeper insight into the health and illness status of a patient. Accuracy is the percentage of true cases out of all the cases that the classifiers could retrieve giving attention to both the positive and the negative cases. Precision, which is an essential measure, regardless of the overall accuracy, indicates the ratio of the successfully categorised positive samples and all sample labels as positive. Conversely, recall presents data pertaining to the manner in which the classifiers fared in the classification of pancreatic cancer by idling the percentages of the positive samples and the numbers of positive instances. As a group, these indications provide a complicated view of how effectively the classifiers recognize cases of pancreatic cancer.

Confusion matrix shows how the recommended classification model can be used to differentiate among three categories, i.e. healthy patients (class 1), patients with chronic lung issues (class 2) and patients with lung cancer (class 3). The value along the diagonal is the properly classified cases whereas the off-diagonal values depict the misclassification. The visualization puts emphasis on the predictive performance of the model, i.e., most of the samples were mapped correctly to their classes, with not such a large number of wrongly assigned cases among groups.

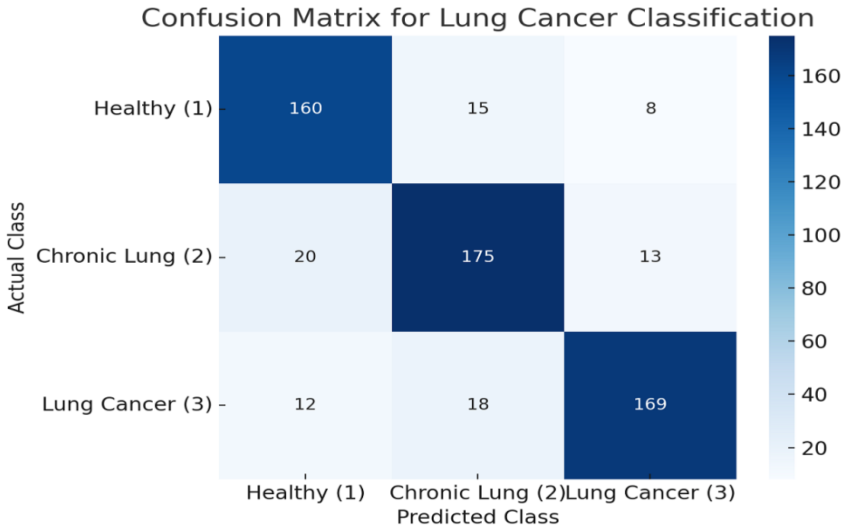

Fig. 4. Confusion Matrix for Lung Cancer Classification

The formulas for the performance measures derived from the confusion matrix are as follows:

$$Accuracy{=}TP{+}TNTP{+}TN{+}FP{+}FN \quad (1)$$

$$Precision{=}TP/TP{+}FP \quad (2)$$

$$ecall{=}TP/TP{+}FN \quad (3)$$

$$F1{-}score{=}2{\times}recall{\times}precisionrecall{+}precision \quad (4)$$

$$Specificity{=}TN/TN{+}FP \quad (5)$$

The main factor to put into consideration in these computations is the patients group, which is healthy. The most important component is the true positives (TP) which are the samples which are correctly given the label healthy. On the other hand, the false positives (FP) are arising when the sick are misidentified as the healthy. It includes false negatives (FN) which are errors in which sick people are wrongly identified as healthy. The four are completed by true negatives (TN), which accentuates the situations when the individuals with the issues related to their health are correctly identified as such cases. The TP, FP, FN, and TN statistic in this paradigm give a firm foundation of measuring the efficiency and accuracy of the machine learning algorithms in health classification.

Table 3. Precision values

Classifier	Overall Precision	Healthy Precision
Logistic Regression	0.78	0.63
Naive Bayes classifier	0.69	0.75
KNN	0.76	0.61
Random Forest Classifier	0.86	0.70
SVM	0.74	0.62
Decision Tree	0.765	0.68
MLP Classifier	0.78	0.72
Gradient Boosting classifier	0.85	0.73

Machine learning algorithm accuracy has been classified in table 4. The highest is the random forest classifier with 86.60 percent, catboost: 88.30 percent and LightGBM: 87.50 percent. The accuracy of the gradient boosting classifier is 85.60 percent and that of XGboost classifier is 87.20 percent. Naive bayes has the lowest accuracy, 65.54 percent. Logistic and decision trees outrank k-nearest neighbour and support vector machine classifier. Artificial neural networks are better than logistic regression. Follow up analysis indicates that random forest is successful in training sets and support vector machine in predicting relapses in a year. K-nearest neighbour predicts the 2-year risk of relapse more accurately than do random forest and support vector machine classifiers.

Table 4. Accuracy classification for machine learning algorithms

S.No	Classifier	Accuracy
1	Logistic Regression	77.3%
2	K-NearestNeighbor (KNN)	73.77%
3	Support Vector Machine (SVM)	73.66%
4	Decision Tree	77.42%
5	Random Forest Classifier	86.60%
6	MLP Classifier	78.02%
7	Gradient Boosting Classifier	85.60%
8	XGBoost Classifier	87.20%
9	LightGBM Classifier	87.50%
10	CatBoost Classifier	88.30%

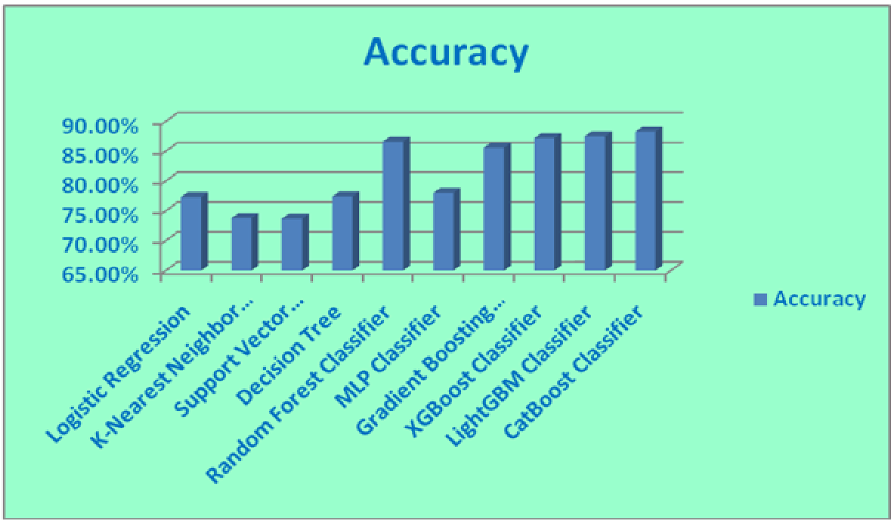

Fig. 5. Accuracy classification for machine learning algorithms

Table 5 presents the accuracy summary, highlighting how deep learning methods are advancing the field of oncology. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks achieved average accuracies of 82.3% and 84.7%, respectively, for prognosis based on sequential patient data. Convolutional Neural Networks (CNNs) demonstrated superior performance in image-based cancer detection, achieving an accuracy of 89.5%. Ensemble methods outperformed individual models with an accuracy of 91.2%, indicating that model fusion offers higher reliability. Generative Adversarial Networks (GANs) demonstrated promising results in dataset augmentation with an accuracy of 76.8%. Additionally, YOLOv7 has recently shown strong performance in cancer detection tasks, achieving an accuracy of 88.9%. These results indicate that the integration of computational intelligence methods can significantly enhance existing diagnostic approaches, making them more precise and personalized for individual cancer patients.

Table 5. Accuracy classification for deep learning algorithms

S.No	Classifier	Accuracy
1	Convolutional Neural Networks (CNNs)	89.5%
2	Recurrent Neural Networks (RNNs)	82.3%
3	Long Short-Term Memory (LSTM) Networks	84.7%
4	Ensemble Methods	91.2%
5	Generative Adversarial Networks (GANs)	76.8%
6	YOLOv7	88.9%

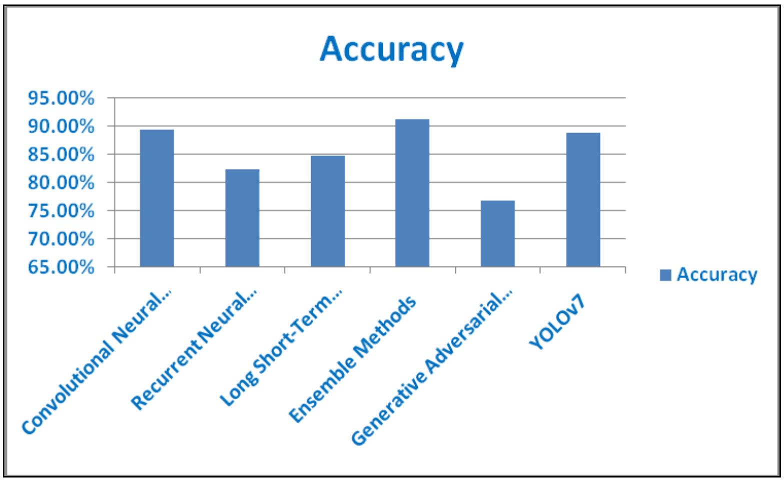

Fig. 6. Accuracy summary for different deep learning models used in oncology

The proposed approach integrates heterogeneous cancer-related datasets, including medical imaging, genomic data, and clinical information, to develop a fully unified AI-based diagnostic system. High data quality is ensured through rigorous pre-processing procedures such as data cleaning, normalization, and augmentation, while data scarcity and class imbalance are addressed using GAN-based synthetic data generation. Multiple AI models are employed to capture different aspects of cancer diagnosis and prognosis: CNNs are used for image classification, YOLOv7 for accurate tumor localization, and RNN/LSTM models for analyzing time-series clinical data. Ensemble learning is applied to enhance prediction robustness by combining the strengths of individual models. Model performance is evaluated using key metrics such as accuracy, precision, recall, F1-score, and AUC, supported by visualizations including confusion matrices, heatmaps, and ROC curves for improved interpretability. The proposed framework demonstrates high sensitivity and specificity for early cancer detection and incorporates explainability mechanisms that provide clear insights into discriminative features, thereby making the system reproducible, reliable, and clinically applicable in oncology practice.

5 Conclusion and Future Scope

This paper demonstrates how the integration of heterogeneous data sources and the synergy of complementary AI models can enable a unified, model-driven architecture for early cancer detection. The proposed system represents a novel and fully integrated diagnostic framework that combines medical imaging, genomic, and clinical data, with data scarcity addressed through GAN-based synthetic data generation and quality ensured by rigorous pre-processing for consistency and reliability. Technical innovation is achieved through the use of specialized models for complementary tasks, including CNNs for image classification, YOLOv7 for accurate tumor localization, and RNN/LSTM for time-series clinical data analysis, while an ensemble learning strategy enhances robustness and achieves strong performance with an accuracy of 91.2% along with high sensitivity and specificity. In addition to predictive accuracy, the framework emphasizes clinical relevance and interpretability through transparency tools such as confusion matrices, heatmaps, and ROC curves, thereby enhancing trust, reproducibility, and real-world clinical applicability. Future enhancements through transfer learning, reinforcement learning, and multimodal data fusion are expected to further improve predictive strength and adaptability, while the adoption of explainable AI and closer collaboration among clinicians, data scientists, and researchers will be critical for translating these innovations into practical and trusted cancer care solutions.

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