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Multimodal Deep Learning for Lung Cancer Analysis Using Data Visualisation

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Abstract*: *Lung cancer is still one of the leading causes of cancer deaths worldwide. Early and accurate risk prediction can help doctors make better decisions and improve patient outcomes. In this work, we develop a deep-learning framework that combines clinical records, imaging features, and survey data to predict lung cancer and its prognosis. For imaging, we use pretrained convolutional neural networks to extract features from CT and X-ray images. For clinical history, we use recurrent models, and for structured data, we apply gradient-ensemble models. We combine these features into a fully connected layer and fine-tune the model end-to-end. We test our model on several open datasets, including Kaggle lung CT sets, IQ-OTHNCCD, and a diagnostic survey dataset. We report accuracy, precision, recall, F1, and ROC-AUC. To ensure a fair evaluation, we use stratified cross-validation, tune hyperparameters, and run ablation studies to see how each data type contributes. Our combined model consistently outperforms both image-only and tabular-only models. It improves ROC-AUC and F1 scores and reduces false negatives, which is especially important for diagnosis. We also provide interactive visualisations in Looker Studio to show which features matter most, how risk is distributed, and confusion matrices, helping clinicians understand the model. We use statistical tests to confirm our improvements and discuss ways to make predictions more understandable for clinical use. Our results demonstrate that combining different data types enhances accuracy and provides valuable insights that support informed clinical decisions. We also discuss limitations, such as differences between datasets and label noise, and suggest further experiments and external validation to move closer to clinical use.

Keywords:* *Machine Learning, Artificial Intelligence, Convolutional Neural Network, Recurrent Neural Network, Receiver Operating Characteristic, Area Under the Curve, Computed Tomography, Comma-Separated Values.

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Nomenclature:

MLP: Multi-Layer Perceptron
CNN: Convolutional Neural Network
ML: Machine Learning
AI: Artificial Intelligence
CNN: Convolutional Neural Network
RNN: Recurrent Neural Network
ROC: Receiver Operating Characteristic
AUC: Area Under the Curve
CT: Computed Tomography
CSV: Comma-Separated Values

I. INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related deaths worldwide, and it plays a significant role in cancer diagnoses and deaths [1]. To improve patient outcomes and survival rates, doctors need to detect the disease early and make rapid predictions about its progression [2]. Recent developments in machine learning (ML) and artificial intelligence (AI) have passed. The way for predictive models to help with fast diagnosis and create personalised treatment plans [1],[3]. By merging all real-world data with machine learning techniques, healthcare has seen notable improvements in predicting lung cancer risk and hospital stay duration [6], [7]. Data visualisation also plays a crucial role in understanding the underlying patterns and relationships in complex data [9]. This paper uses Looker Studio to create interactive dashboards and visualise data, including patient demographics, survival, and risk factors. Looker Studio's powerful visualisation tools make it easy to view and analyse model predictions, helping healthcare professionals achieve fast results and identify trends. By clearly and easily presenting complex data, visualisation supports decision-making and ensures transparency in healthcare analytics. These advances present significant challenges that remain, particularly in achieving high prediction accuracy while reducing bias and error. To tackle these issues, ensemble methods and deep learning models show promise. They have given strong forecasts for lung cancer outcomes [11], [5]. Also, doctors need to understand model outputs to make informed choices. This makes explainability key for clinical use [10]. This focuses on developing a multimodal machine learning system to predict lung cancer outcomes using diverse data types. By integrating structured clinical information with unstructured text, the model aims to enhance prediction accuracy and provide clear, actionable insights to support doctors in making informed decisions.

II. PROJECT OVERVIEW

The project aims to apply multimodal machine learning techniques to analyse lung cancer data, leveraging extensive data management and Looker Studio for visualisation. The goal is to combine various types of data, such as clinical information, imaging features, and genetic markers, to improve the accuracy of lung cancer predictions.

III. LITERATURE WORK

Kourou et al. (2020) presented a machine learning model for lung cancer. The authors applied a CNN to the lung cancer dataset collected from Kaggle. The authors discussed the performance of the proposed model using precision and accuracy [2]. Kourou et al. (2015) proposed a machine learning model to predict cancer prognosis. The authors applied machine learning techniques to cancer datasets and reported the performance

using various measures [1]. Yang et al. (2022) presented a machine learning framework to predict recurrence and survival from lung cancer. The authors employed machine learning approaches on individualised lung cancer datasets and evaluated the model using precision and accuracy parameters [2]. Shmatko et al. (2022) proposed an artificial intelligence model for histopathological investigation. The authors employed AI strategies to enhance research on cancer and clinical oncology, discussing performance improvements [3]. Mithoowani and Febbraro (2022) presented a summary of non-small cell lung cancer for general practitioners. The authors discussed emerging trends and issues in the treatment of lung cancer [4]. Chauhan et al. (2020) presented a machine learning-based model for the diagnosis of lung cancer. The authors applied machine learning algorithms to routine blood indices and tested the model's performance [5]. Chandran et al. (2023) proposed a machine learning model for lung cancer risk prediction. The authors performed real-world data analysis and compared model performance using risk prediction metrics [6]. Alsinglawi et al. (2022) proposed a machine learning model to predict hospital length of stay for patients with lung cancer. The authors dealt with model interpretability and performance metrics [7]. Earnest et al. (2023) presented a machine learning model for predicting the timeliness of care for lung cancer patients. The authors discussed model performance based on patient care outcomes [8].

Valentine et al. (2022) published a study on illness perception profiles for late-stage non-small-cell lung cancer. The authors described psychological and physical symptoms in incidentally diagnosed patients [9]. Nahm (2022) presented an overview of receiver operating characteristic (ROC) curves. The author presented the practical usability of ROC and AUC metrics in medical studies [10]. Pokkuluri et al. (2022) proposed a deep learning model for lung cancer prediction. The authors employed a non-linear CA mechanism and discussed model accuracy and stability [11]. Venkatesh and Raamesh (2022) proposed a cast learning method for lung cancer prediction. The authors applied the technique to SEER data and evaluated model performance [12].

Faisal et al. (2018) proposed a comparative analysis of machine learning classifiers for early-stage lung cancer prediction. The authors discussed model performance in terms of accuracy and ensemble methods [13]. Patra (2020) proposed a machine learning model for lung cancer prediction. The author used various classifiers and compared their performances based on predictive accuracy [14].

Qureshi et al. (2022) proposed a machine learning model to predict individualised drug response in lung cancer patients. The authors compared model performance with patient-specific information [15]. Hamann et al. (2018) The Tencent ML-Images dataset provides a large-scale, multi-label image collection that enhances visual representation learning across diverse domains (Wu et al., 2019) [16]. Theoretical advancements in t-SNE have strengthened its mathematical foundations for effectively visualising high-dimensional clustered data (Cai & Ma, 2021) [17]. Dritsas and Trigka (2023) described an AI and real-world data-driven machine learning model for predicting lung cancer risk. The authors commented on model performance and accuracy in risk measurement [18]. Muschelli (2020) documented an analysis of ROC and AUC metrics with binary predictions. The author provided and explained potential challenges in using these metrics [19].

IV. IMPLEMENTATION

A. Dataset Description

The data used for this research were obtained from publicly available medical databases and also from Kaggle. It includes several data modalities, such as patient information like gender, age, genetic predisposition, and smoking status. And clinical information like diagnosis reports, symptoms. Moreover, imaging information, such as CT scan features. These datasets enable end-to-end analysis of lung cancer modelling.

The primary datasets are:

- Lung Cancer Analysis (Kaggle):
- The IQ-OTHNCCD Lung Cancer Dataset
- Lung Cancer survey Dataset

which contains test cases categorised into benign, malignant, and normal cases, And In the survey dataset, numerical data is available. The multimodal dataset enables the generation of robust machine learning models and gives accurate lung cancer prediction and analysis.

B. Methodology

The goal of this project is to create a trustworthy multimodal machine learning model that can predict both the risk and prognosis of lung cancer. The process described below summarises each step taken to produce accurate, interpretable, and meaningful results.

C. Data Collection and Preparation

To facilitate effective processing and storage, the data for this research were obtained from publicly accessible lung cancer datasets. To facilitate effective processing and storage, the data for this research were taken from the publicly accessible lung cancer datasets in the preprocessing methods using:

i. *Data Cleaning:* Dealing with missing values, deleting duplicates, and handling outliers.
ii. *Data Normalisation:* Numerical features were scaled to maintain coherence across datasets.

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iii. *Feature Engineering:* Merging various types of data, such as clinical data alongside a patient's medical history and known risk factors, to extract useful features to enhance model predictions and performance.

D. Multimodal Deep Learning Model Development

To establish a robust forecasting model, the following approaches of machine learning were implemented:
- The Random Forest algorithm for structured tabular data analysis.
- Convolutional Neural Networks (CNNs) for image data.
- Recurrent Neural Networks (RNNs) for sequential time-series data.
- A combination of predictions made by different algorithms in Ensemble Models for greater accuracy.

To achieve optimal accuracy and generalisation, methods such as hyperparameter tuning and cross-validation were used during model training.

E. Visual Analysis with Looker Studio

Looker Studio was used to develop interactive visual dashboards providing insights into model behaviour and data trends. Major visualisations included: Accuracy and loss curves for monitoring model learning. ROC curves for assessing classification performance. Feature importance plots focus on the variables that contributed most to the predictions.

F. Algorithmic Methods

The project applied and evaluated numerous algorithms, including Random Forest, which is well-suited for exploring structured datasets using ensemble methods.

i. *CNNs:* Utilised to identify lung nodules in imaging data.
ii. *RNNs:* Applied to model time-dependent data like patient clinical history.
iii. *Ensemble Learning:* Averaged predictions from multiple models to improve stability and accuracy.

G. Performance Metrics

The models' performance was evaluated using several key metrics. Accuracy is the model's overall performance, computed as the ratio of correctly predicted cases to the total number of predictions. Precision measures the positive predictive value, i.e., the proportion of predicted positives that are correct. Recall, conversely, measures how well the model detects all relevant positive cases, ensuring it does not miss true positives. The F1 Score, therefore, exists to balance the precision-recall trade-off, providing a single measure that accounts for both. Lastly, the ROC-AUC (Receiver Operating Characteristic – Area Under the Curve) measure assesses the model's ability to discriminate between classes, providing insight into its ability to separate positive and negative samples.

Table I: Analysing the Details of Precision and Recall, F1score, and ROC Accuracy

Index	Gender	Age	Smoking	Swallowing Difficulty	Chest Pain	Lung Cancer
0	M	69	1	2	2	Yes
1	M	74	2	2	2	Yes
2	F	59	1	1	2	Yes
3	M	63	2	2	2	No
4	F	63	1	2	1	No

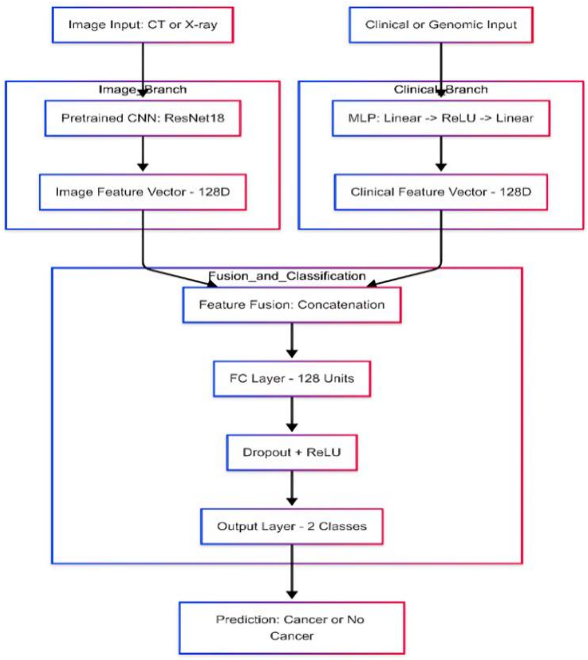
Accuracy	0.97
Precision	0.97
Recall	1.00
Fi - Score	0.98

H. Statistical Analysis

To verify the importance of model enhancements and assess reliability, statistical tests such as ANOVA and Chi-Square were conducted during the validation process.

This architecture combines both image-based and clinical/genomic data to enhance the accuracy of cancer detection. It uses a dual-branch neural network that processes different data modalities in parallel and then merges the extracted features for final classification.

The suggested model utilises a dual-branch deep learning structure that combines imaging and clinical information to predict cancer. The initial branch processes medical images, e.g., CT or X-ray, using a pretrained ResNet18 convolutional neural network (CNN) to extract high-level visual features, which are then compressed into a 128-dimensional image feature vector. The second branch processes clinical or genomic inputs using a multi-layer perceptron (MLP) composed of linear and ReLU layers to produce a 128-dimensional clinical feature vector. The outputs from both branches are then combined using feature concatenation to create an extensive multi-modal representation. This combined vector is fed into a fully connected layer of 128 units, followed by dropout and ReLU activation to improve generalisation and prevent overfitting. Lastly, there is an output layer of two neurons that performs binary classification to predict whether a patient has cancer. By integrating complementary information from imaging and clinical data, this architecture aims to enhance diagnostic accuracy and robustness compared to single-modality solutions.



[Fig.1: Multimodal Cancer Prediction Architecture Using Image and Clinical Data]

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I. Expected Outcomes

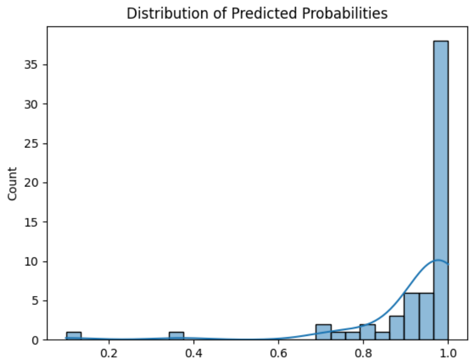
Enhanced Lung Cancer models to use for prediction. Better Understanding of the correlation between multimodal features. Interactive visualisations for medical analysis and decision making.

Dataset Preview – Encoded features like gender, smoking, and lung cancer labels.

Training Progress – Accuracy improves from42.91% to 85.02% over 10 epochs.

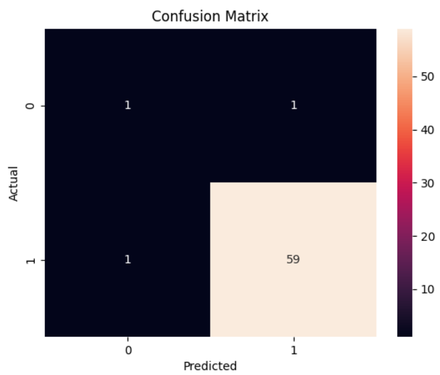
Final Test Accuracy – Achieves 96.77%, indicating strong model performance.

This histogram with a density curve represents the probability scores assigned by the model. A well-separated distribution suggests strong predictive performance.



[Fig.2: Distribution of Predicted Probabilities]

This heatmap visualises the model's performance by comparing actual vs. predicted labels.



[Fig.3: Confusion Matrix]

It is the confusion matrix between actual and predicted values.

Table II: Distribution of Predicted Probabilities

Epoch	Loss	Accuracy
1/10	0.706	42.91%
2/10	0.6295	81.78%
3/10	0.5576	85.02%
4/10	0.4908	85.02%
5/10	0.4268	85.02%
6/10	0.3908	85.02%
7/10	0.3456	85.02%
8/10	0.3314	85.02%
9/10	0.307	85.02%
10/10	0.2767	85.02%

Table III: The Analysis of Accuracy

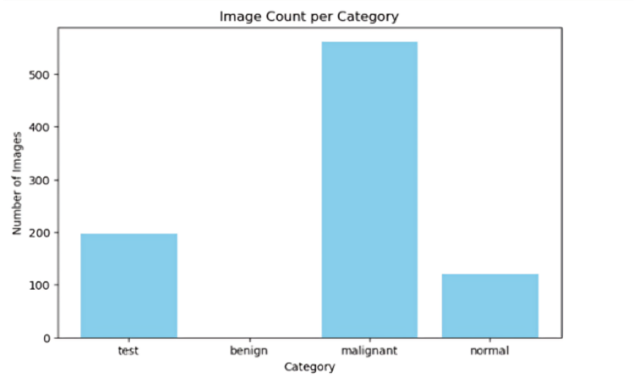
Metric	Value
Test Accuracy	Is 96.77%

J. Cloud Services

Amazon S3 (Simple Storage Service) - Store lung cancer images and metadata.

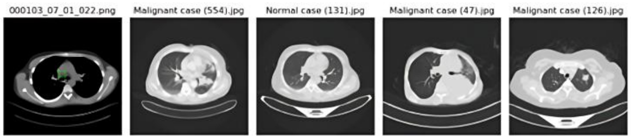
Amazon SageMaker - Builds and trains machine learning models for analysis and prediction.

AWS IAM (Identity and Access Management) - Manage permissions and security.



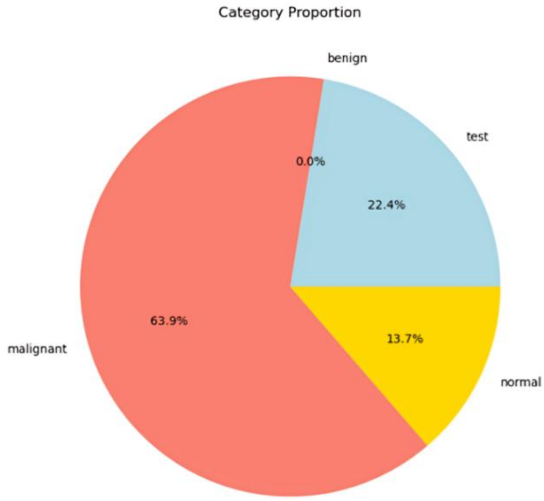
[Fig.4: Images Count Per Category]

This figure shows that the dataset's images must include a category indicating the total number of images, as well as the images themselves.



[Fig.5: Random CT scans of Cancer]

This Figure shows sample images from the Kaggle dataset, including malignant and normal images, to illustrate the images that will be identified.



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[Fig.6: Category Proportion]

This Pie Chart Shows the percentage of data for each type of lung cancer. Most lung cancers will be malignant, more than 60%, with the remaining ones and normal cells also.

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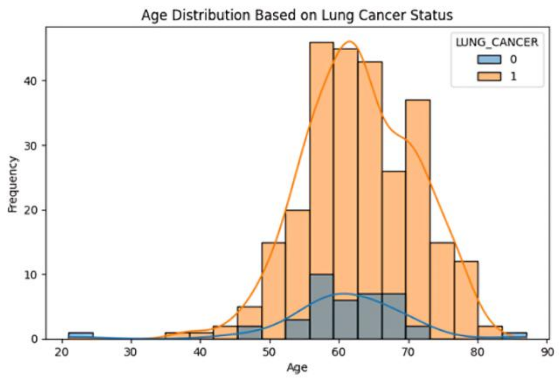
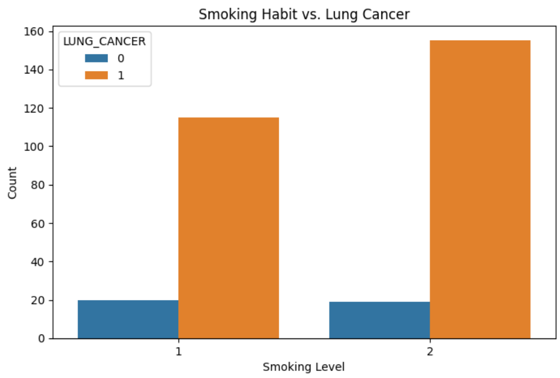


Present.

[Fig.7: Age Distribution Based on Lung Cancer Status]

This bar graph shows the age distribution of lung cancer status.



[Fig.8: Smoking Habit Vs Lung Cancer Bar Graph]

This bar graph shows the percentages of smoking and lung cancer.

K. Looker Studio Services

This Looker Studio table shows lung cancer data with CHEST PAIN, AGE, and Record Count. It highlights the prevalence of chest pain across age groups, helping analyse symptom distribution and potential risk patterns.

Table IV: Looker Studio Data

chest pain	age	record count
2	56	14
2	64	13
2	62	12
1	63	10
2	60	10
1	61	9
2	63	9
2	70	9
2	59	8
1	60	7
2	58	7
2	71	7
1	64	7
2	61	7
1	59	7
2	67	7

V. CONCLUSION

This project illustrates the value of multimodal deep learning for lung cancer analysis by leveraging diverse data sources, including clinical, imaging, and genomic data. With the power of sophisticated machine learning algorithms and data visualisation by SageMaker and Looker Studio, the platform improves prediction performance and enables effective decision-making in healthcare. The research emphasises the need for explainable AI in a clinical environment to address data heterogeneity and the demand for personalised medicine. Ultimately, this method is responsible for early diagnosis, specific interventions, and better patient outcomes in lung cancer treatment.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** Yes, the datasets used in this study are publicly available. The data were obtained from open-access medical repositories and Kaggle datasets related to lung cancer research, accessible under open data terms.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals. Dharmaiah Devarapalli – Supervision and technical guidance, M. Kavitha – Guidance, critical review J.Adithya Narasimha – Conceptualisation, model design, and manuscript preparation M. Soma Shekar – Data preprocessing and visualisation using Looker Studio K. Jaswanth – Dataset integration and analysis

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K. Jaswanth, Department of CS-IT, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P., India. K. Jaswanth is working toward a degree in information technology and computer science. He is interested in computational intelligence, biomedical analysis, and data visualisation. Jaswanth uses cutting-edge deep learning techniques in his research on lung cancer analytics.
