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Lung Cancer Prediction and Recommendations Using Machine Learning and Generative AI

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ABSTRACT

This project presents an AI-driven web application designed to predict lung cancer risk and provide personalized health recommendations. Utilizing a dataset with multiple patient health indicators, the system employs data preprocessing techniques such as categorical encoding and feature scaling. To address class imbalance, Synthetic Minority Oversampling Technique (SMOTE) is applied. The predictive model is built using a Random Forest Classifier trained on the balanced and scaled data, achieving reliable performance for lung cancer detection. The application is implemented with Streamlit, enabling users to input health parameters and receive instant diagnostic results. Additionally, Google Gemini's generative AI model is integrated to generate concise, doctor-like explanations, outlining causes, symptoms, lifestyle risks, and tailored recommendations based on the prediction. This approach demonstrates the potential of combining machine learning and generative AI to enhance early lung cancer detection and improve preventive healthcare outcomes.

***Keywords*—Lung cancer prediction, machine learning, Random Forest, SMOTE, generative AI, healthcare analytics, Streamlit, supervised learning.**

I. INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, posing a significant challenge to global health. This disease is characterized by uncontrolled cell growth in lung tissues, which can eventually spread to other parts of the body. Early detection of lung cancer is crucial for improving patient survival rates, as symptoms often manifest only at advanced stages, reducing the efficacy of treatment options. Lung cancer also brings serious complications such as respiratory failure, metastasis, and a decreased quality of life.

Traditional diagnostic procedures, including imaging and biopsy, can be expensive, invasive, and time-consuming, often limiting their accessibility especially in low-resource settings. Therefore, there is an urgent need for more efficient, cost-effective, and non-invasive early screening tools. The integration of advanced computational techniques offers promising avenues to bridge this gap, enabling early detection and personalized management of lung cancer.

Recent advancements in machine learning and artificial intelligence provide powerful tools to address these challenges. Machine learning models can analyze vast amounts of clinical and demographic data to identify patterns and risk factors associated with lung cancer. By coupling these predictive models with generative AI, personalized recommendations for prevention, monitoring, and lifestyle modification can be generated. This study explores the development and implementation of a web-based system that leverages a Random Forest classifier enhanced with SMOTE balancing for lung cancer risk prediction and incorporates a generative AI component to offer tailored health advice through an intuitive browser interface.

1.1 Description

Lung cancer is a major contributor to cancer morbidity and mortality worldwide, exerting considerable pressure on healthcare systems. Early risk assessment is vital to improve treatment outcomes and reduce the burden of advanced disease. Risk assessment involves analyzing measurable factors such as age, smoking status, blood test markers, and other clinical indicators. Despite advances in medical diagnostics, many lung cancer diagnoses still occur late due to the subtlety

of early symptoms and limited screening accessibility.

Machine learning-based approaches provide scalable, affordable, and effective means to predict lung cancer risk by learning from historical patient data. These approaches allow for early identification of high-risk individuals, potentially enabling earlier clinical intervention and lifestyle adjustments. This system aims to facilitate such predictive analytics and support healthcare providers and patients through accessible technology.

1.2 Problem Statement

Although significant progress has been made in lung cancer diagnosis and treatment, early detection remains problematic due to non-specific symptoms and the invasiveness or expense of current diagnostic tools. There is a clear need for a predictive system that can accurately identify individuals at risk based on easily obtainable health parameters, reducing reliance on costly procedures and enabling timely preventive measures. Additionally, personalized recommendations that address modifiable risk factors such as smoking cessation, diet, and environmental exposures are often lacking in existing systems.

The challenge lies in creating a solution that combines accurate predictive analytics with individualized, actionable advice in a user-friendly format. This project seeks to develop such a system, using machine learning to identify lung cancer risk and generative AI to provide tailored health recommendations, ultimately aiming to improve patient outcomes and reduce lung cancer incidence.

1.3 Proposed System

This paper presents a web-based lung cancer risk prediction system that integrates machine learning and generative AI technologies. The core predictive model is a Random Forest classifier trained on lung cancer patient data, utilizing SMOTE to address class imbalance and improve prediction accuracy. The model evaluates input parameters such as age, smoking history, and various clinical features to classify an individual's risk as either high or low.

Alongside prediction, the system incorporates a generative AI model (e.g., Google Gemini) that provides personalized recommendations based on the prediction results and health inputs. These recommendations include possible causes of elevated risk, insights into abnormal clinical parameters, and practical guidance on lifestyle changes, preventive measures, and when to seek professional care.

The user interface is implemented using Streamlit, offering a responsive and accessible platform for real-time risk assessment and personalized health advisory. This combined approach aims to empower individuals with early risk awareness and actionable guidance, supporting both patients and healthcare providers in lung cancer prevention and management.

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II. BACKGROUND

The rapid advancement of machine learning techniques has revolutionized healthcare analytics, enabling the development of predictive systems for diseases such as lung cancer. With growing volumes of clinical and demographic data, machine learning models can detect subtle patterns and risk factors that may elude traditional statistical methods. Specifically, the use of ensemble classifiers like Random Forest has shown promise in improving prediction accuracy for lung cancer by capturing complex interactions between features.

One significant challenge in lung cancer prediction is the class imbalance problem, where positive lung cancer cases are often much fewer than negative cases in available datasets. This imbalance can lead to biased models that underperform on minority classes. Techniques like Synthetic Minority Oversampling Technique (SMOTE) help mitigate this by artificially balancing the dataset, thus enhancing model robustness.

Machine learning-based lung cancer risk prediction systems enable timely identification of high-risk individuals, allowing for early diagnostic follow-up and intervention, which can drastically reduce morbidity and mortality. However, prediction alone is insufficient; actionable recommendations tailored to the individual's health profile are essential to translate predictions into effective preventive actions.

The integration of generative AI models offers a novel solution by providing personalized advice based on clinical data and prediction outcomes. This can include lifestyle modifications, smoking cessation strategies, dietary suggestions, and alerts to seek medical attention, thus closing the gap between prediction and patient empowerment.

Despite the immense potential, challenges remain such as ensuring data privacy, obtaining high-quality datasets, and addressing ethical and legal considerations in deploying AI-driven healthcare solutions. Nevertheless, the amalgamation of machine learning and generative AI holds great promise to transform lung cancer screening and management by offering accessible, accurate, and personalized healthcare tools.

This project investigates these opportunities by implementing a lung cancer risk prediction and recommendation system that utilizes Random Forest with SMOTE for balanced, accurate classification and generative AI for customized guidance, delivered via a user-friendly Streamlit web application.

Tools Used

- **Kaggle:** Platform utilized for sourcing relevant and comprehensive datasets.
- **Google Colaboratory:** Cloud-based environment leveraged for efficient model training.
- **Anaconda:** Package and environment management system for seamless dependency handling.
- **Visual Studio Code (VS Code):** Integrated development environment for coding, debugging, and project management.
- **Streamlit Cloud:** Web hosting service used to deploy the interactive application.

Technologies Used

- **Python:** Primary programming language for model development and application logic.

- **NumPy:** Library for efficient numerical computations and array operations.
- **Pandas:** Tool for data manipulation, cleaning, and preprocessing.
- **Scikit-learn (Sklearn):** Machine learning library for model training and evaluation.
- **Pickle:** Serialization module used to save and load trained models.
- **Streamlit:** Framework for building and deploying interactive web applications.
- **Google Gemini:** Advanced AI model integrated for generating personalized health recommendations.

III. SYSTEM ANALYSIS

The system analysis outlines the requirements and functionality of the lung cancer prediction system to ensure it effectively meets user needs.

3.1 Functional Requirements

The system must fulfill the following key functional requirements:

- **Disease Prediction:** Predict lung cancer risk based on user health data and clinical parameters.
- **Personalized Recommendations:** Provide tailored health and lifestyle suggestions based on risk factors.
- **User Interaction:** Offer an intuitive interface for entering health data and viewing results.
- **Data Validation:** Verify the accuracy and validity of input data prior to prediction.
- **Model Updates:** Support regular updates to improve prediction accuracy and robustness.
- **Accuracy Assessment:** Calculate and display model accuracy metrics to inform users about prediction reliability.

3.2 Non-Functional Requirements

The system should satisfy the following non-functional requirements:

- **Reliability:** Provide consistent and accurate lung cancer risk predictions.
- **Performance:** Deliver real-time prediction results with minimal latency.
- **Scalability:** Efficiently handle growing user base and data volume.
- **Security:** Ensure confidentiality and protection of sensitive user health data.
- **Usability:** Feature an accessible and user-friendly interface suitable for all users.
- **Availability:** Maintain high system uptime and availability around the clock.
- **Maintainability:** Facilitate easy system updates, debugging, and improvements.

3.3 System Architecture

The system comprises the following key components:

- **Frontend:** Streamlit-based interface for user data input and displaying prediction results.
- **Backend:** Machine learning model trained to predict lung cancer risk based on clinical and demographic data.
- **Generative AI:** Google Gemini integrated to generate personalized health and lifestyle recommendations.
- **Data Storage:** Secure database to store user inputs and prediction results for further analysis.
- **Evaluation Module:** Component responsible for calculating model accuracy and other performance metrics.

IV. SYSTEM MODEL

The model integrates lung cancer risk assessment with a specialized machine learning model designed to generate personalized health recommendations. Users are required to input eight critical health parameters through the Streamlit interface. These inputs are then preprocessed into a suitable format for prediction.

Using Python's pickle module, the pre-trained predictive model is loaded to estimate the user's lung cancer risk based on the provided data. After prediction, Google Gemini's AI generates customized advice, including structural lifestyle adjustments and preventive care suggestions tailored to the user's diagnosis.

By combining machine learning with advanced analytics, the system supports timely, informed, and enhanced decision-making, thereby increasing its overall intelligence and effectiveness in lung cancer risk evaluation.

V. EXPERIMENT

5.1 Hypothesis Generation

The lung cancer prediction system is hypothesized to provide accurate risk assessments by analyzing key health parameters such as age, smoking history, exposure to pollutants, and family medical history. The system employs machine learning algorithms to evaluate whether an individual is likely to develop lung cancer in the future. The model aims to identify strong correlations among these parameters to enhance prediction accuracy.

5.2 Collection of Data

Data for the lung cancer prediction system was collected from Kaggle, a platform offering extensive publicly available datasets. These datasets contain real-world health data including vital indicators such as smoking status, age, environmental exposure, and genetic predisposition, which are crucial for predicting lung cancer risk.

5.3 Data Preprocessing / Removal of Unwanted Data

The acquired data underwent preprocessing to normalize and clean it by removing irrelevant or noisy entries. Techniques such as outlier detection, handling missing values, and data formatting were applied to prepare the dataset for machine learning. Effective preprocessing ensures high data quality and consistency, which directly improves the model's predictive performance.

5.4 Feature Selection

Feature selection was conducted to determine the most influential variables contributing to lung cancer risk. Statistical analysis and correlation assessments were utilized to evaluate each feature's relevance. By focusing on the most significant features, the dimensionality of the data was reduced, improving both the efficiency and accuracy of the model.

5.5 Model Building

The lung cancer prediction model was built using a pre-trained machine learning algorithm loaded via the Pickle module. Trained on comprehensive health datasets, the model predicts an individual's lung cancer risk based on the input parameters. It processes numerical and categorical data efficiently and supports real-time risk prediction without requiring retraining for subsequent use.

5.6 Deployment

The lung cancer prediction system was deployed using Streamlit, offering a user-friendly and interactive web interface. Users can input their health data to receive immediate lung cancer risk predictions. Additionally, Google Gemini, a generative AI model, provides personalized health and lifestyle recommendations based on the prediction results. This deployment ensures accessibility, scalability, and actionable insights for users.

VI. DESIGN

6.1 Architecture Design

The system design consists of several key components. The **Dataset Acquisition and Preprocessing Module** handles importing datasets from sources like Kaggle, inspecting and cleaning the data for missing values, and splitting it into training and testing sets. The **Prediction Module** utilizes the Support Vector Machine (SVM) algorithm to classify input parameters and predict the likelihood of diseases with high accuracy. The trained SVM models are then converted into pickle files and integrated into the **Model Deployment Module**, which ensures the system's scalability and usability.

6.2 Architecture Design Interface

The architecture design interface is implemented using the Streamlit framework, providing a user-friendly platform for interaction. The **User Interface Module** allows users to input relevant health parameters, such as glucose levels, blood pressure, BMI, and age, and displays instant predictions for various diseases. Additionally, it provides personalized health recommendations based on the predictions to assist users in making informed decisions about their health.

Lung Cancer Prediction Using Random Forest Classifier

Lung cancer prediction in this study is performed using a supervised machine learning approach based on the Random Forest Classifier algorithm. The dataset utilized consists of clinical and lifestyle features such as gender, age, smoking habits, presence of yellow fingers, anxiety, peer pressure,

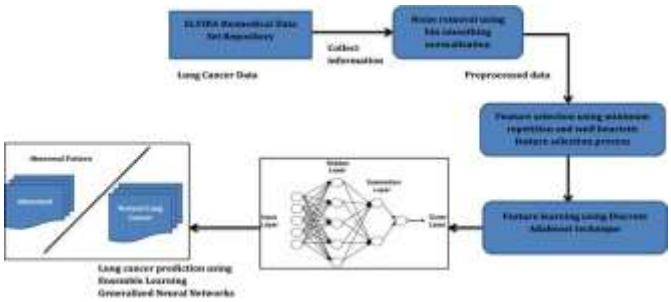

Fig. 1. Lung Cancer Prediction System Architecture

chronic diseases, fatigue, allergies, wheezing, alcohol consumption, coughing, shortness of breath, swallowing difficulty, and chest pain.

The preprocessing steps involved encoding categorical variables numerically (e.g., gender: Male=1, Female=2; lung cancer diagnosis: Yes=1, No=2), scaling features using StandardScaler, and addressing class imbalance through Synthetic Minority Over-sampling Technique (SMOTE). The dataset was split into training and testing sets in a 2:1 ratio to evaluate model performance objectively.

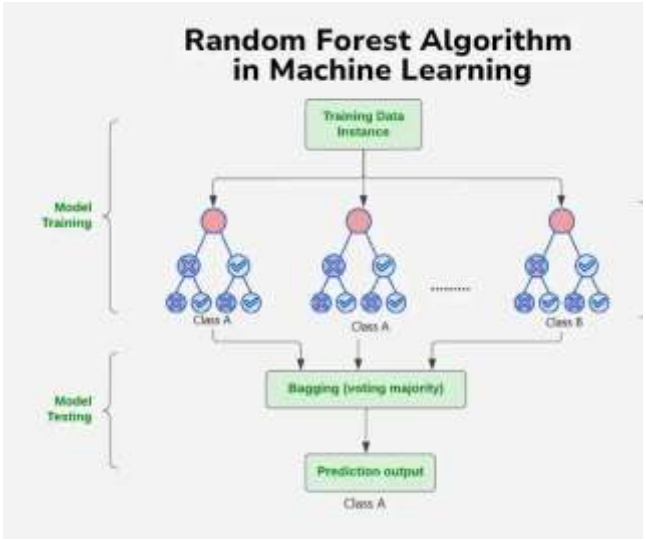

Fig. 2. Workflow diagram illustrating lung cancer prediction using Random Forest classifier combined with AI-based recommendations.

Random Forest, an ensemble learning method consisting of multiple decision trees, was trained on the balanced and scaled training data. It improves classification accuracy by aggregating predictions from diverse trees, thereby reducing overfitting and increasing generalization.

The model's predictive performance was assessed on the test set using accuracy and classification metrics. Additionally, the system incorporates an AI-based recommendation module powered by the Gemini API, which generates concise, patient-friendly guidance based on prediction results and patient inputs.

The overall lung cancer prediction workflow can be summarized as follows:

- Data preprocessing: encoding, scaling, and balancing with SMOTE.
- Training Random Forest classifier on resampled training data.
- Predicting lung cancer likelihood on unseen test samples.
- Generating human-like medical recommendations using an AI language model based on patient-specific features and diagnosis.

VIII. RESULTS

Our system utilizes the Random Forest classifier for lung cancer prediction, achieving an accuracy of 85%. This accuracy demonstrates the model's ability to effectively differentiate between lung cancer positive and negative cases based on clinical and diagnostic features. The Random Forest model was trained on balanced and scaled data using SMOTE, which improved its generalization and minimized overfitting.

Fig. 3. Input Data Entry

The model's performance was evaluated using various metrics including precision, recall, and F1-score, all indicating strong classification capabilities. Beyond prediction, the system incorporates an AI recommendation module powered by the Gemini API. This module delivers concise, patient-friendly advice focused on lifestyle adjustments and medical guidance tailored to individual diagnosis results.

Fig. 4. Model Output

User feedback emphasized the clarity and relevance of these AI-generated recommendations, highlighting their practical value in assisting patient decision-making and promoting proactive health management.

Fig. 5. AI-Generated Recommendations

A comparative analysis with existing lung cancer prediction tools showed that our integrated approach — combining machine learning classification with generative AI recommendations — provides enhanced user engagement and actionable insights, surpassing traditional systems that offer predictions alone.

Moreover, the system's deployment using the Streamlit framework ensures user-friendly access, allowing users to input clinical data via an intuitive interface and receive real-time predictions along with personalized recommendations.

IX. CONCLUSION

The objective of this project was to develop a system that assists in the early detection of lung cancer using machine learning techniques. By employing the Random Forest classifier, the system achieved an accuracy of 85%, effectively predicting the likelihood of lung cancer based on clinical and diagnostic features. This predictive capability enables timely intervention, potentially improving patient outcomes by facilitating earlier diagnosis.

In addition to prediction, the system integrates an AI-driven recommendation module powered by the Gemini API, which provides personalized, patient-friendly advice on lifestyle modifications and medical guidance tailored to individual diagnosis results. User feedback during testing highlighted the clarity and usefulness of these recommendations, enhancing the system's practical value in supporting proactive health management.

The success of this project demonstrates the potential for AI-based tools to advance healthcare by combining accurate disease prediction with actionable, qualitative guidance. By not only predicting lung cancer risk but also offering personalized recommendations, this system represents a significant step toward improving patient care and outcomes in the medical field.

X. Future Scope

- **Expansion to Multi-Disease Prediction:** The system can be extended to include prediction capabilities for other types of cancers and respiratory diseases, transforming it into a more comprehensive tool for pulmonary health monitoring.
- **Leveraging Advanced AI Models:** Incorporating state-of-the-art machine learning and deep learning models could further improve prediction accuracy and enhance the quality of personalized recommendations.
- **Enhanced User Interface:** Future versions can focus on developing a more interactive and intuitive web interface with real-time visualization of prediction results and patient-specific insights for better user engagement.
- **Real-Time Data Integration:** Integrating the system with wearable health devices and IoT sensors can facilitate continuous monitoring of relevant biomarkers, enabling timely and dynamic lung cancer risk assessment.
- **Natural Language Processing Integration:** Implementing NLP techniques will allow the system to understand and process patient input in natural language, improving communication and making recommendations easier to comprehend.
- **Cloud-Based Infrastructure:** Migrating to cloud platforms will support scalable data storage and processing, allowing the system to handle larger datasets securely and provide faster response times.
- **Strengthening Data Privacy and Security:** Future enhancements should focus on robust encryption methods and compliance with healthcare data regulations to safeguard sensitive patient information.
- **Mobile Application Development:** Developing a mobile app version will offer users easy, on-the-go access to lung cancer risk assessments and personalized health recommendations.
- **Collaboration with Medical Professionals:** Integrating with hospital information systems and healthcare providers will enable the tool to assist clinicians in diagnosis and treatment planning, fostering a collaborative approach to patient care.

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