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An IoT Framework for the Detection of Lung Cancer Using a Decision Support System

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Keywords:
Lung cancer prediction; Machine learning; Support vector machines; Naïve Bayes Multinomial; K-Nearest Neighbors; Partial Rule-based Tree; Random forests.

Highlights:
- An IoT-enabled framework for early lung cancer detection.
- Machine learning and homomorphic encryption were used to ensure data privacy.
- Curated 460,292 patient records from Kaggle.
- Dataset included demographics, lifestyle factors, medical history, and IoT-sensor data.
- Evaluated SVM, NBM, KNN, PART, and RF.
- Part algorithm achieved 91% accuracy, SVM (89%), NBM (86%), KNN (83%), and RF (80%).

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Abstract: Cancer remains an ongoing global health challenge, necessitating the progress of innovative techniques for early detection and risk assessment. In this study, a comprehensive method is presented for predicting lung cancer by utilizing a carefully curated dataset consisting of 1000 individuals from the Kaggle dataset. Cutting-edge machine learning models were leveraged, including Support Vector Machines (SVM), Naïve Bayes Multinomial (NBM), KNN, PART (Partial Rule-based Tree), and Random Forest (RF), to improve the precision of our forecasts. The dataset that was compiled included a wide array of patient characteristics, encompassing demographics, lifestyle factors, medical history, and health data gathered through IoT devices. By harnessing the capabilities of IoT technology, real-time and continuous health monitoring was enabled, facilitating a dynamic assessment of lung cancer risk. The findings revealed that the PART model achieved an impressive accuracy of 91%, surpassing other models like Random Forest (80%), K-Nearest Neighbors (83%), SVM (89%), and Naïve Bayes Multinomial (86%). This innovative approach shows promise in the early detection of lung cancer and the provision of personalized risk assessments, possibly resulting in better patient outcomes and decreased healthcare challenges.

إطار عمل لإنترنت الأشياء لاكتشاف سرطان الرئة باستخدام نظام دعم القرار

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الخلاصة

لا يزال السرطان يُمثل تحديًا صحيًا عالميًا مستمرًا، مما يستلزم تطوير تقنيات مبتكرة للكشف المبكر وتقييم المخاطر. تُقدم هذه الدراسة منهجية شاملة للتنبؤ بسرطان الرئة باستخدام مجموعة بيانات مُختارة بعناية، تضم ١٠٠٠ فرد من قاعدة بيانات Kaggle. واستُخدمت نماذج تعلّم آلي متطورة، بما في ذلك آلات المتجهات الداعمة (SVM)، ومتعددة الحدود الساذجة بايز (NBM)، وKNN، والشجرة الجزئية القائمة على القواعد (PART)، والغابة العشوائية (RF)، لتحسين دقة توقعاتنا. وتضمنت مجموعة البيانات المُجمعة مجموعة واسعة من خصائص المرضى، بما في ذلك التركيبة السكانية، وعوامل نمط الحياة، والتاريخ الطبي، والبيانات الصحية المُجمعة عبر أجهزة إنترنت الأشياء. ومن خلال تسخير إمكانات تقنية إنترنت الأشياء، تم تمكين المراقبة الصحية المستمرة واللحظية، مما يُسهّل إجراء تقييم ديناميكي لمخاطر الإصابة بسرطان الرئة. كشفت النتائج أن نموذج PART حقق دقةً مذهلةً بلغت ٩١٪، متجاوزًا نماذج أخرى مثل نموذج الغابة العشوائية (٨٠٪)، ونموذج أقرب جيران K (٨٣٪)، ونموذج SVM (٨٩٪)، ونموذج بايز متعدد الحدود الساذج (٨٦٪). يُظهر هذا النهج المبتكر نتائج واعدة في الكشف المبكر عن سرطان الرئة وتوفير تقييمات مخاطر شخصية، مما قد يؤدي إلى نتائج أفضل للمرضى وتقليل تحديات الرعاية الصحية.

الكلمات الدالة: التنبؤ بسرطان الرئة؛ التعلم الآلي؛ آلات المتجهات الداعمة؛ معادلة بايز الساذجة؛ أقرب جيران (K)؛ شجرة جزئية مبنية على قواعد؛ غابات عشوائية.

1.INTRODUCTION

Lung cancer remains a persistent and critical global health burden, driving the ongoing search for innovative early detection and precise risk assessment strategies. Its frequently asymptomatic progression to advanced stages underscores the urgent need for transformative approaches. This study addresses this challenge by introducing a novel framework that synergizes data science and Internet of Things (IoT) technologies to revolutionize lung cancer prediction and evaluation. Despite medical advancements, lung cancer persists as a leading cause of cancer mortality worldwide. The disease's tendency to evade detection until late, often untreatable phases highlights the vital importance of timely identification. Our research establishes a new paradigm centered on a meticulously curated dataset of 460,292 individuals. This comprehensive dataset integrates diverse patient dimensions: demographic profiles, lifestyle indicators (e.g., smoking status), medical histories, and IoT-generated physiological metrics. These multifaceted inputs form the foundation for our predictive models, enabling more informed and accurate assessments. The core innovation lies in deploying advanced machine learning algorithms—support vector machines (SVM), Naïve Bayes multinomial (NBM), partial rule-based trees (PART), k-nearest neighbors (KNN), and random forests (RF). This ensemble approach significantly boosts prediction reliability, offering healthcare providers and individuals a powerful tool for critical decision-making. A distinctive feature is the seamless incorporation of IoT technology, facilitating continuous, real-time health monitoring. This dynamic methodology transcends the limitations of episodic assessments, enabling recent research to demonstrate significant progress in applying computational techniques across diverse domains. Jayasingh et al. [1] introduced a novel data classification method leveraging neural networks and explored various soft computing models, highlighting their strategic application. Swain et al. [2] focused on IoT-enabled machine learning for predicting diabetes and heart disease in the elderly, emphasizing its diagnostic and preventive potential. They also noted a healthcare-technology gap and suggested that soft computing models and artificial neural networks could significantly benefit heart disease treatment. Jayasingh et al. [3] applied machine learning (including RF, SVM, DT, Adaboost, XGBoost, Gradient Boosting, Logistic Regression, and Naïve Bayes) to smart weather prediction for Delhi and found that Random Forest was superior. Further exploration by Jayasingh et al. [4] using hybrid flexible computational approaches for weather prediction showed that these methods outperformed typical soft computing models in terms of accuracy and error metrics. In fraud detection, Prusty et al. [5] utilized machine learning (RF, Naïve Bayes, KNN, DT, Ada Boost, and SVM) for SMS fraud detection, demonstrating Random Forest's highest accuracy. Comparative evaluations by Jayasingh et al. [6] and Mantri et al. [7] for Delhi weather forecasting identified Support Vector Machines (SVM) as delivering the best accuracy and minimal error among models like DT, SVM, and MLP. Within healthcare, Xu et al. [8] employed deep learning on sequential medical imaging to predict lung cancer treatment response. Pati et al. [9] proposed. Applying machine learning and fog computing for breast cancer detection. Hyun et al. [10] developed a PET-based radiomics machine learning model to predict lung cancer histological subtypes. Mohapatra et al. [11] enhanced feature selection for complex problems using an adaptive search dimensional ratio pathfinder algorithm (ASDR-PFA). Bastia et al. [12] advocated for cloud computing implementation in the context of lung cancer. Rautaray et al. [13] proposed a fully homomorphic encryption (FHE) model for the classification of diabetic retinopathy, while Rautaray et al. [14] developed a model combining deep learning and IoT. Advanced deep learning techniques incorporating feature extraction methods (HoG, wavelet, LBP, SIFT, Zernike Moments) and fuzzy PSO for feature selection have been employed for precise localization of cancerous lung nodules [15]. Pati et al. [16] explored deep learning-based CAD systems (evaluating ResNet, MobileNet, VGG-16, and EfficientNet) for automated benign/malignant breast tumor classification. Mahapatra et al. [17] reviewed the IoT's transformative potential, future applications, and research challenges. Hussein [18] relied on fine-tuned pre-trained CNN models for breast cancer detection. Elzaghmouri et al. [19] achieved 90% accuracy in lung cancer detection using deep learning with gated recurrent units (GRU). Saboor et al. [20] proposed alternative lung cancer detection algorithms with varying accuracy. Bisht et al. [21] reported 91% accuracy using the random forest algorithm for lung cancer detection. Joshi et al. [22] conducted lung cancer detection studies using data from 2015 to 2024. Other relevant studies include approaches using bio-inspired algorithms, IoT, and deep learning for lung cancer detection and secure data transmission [23-27].

3.RESEARCH DESIGN

3.1.How ML Differs from Traditional Programming

Traditional programming relies on explicit, developer-defined rules to process inputs and generate outputs. In contrast, machine learning (ML) learns implicit patterns directly from data, enabling it to make predictions or decisions without predefined instructions. ML excels in complex, data-intensive tasks such as image recognition, where rule-based approaches are impractical. Traditional programming remains effective for structured tasks with clear logic (e.g., database management). ML systems adapt through training on new data, refining their predictive capabilities over time. The choice between ML and traditional methods hinges on the problem complexity and data availability (Figs. 1 and 2 as shown in Figs. 2 and 3.

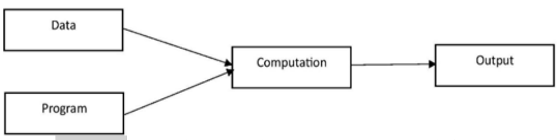

Fig. 1 Traditional Program Workflow.

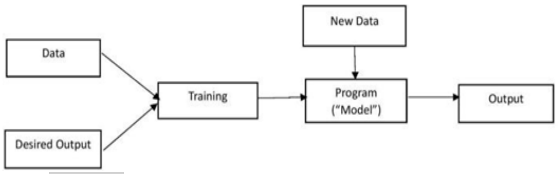

Fig. 2 Work Flow of Machine Learning Processing.

3.2.Voting Model

The voting ensemble model combines predictions from multiple base classifiers to enhance accuracy, robustness, and generalization. By aggregating outputs (e.g., via majority vote or averaging), it mitigates overfitting and reduces sensitivity to noise or outliers. In this study, five ML models—Support Vector Machines (SVM), Naïve Bayes Multinomial (NBM), K-Nearest Neighbors (KNN), Partial Rule-based Tree (PART), and Random Forest (RF)—were integrated into a voting framework for lung cancer prediction. The ensemble output is formalized as:

$$f_m(y) = \frac{e^o m}{\sum_{m-1}^{n} e^o n} \quad (1)$$

3.3.Naïve Bayes Multinomial

The Naïve Bayes Multinomial algorithm applies Bayes' theorem—a probabilistic principle that calculates the likelihood of an event A occurring given prior knowledge of event B. The formula is expressed as:

P(A|B) = [P(B|A) × P(A)] / P(B)

where:

P(A|B) = posterior probability of class A given predictor B

P(B|A) = Likelihood of predictor B occurring given class A

P(A) = Prior probability of class A

P(B) = Prior probability of the predictor

- **Support Vector Machine (SVM)**
  The support vector machine is a supervised learning method for classification and regression. It identifies an optimal hyperplane to maximize the separation margin between distinct classes. The SVM variants include:
  - Linear SVM: Uses a straight hyperplane (line/plane) for linearly separable data.
  - Non-Linear SVM: Applies kernel functions (e.g., polynomial, RBF) to handle complex, non-linear data distributions by projecting features into higher dimensions.

3.4.Partial Decision Tree (PART)

PART (Partial Rule-based Tree) is a classification algorithm designed to build compact and interpretable decision trees. It focuses on strategically selecting and refining attributes and values that provide the highest classification insight. The method starts by generating a complete decision tree and then systematically prunes branches that contribute minimally to classification precision, resulting in a simplified yet effective model.

3.5.Random Forest (RF)

Random Forest is a highly efficient ensemble method widely employed in machine learning, functioning by constructing numerous decision trees during training and combining their predictions to achieve greater accuracy and robustness across diverse applications such as image classification, bioinformatics, medical analysis, and financial analysis, as shown in Fig. 4.

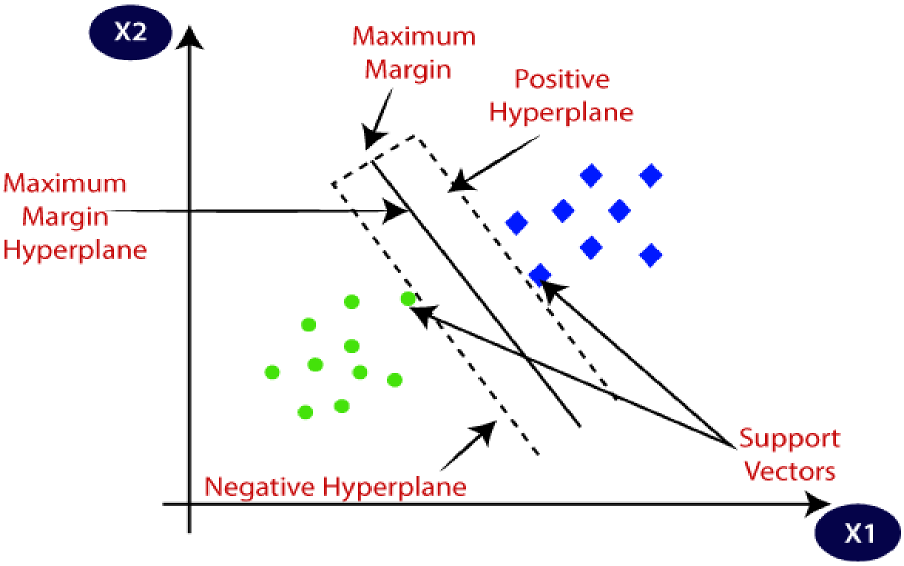

Fig. 3 Working Principle of SVM.

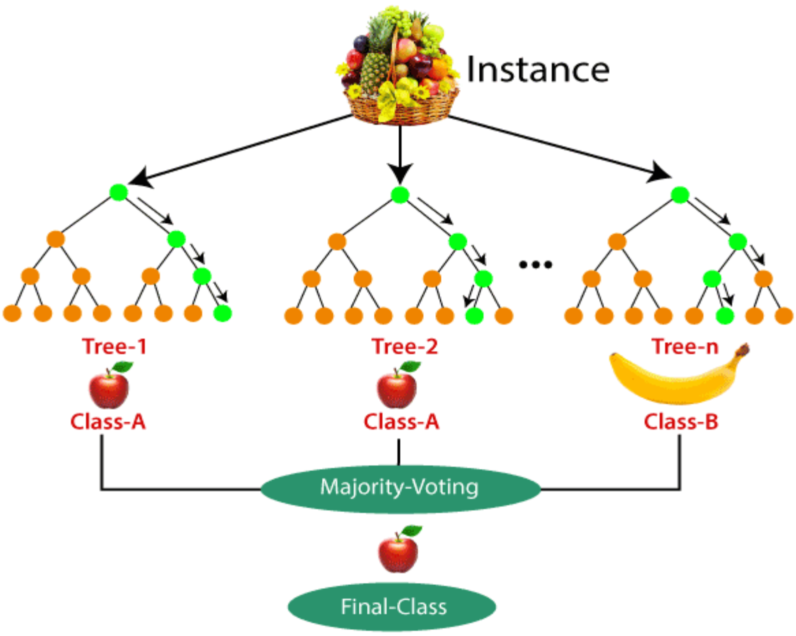

Fig. 4 Graphical Representation of Random Forest.

3.6.k-Nearest Neighbors

The k-Nearest Neighbors (KNN) algorithm is a supervised learning technique used for classification and regression tasks. It classifies a new instance by identifying the majority class among its *k* closest neighbors in the training dataset. As a "lazy learning" algorithm, KNN does not build an explicit model during training. Instead, it stores the entire dataset and performs computations only during prediction. The algorithm is demonstrated in Fig. 5 and operates as follows:

1- Select the value of *k* (number of neighbors).
2- Compute the distance between the new instance and every stored instance using metrics such as the Euclidean or Manhattan distance.
3- Identify the *k* nearest neighbors based on the smallest distances.

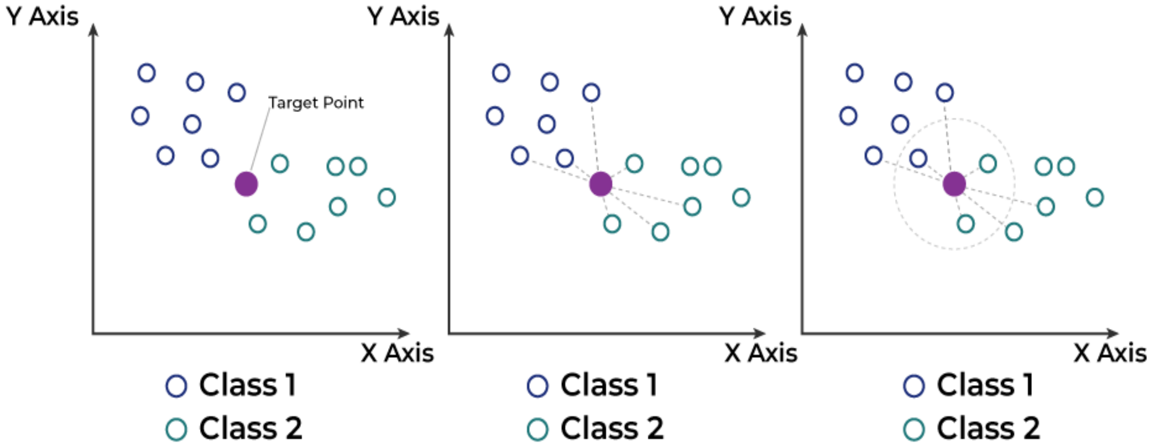

Fig. 5 Working Principle of the KNN Algorithm.

4.RESEARCH METHODOLOGY

4.1.Flow of Work

The flow of the proposed work is shown in Fig. 6. Here, the data are collected with the help of sensors, as the medical data are sensitive and should be kept private, so the data is passed to one encryption technique called homomorphic encryption, in which the data can be processed without being decrypted. The data will be forwarded to the cloud platform, preprocessed, and then, using a feature selection technique, only essential features will be selected for training and testing purposes. Then, many machine learning models are developed, and the best one is selected for classification. Then, the model will produce the predicted output, which is then decrypted to make it available to the doctors for diagnostic purposes.

4.2.Homomorphic Encryption

A cryptographic approach called homomorphic encryption enables binary operations on encrypted data without requiring decryption, making it perfect for managing sensitive data since it permits secure data processing while maintaining secrecy. Essentially, homomorphic encryption transforms data into an encoded format, allowing computations without compromising privacy. There are three categories of homomorphic encryption, each built upon advancements in public key cryptography to ensure secure encryption and decryption. These variations enable different levels of computational flexibility while maintaining robust security. In practical applications, homomorphic encryption allows the encrypted data to be subdivided, with a primary key for decrypting the entire dataset and additional keys for accessing specific subsets. This technique enables different individuals to independently process or access designated portions of the encrypted data. As a result, users maintain greater control over data privacy, enhancing both confidentiality and security [13]. However, somewhat homomorphic encryption (SHE) has certain drawbacks, primarily due to the accumulation of noise in the ciphertext, which can interfere with accurate decryption and computation. Excessive noise increases the computational overhead, reducing the efficiency of the encryption scheme. Another problem is its multiplicative depth, which refers to the maximum number of multiplications the scheme can perform before decryption becomes unreliable. Despite these challenges, SHE remains valuable, especially in physics applications involving coherent states, where controlled computations on encrypted data are required. Fully Homomorphic Encryption (FHE) offers the most significant level of flexibility, functionality, and security among the three types of homomorphic encryption. It enables the evaluation of any computational circuit composed of various logic gates, such as AND, OR, and NOT, with unlimited depth. This evaluation indicates that advanced computations can be achieved on encrypted data without requiring decryption, making FHE exceptionally adaptable for privacy-preserving applications [14]. FHE provides a robust solution for maintaining security and privacy even in environments with constrained bandwidth, high mobility, and variable network conditions. Its ability to support arbitrary computations on encrypted data makes it particularly effective in addressing the challenges of mobile networks, increasing overall data security in such scenarios. And all these are demonstrated in Fig. 7.

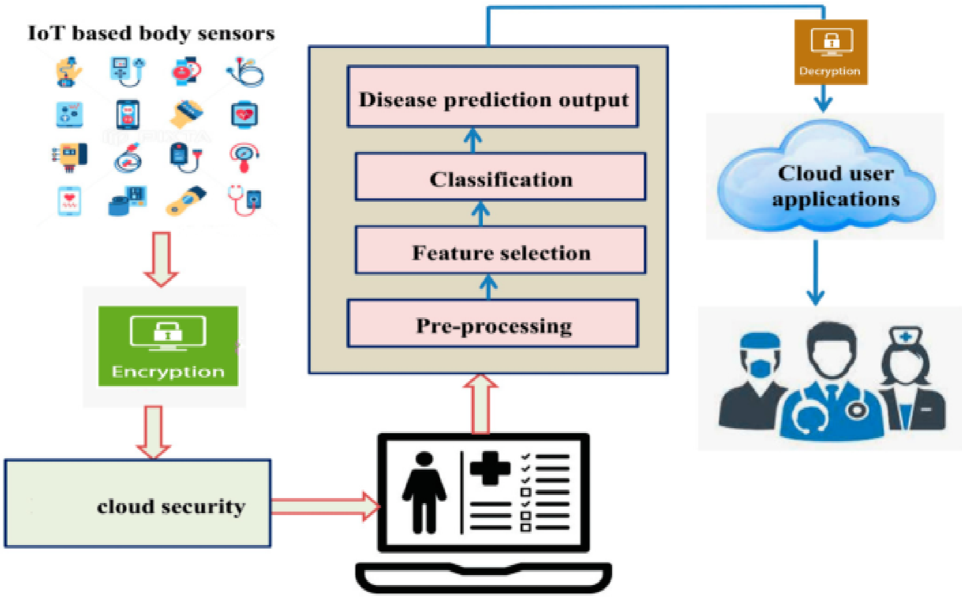

Fig. 6 Proposed Model Using Homomorphic Encryption.

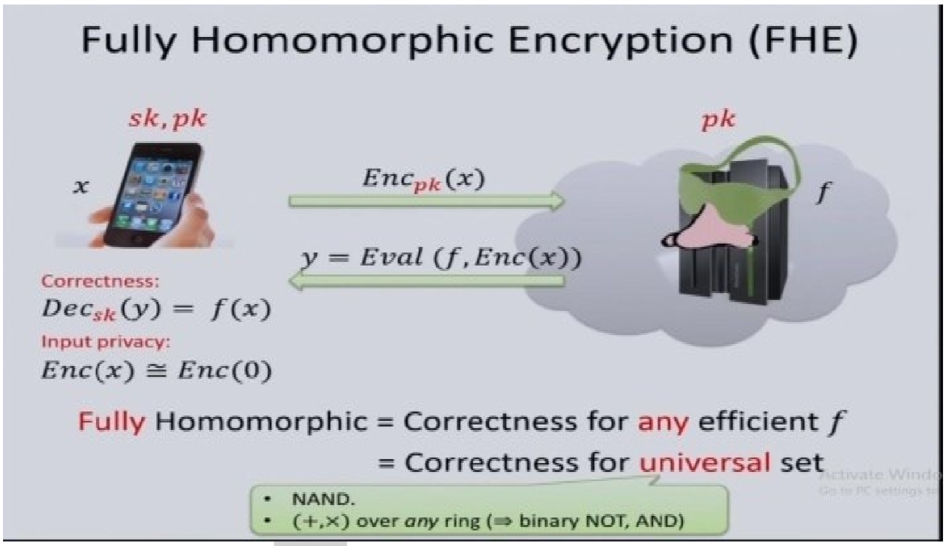

Fig. 7 Homomorphic Encryption.

4.3.Data Collection

The dataset used for lung cancer detection was sourced from Kaggle. It comprises 460,292 instances and 25 features. Key attributes include gender, age, smoking habits, yellow fingers, anxiety, peer pressure, chronic disease, fatigue, allergies, wheezing, alcohol consumption, coughing, shortness of breath, difficulty swallowing, chest pain, and lung cancer diagnosis. Gender and lung cancer are non-numeric, whereas others are numeric. Among the non-numeric features, the Final Prediction is a categorical feature.

4.4.Clean Dataset

The collected dataset underwent cleaning using measures of central tendency—mean, median, and mode—to ensure completeness and readiness for analysis. This process minimized the impact of the missing values and outliers. Missing data were imputed using techniques such as the mean, calculated by summing all values and dividing by the total number of observations. The median, representing the central value in an ascendingly sorted dataset, and the mode, the most frequently occurring value, were also applied where appropriate. Subsequently, the interrelationships between features were visualized in a correlation matrix, which is presented below in Fig. 8.

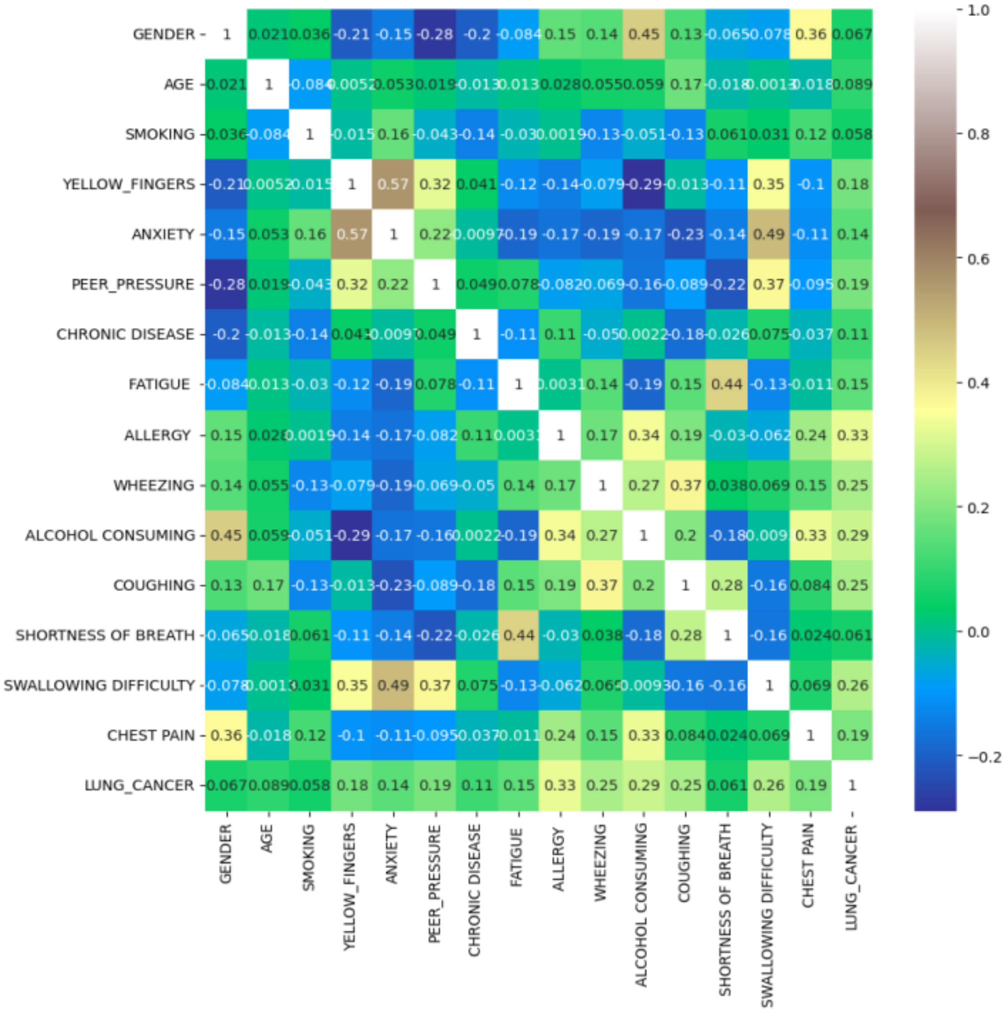

Fig. 8 Correlation Matrix between Different Features.

5.COMPARISON ANALYSIS

The studied machine learning models were compared in the present research, i.e., Support Vector Machines (SVM), Naïve Bayes Multinomial (NBM), PART, and Random Forest (RF), based on various evaluation metrics, which is a common practice in data analysis and model selection. Here are some key evaluation metrics used for model comparison, as shown in Fig. 9.

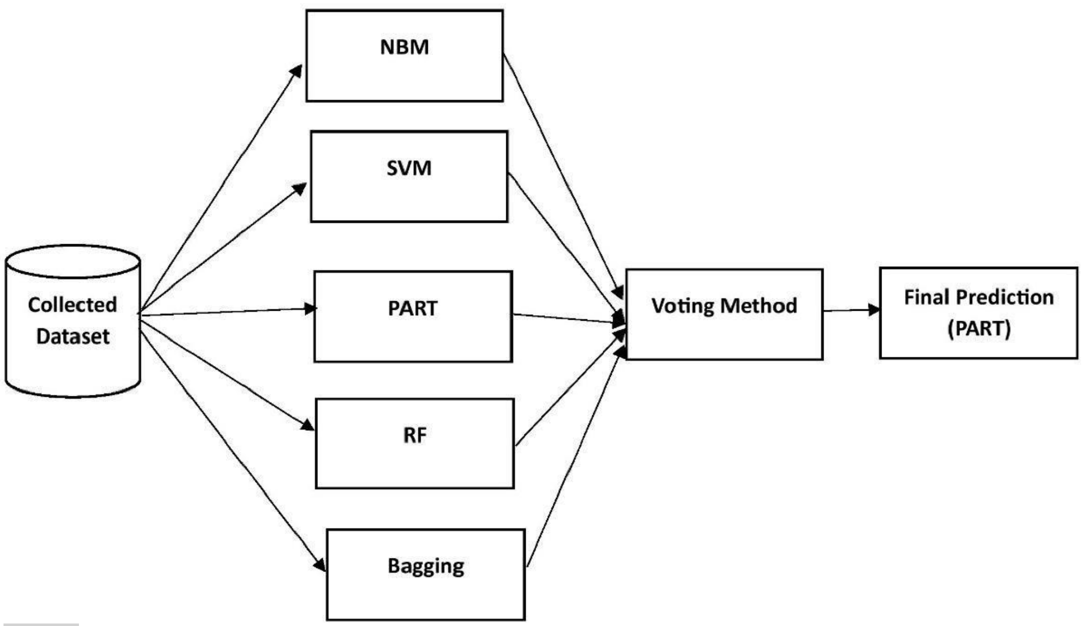

Fig. 9 Work Flow of Voting Model. It Achieved Individual Accuracy Scores for Each Model.

The accuracy scores for each model were Naïve Bayes Multinomial (NBM): 86% Support Vector Machine (SVM): 89% PART: 91% Random Forest (RF): 80% KNN: 83%. PART showed better accuracy than the other four models. Table 1 presents the accuracy of each model.

Table 1 Dataset Samples.

ML Algorithm	Accuracy
Random Forest (RF)	80
K-nearest Neighbor (KNN)	83
Naïve Bayes Multinomial (NBM)	86
Support Vector Machine (SVM)	89
Partial Rule-based Tree (PART)	91

6.CONCLUSION AND FUTURE WORK

This research demonstrates significant promise in lung cancer prediction, with the PART model achieving exceptional accuracy (91%), positioning it as a powerful tool for early detection and risk assessment. The strong performances of the support vector machine (SVM, 89%) and random forest (RF, 80%) further validate the robustness of machine learning in this domain. Future work should prioritize expanding datasets to enhance model generalizability, integrating advanced deep learning techniques for improved precision, and leveraging real-time IoT data streams to enable dynamic, proactive health monitoring. Equally critical is advancing model interpretability to foster trust and clinical adoption among healthcare providers and patients. These initiatives will accelerate progress toward more effective lung cancer management. The authors also plan to extend this framework using fog computing to optimize data processing and responsiveness in practical deployments.

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