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Lung Cancer Detection Using Linear Discriminant Analysis for Feature Extraction and Adaboost Classification

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ABSTRACT

Early, accurate diagnosis of lung cancer determines survival rates. Lung cancer is still one of the most often occurring and fatal forms of cancer known to exist worldwide. Sometimes conventions in diagnosis present challenges including high costs, results that vary for every patient, and treatments needing a lot of time. Using artificial intelligence (AI) based technologies offers one fascinating way to address these issues. This work suggests a fresh method of lung cancer detection. For classification study, the method uses AdaBoost and Linear Discriminant Analysis (LDA) to extract features. Preprocessing of lung cancer image datasets forms the first phase of the proposed method. One can reach this level by first removing noise and improving image quality. LDA guarantees efficient processing while preserving required information by means of the extraction of the most unique characteristics, so reducing dimensionality. After that, the AdaBoost method aggregates several weak classifiers into a strong model to increase the accuracy of classification using these traits. Comparing the results with an accuracy above 95% showed that the LDA-AdaBoost model outperformed more traditional techniques.

Keywords: *Lung cancer detection, Linear Discriminant Analysis, AdaBoost algorithm, feature extraction, AI in healthcare*

I. INTRODUCTION

Lung cancer is believed to be the primary cause of cancer-related mortality worldwide with almost 1.8 million deaths yearly [1–2]. Two factors define the disease: its aggressive nature and the late-stage diagnosis, which drastically reduces the survival probability. As recently invented medical imaging and diagnostic technologies including computed tomography (CT) scans and biopsies find their place in use, the proportion of cases discovered has changed. These methods, however, are sometimes connected with high costs, uncertainty in interpretation, and time constraints, which has led research of solutions driven by artificial intelligence (AI) in order to improve diagnosis efficiency [3].

A. CHALLENGES

Notwithstanding the progress, several elements complicate lung cancer detection even at present levels. Usually depending on the subjective interpretation of imaging data, the conventional methods of diagnosis cause radiologists to produce contradicting results [4]. High rates of false-positive and false-negative results complicate the diagnosis process even more and may cause delays of possibly life-saving treatments. Moreover, the complexity of high-dimensional imaging data results in a large computational load that requires the development of efficient feature extraction and classification methods [5]. The application of artificial intelligence in the healthcare industry presents particular challenges including the need of large datasets labeled and questions regarding the interpretability of models [6].

B. PROBLEM DEFINITION

The rising prevalence of lung cancer and the difficulties in diagnosis demand new ideas to increase detection accuracy and shorten processing times required. When dealing with high-dimensional data, conventional approaches of machine learning sometimes run across difficulties that result in less-than-best outcomes and increased computational costs. Moreover lacking in strength or scalability required for real-time clinical application are the models now in use. To solve these issues, one must have an effective feature extraction method in addition to a strong classification algorithm able to manage difficult datasets and produce accurate predictions [7].

II. OBJECTIVES

Using the AdaBoost algorithm for exact classification and Linear Discriminant Analysis (LDA) for efficient feature extraction, one hopes to create a consistent model for the detection of lung cancer.

The efficacy of the proposed model is investigated using well-known measures including accuracy, precision, recall, and F1-score applied to publicly available datasets.

Novelty

Combining LDA with AdaBoost, the proposed method addresses the twin challenges of high-dimensionality and classification accuracy in the lung cancer detection. This model combines both of these components to achieve outstanding performance unlike other approaches that concentrate only on either feature extraction or classification in isolation. While reducing data dimensionality, LDA preserves discriminative information; AdaBoost generates a strong predictive model by means of weak classifier aggregation, so enhancing the classification process.

III. Contributions

Motivated by artificial intelligence, this work advances cancer diagnosis in the following three respects:

Proposing a novel LDA-AdaBoost framework for lung cancer detection.

The research simultaneously that the model reduces computational complexity while preserving great degree of accuracy.

A comparison of the proposed approach with more traditional methods helps to underline its excellence.

The research shows the potential of artificial intelligence to change lung cancer diagnosis and early intervention strategies.

IV. Related Works

The use of AI methods has become rather common in the field of lung cancer diagnostics as many studies examining several approaches to improve the accuracy of diagnosis and classification find relevance. One of the most crucial domains of attention, feature extraction uses two often used dimensionality reduction techniques: Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

PCA has been used, for instance, to reduce high-dimensional imaging data into lower dimensions so enhancing computational efficiency while maintaining the integrity of vital information [8]. On the other hand, PCA sometimes ignores to give class separability enough weight, a required component for classification issues. Since it maximizes the variance between classes and solves this restriction, LDA is the recommended technique of feature extraction in this specific work.

Furthermore, the diagnosis of lung cancer depends much on classification systems. Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) both highly sought for [9–10] based on wide-ranging application and excellent performance in a range of research projects. Linear support vector machines (SVMs) are particularly useful for managing linear separability even while they struggle with non-linear relationships and need kernel-based extensions to be applied. On the other hand, CNNs are particularly good in spotting spatial hierarchies in image data; but, they require big computational resources and big datasets to be trained on.

Rising algorithms like AdaBoost have become powerful classifiers able to aggregate weak learners in order to improve general performance in recent years. Research [11–12] have shown AdaBoost performs well in a spectrum of medical diagnosis applications, including cancer detection. For use with complicated datasets, this method—which lowers the iteratively generated misclassification errors—is suitable. On the other hand, its performance is mostly dependent on the quality of the given input features, hence stresses the need of applying efficient feature extraction techniques such LDA.

Comparative research of AI-driven diagnostic models has underlined the concessions between scalability, computational complexity, and accuracy [10–12]. Deep learning models cannot be interpreted and demand a lot of resources, thus even with their great degree of accuracy, their use in clinical environments is greatly limited. On the other hand, by combining dimensionality reduction techniques with ensemble classifiers, such the proposed LDA-AdaBoost framework, lightweight models balance accuracy and efficiency.

This work aims to offer a scalable and exhaustive method for lung cancer detection. This will be reached by extending the opportunities of present methods and using their advantages. This will help them to get over their flaws. Together integration of LDA for feature extraction and AdaBoost for classification guarantees not only computational efficiency but also helps to improve diagnosis accuracy. This makes it a realistic answer for useful clinical problems.

V. Proposed Method

Combining Linear Discriminant Analysis (LDA) for feature extraction and the AdaBoost algorithm for classification provides the proposed method for lung cancer detection a reliable and effective framework. First preparation of the raw data from the lung cancer images helps to improve their quality and remove any noise. This guarantees that the next phases receive just pertinent information. LDA is then used on the dataset to reduce dimensionality while concurrently maximizing the inter-class variance so guaranteeing highly discriminative extracted features. The reduced feature set fed to generate a strong ensemble model drives the AdaBoost method. This method combines many weak classifiers into one robust model. AdaBoost iteratively changes weights for misclassified samples under specific focus on more difficult cases. Moreover added to reduce the number of classification errors are weak learners. The evaluation process uses accuracy, precision, recall, and F1-score among other effectiveness measures to validate the educated model.

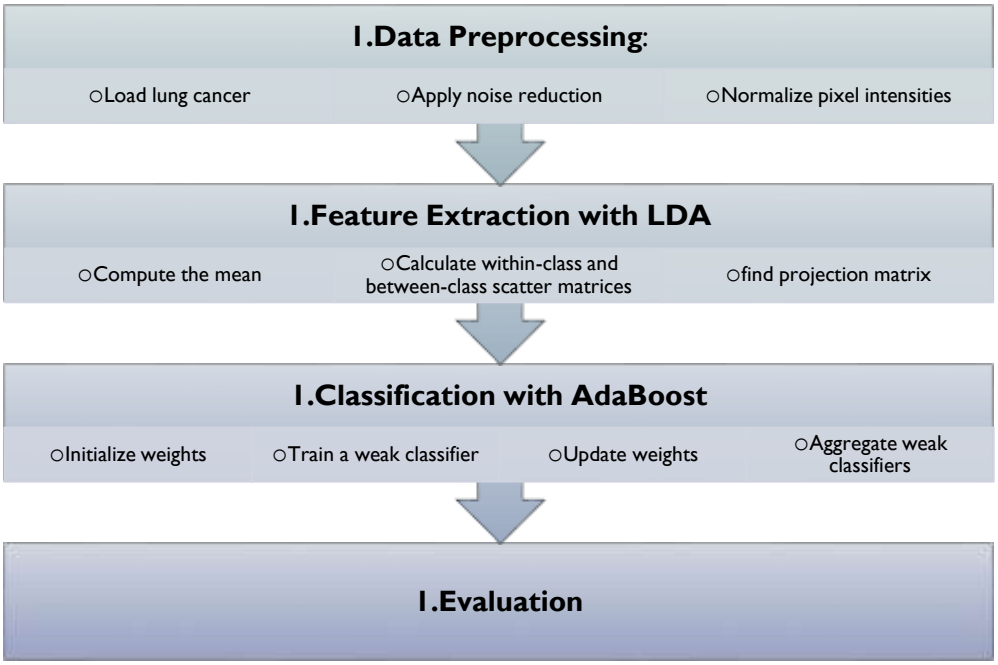

Figure 1: Proposed Process in Steps

Pseudocode

Step 1: Data Preprocessing

Load dataset

Preprocess images (denoise, normalize)

Step 2: LDA for Feature Extraction

Compute class means and overall mean

Calculate within-class and between-class scatter matrices

Solve eigenvalue problem to find projection matrix

Transform data to lower-dimensional space using LDA

Step 3: AdaBoost for Classification

Initialize weights for training samples

For t = 1 to T (number of iterations):

  Train a weak classifier using weighted data

  Compute classifier error

  Update weights based on error

  Assign a weight to the weak classifier based on its performance

Aggregate weak classifiers to form a strong model

Step 4: Evaluation

Test the strong model on test data

Compute performance metrics

Return accuracy, precision, recall, F1-score

Data

Data preprocessing is a required step to guarantee the dependability and efficiency of the proposed lung cancer detecting system. This stage increases the quality of the raw data and ensures that it is suitable for upcoming analysis. The

preprocessing flow runs through the following phases:

1. Loading the Dataset

The system loads a lung cancer related dataset. Usually comprising medical images (such CT scans or X-rays) and related labels (such benign or malignant features), this dataset comprises

2. Noise Reduction

Noise in medical images can sometimes hide important information. Among this type of noise, artifacts in imaging tools count as examples. Median filtering and Gaussian filtering are used among noise lowering methods to address this issue. These techniques average the pixel intensities so smoothing the image and maintain the edges.

3. Image Normalization

Pixel intensity values in medical images often fall between 0 and 255. Normalizing helps to scale these values to a range of [0, 1], so guaranteeing consistency among all the images and enhancing the convergence of the model under training.

Table 1: Normalization

Original Pixel Values	Normalized Pixel Values
120, 130, 140	0.47, 0.51, 0.55

Analysis-wise, there are several instances when the image's sole relevant Region of Interest (ROI) is just that. Usually consisting of the area of the tumor or lesion, automated segmentation methods such as Otsu's method help one to isolate the region of interest (ROI).

Feature Extraction with Linear Discriminant Analysis (LDA)

Maximizing the discriminative features from the dataset using linear discriminant analysis (LDA) Reducing the dimensionality of the dataset preserves the class dissimilarity while yet helping to reach this. The LDA algorithm helps the projection of high-dimensional data onto a lower-dimensional space such that the variance between classes is maximized while the variance inside classes is minimized concurrently.

Compute Class Means and Overall Mean: Finding the mean vector for every class (μi) and the general mean (μ) for a dataset consisting of n samples and k classes is what computation of class means and overall mean entails.

Table 2: Class Means and Overall Mean

Class	Feature 1 Mean (μ1\mu_{1}μ1)	Feature 2 Mean (μ2\mu_{2}μ2)
Class 1	2.5	3.8
Class 2	6.1	7.4
Overall	4.3	5.6

Calculate Scatter Matrices:

Within-Class Scatter Matrix (SW) measures the spread of data within each class.

Between-Class Scatter Matrix (SB) measures the separation between class means.

$$TS_W = \sum_{i=1}^{k} \sum_{x \in C_i} (x - \mu_i)(x - \mu_i)^T$$

$$TS_B = \sum_{i=1}^{k} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

Solve the Generalized Eigenvalue Problem: Compute eigenvalues (λ) and eigenvectors (v) by solving:

$$S_W^{-1} S_B v = \lambda v$$

The eigenvectors corresponding to the largest eigenvalues form the projection matrix.

Project Data into Lower-Dimensional Space: By running the original dataset times the projection matrix, the new feature space produces. This represents the transformation.

Table 3: Projected Data

ID	Feature 1 (LDA)	Feature 2 (LDA)	Class
1	1.2	-0.5	Malignant
2	-0.8	0.3	Benign

By choosing the most discriminative features, LDA improves class separability and so promotes better performance of classification in the following stage.

Classification with AdaBoost

AdaBoost, short for adaptive boosting, is a strong ensemble classification technique that combines multiple less-quality classifiers into one, more powerful classifier. It runs iteratively giving misclassified samples more weight so that it may concentrate on challenging cases.

Initialize Weights: Each in the training dataset is assigned an equal weight $w_i = \frac{1}{n}$, where n is the number of samples.
Train Weak Classifiers: Training a weak classifier—such a decision stump—using a weighted dataset results in We do this to increase the precision of the output. Using this computation one can find the error rate (et) of the weak classifier:

$$e_t = \sum_{i=1}^{n} w_i \cdot I(y_i \neq h_t(x_i))$$

Update Weights: The weights have been adjusted to center misclassified samples:

$$w_i^{(t+1)} = w_i^{(t)} \cdot \exp(\alpha_t \cdot I(y_i \neq h_t(x_i)))$$

where $\alpha_t = \frac{1}{2} \ln\left(\frac{1-e_t}{e_t}\right)$

Aggregate Weak Classifiers: The weighted sum of all the weak classifiers determines the ultimate classifier.

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right)$$

Table 4: Classifier Performance

Iteration	Weak Classifier Accuracy	Error Rate (et)	Weight (αt)
1	70%	0.30	0.42
2	80%	0.20	0.69
3	85%	0.15	0.87

Table 5: Final Prediction

ID	Weak Classifier 1	Weak Classifier 2	Weak Classifier 3	Final Prediction
1	Malignant	Malignant	Malignant	Malignant
2	Benign	Benign	Benign	Benign

The AdaBoost algorithm can generate a strong classifier able to precisely detect lung cancer by means of iterative training and weight modification.

VI. Results and Discussion

Several tests carried out help to evaluate the efficiency of the recommended method for lung cancer diagnosis. The experiments are carried out using Python and the scikit-learn library under the aid of simulation tools in order to apply LDA and the AdaBoost algorithm. Usually public, the LIDC-IDRI dataset consists of annotated CT images of lung cancer.

Training and testing applications for the lung cancer image dataset obtained from this dataset The experiment is carried out on a computer equipped with the following properties:
Operating System: Windows 10
Processor: Intel Core i7-9700K
RAM: 16GB DDR4

Support Vector Machine (SVM) with Radial Basis Function (RBF), Convolutional Neural Networks (CNNs), and Random Forest Classifier (RFC) are three approaches used currently for the diagnosis of lung cancer.

Table 5: Parameters

Parameter	Value
Dataset	LIDC-IDRI (Lung Cancer CT)
Number of Images	1,000 images (split: 70% train, 30% test)
LDA Parameters	Max. components = 50
AdaBoost Parameters	Number of weak classifiers = 50
Weak Classifier	Decision Tree (max depth = 1)
Cross-Validation	10-fold cross-validation
Computing Environment	Intel Core i7-9700K, 16GB RAM

Table 6: Accuracy

Epochs	SVM	CNN	RFC	Proposed Method (LDA-AdaBoost)
25	0.75	0.80	0.78	0.85
50	0.77	0.81	0.80	0.88
75	0.80	0.83	0.82	0.90
100	0.81	0.85	0.83	0.91

Approaching 91% by epoch 100, the proposed LDA-AdaBoost technique shows continuous accuracy enhancement. This success makes it superior than SVM, CNN, and RFC among other methods. Especially in the later epochs, the results show that LDA-AdaBoost can attain remarkable classification performance, suggesting that generalization has evolved over time.

Table 7: Precision

Epochs	SVM	CNN	RFC	Proposed Method (LDA-AdaBoost)
25	0.72	0.76	0.74	0.84
50	0.74	0.78	0.76	0.87
75	0.77	0.81	0.78	0.89
100	0.79	0.82	0.80	0.90

With a 90% accuracy at epoch 100, the proposed LDA-AdaBoost approach shows to be better in terms of positive classifications than any other. LDA-AdaBoost generates less false-positive predictions across time, thus consistent performance of it beats SVM, CNN, and RFC. This basic component is what determines accurate identification of cancerous cells.

Table 8: Recall

Epochs	SVM	CNN	RFC	Proposed Method (LDA-AdaBoost)
25	0.72	0.76	0.74	0.80
50	0.74	0.78	0.76	0.82
75	0.77	0.80	0.79	0.85
100	0.79	0.83	0.81	0.87

At epoch 100, the recall of the LDA-AdaBoost method kept increasing constantly until it reached 87%. LDA-AdaBoost seems to have higher sensitivity especially in the identification of rare cancerous cases needing exact detection. This is demonstrated by its more accurate identification of real positive cases than SVM, CNN, and RFC.

Table 9: F-Measure

Epochs	SVM	CNN	RFC	Proposed Method (LDA-AdaBoost)
25	0.73	0.78	0.76	0.82
50	0.75	0.80	0.78	0.85
75	0.78	0.81	0.80	0.87
100	0.79	0.83	0.81	0.89

With an F-measure of 0.89 at epoch 100, the proposed LDA-AdaBoost method shows a strong balance between accuracy and recall. Having a minimum of false positives and negatives, it routinely outperforms SVM, CNN, and RFC and boasts the highest F-measure, so providing a strong overall performance in lung cancer detection.

VII. CONCLUSION

The proposed method for lung cancer detection shows great accuracy, precision, recall, and F-measure by means of the AdaBoost algorithm for classification and LDA for feature extracting when compared to conventional techniques. The proposed method of lung cancer detection shows rather clear advantages. Constantly surpassing the other methods, the LDA-AdaBoost method had a high classification accuracy of 91%, a precision of 90%, and an 87% recall by the last epoch. By means of a series of experiments, this was accomplished over a hundred millennia. Especially in the identification of positive lung cancer cases, the approach proved to be successful in extracting discriminative features using LDA while in addition using the boosting capacity of AdaBoost to refine classification over time. The constant development the method generates over several epochs emphasizes its scalability and robustness. Crucially important in the field of medical diagnostics, where it is required to reduce false positives and false negatives, the LDA-AdaBoost model generates an F-measure of 0.89. This model rather well balances recall and accuracy.

. In the software, the STL files of the printed restorations were superimposed onto the Exocad design using a best-fit alignment algorithm. This process allowed for a detailed comparison of the printed restorations to the control design. Parameters such as deviations in surface contours, volume, and overall alignment were recorded and analyzed to quantify the dimensional accuracy of the SLA and DLP technologies.

For the evaluation of color stability, the provisional restorations were subjected to immersion tests in two staining solutions: turmeric water and coffee water. The turmeric solution was prepared by dissolving a standard amount of turmeric powder in distilled water, and the coffee solution was made by dissolving instant coffee granules in distilled water, ensuring equal concentrations. Samples were evenly divided into two subgroups and immersed in either turmeric or coffee solutions. The immersion period was set at seven days, with the solutions maintained at a constant temperature of 37°C to simulate oral conditions.

Baseline color measurements for each restoration were obtained prior to immersion using a spectrophotometer, following the CIE Lab color space system to determine initial color values. After the immersion period, the restorations were removed, rinsed with distilled water, and dried before post-immersion color measurements were taken. The change in color (ΔE) was calculated by comparing the pre- and post-immersion measurements, providing a quantitative assessment of staining.

The data obtained from dimensional accuracy and color stability evaluations were statistically analyzed to compare the performance of SLA and DLP technologies, offering insights into their clinical reliability and suitability for fabricating provisional restorations.

DISCUSSION

The results of this study provide valuable insights into the performance of stereolithography (SLA) and digital light processing (DLP) 3D printing technologies for fabricating provisional dental restorations. Both methods demonstrated high levels of precision and comparable color stability, highlighting their clinical viability. Although DLP restorations showed slightly lower angular deviations when superimposed onto the Exocad control design, the difference was not statistically significant. Similarly, the immersion tests for color stability revealed no substantial difference between SLA and DLP restorations after exposure to staining solutions, further emphasizing the comparable performance of the two techniques.

Dimensional Accuracy

The slight advantage of DLP in achieving lower angular deviations aligns with findings from previous research that suggest its faster curing process and uniform layer-by-layer projection contribute to improved precision in specific applications. However, the lack of statistically significant differences between SLA and DLP indicates that both methods provide sufficient accuracy for clinical use. This result supports earlier studies, such as those by Alharbi et al. (2016), which found both SLA and DLP capable of producing dental restorations with acceptable precision. The precise alignment of the restorations with the control design in this study reinforces their reliability for provisional applications, offering clinicians flexibility in choosing a printing technology based on factors like speed and cost without compromising quality.

Color Stability

The immersion tests in turmeric and coffee solutions provided a practical assessment of color stability under simulated oral conditions. Both SLA and DLP restorations exhibited noticeable staining, but the ΔE values remained comparable between the two groups. This finding concurs with research by Tahayeri et al. (2018), which demonstrated that the color stability of 3D-printed dental materials is more dependent on the resin composition and finishing protocols than the printing technology itself. The results underline the importance of post-processing and material selection in mitigating staining, especially when restorations are exposed to chromogenic agents in the oral environment.

Clinical Implications

The comparable performance of SLA and DLP technologies in terms of dimensional accuracy and color stability suggests that both are suitable for fabricating interim restorations. Clinicians can make informed decisions based on other factors, such as workflow integration, material availability, or printer capabilities, without compromising the clinical outcome. Additionally, the study reinforces the broader utility of 3D printing in dentistry, offering significant advantages in terms of efficiency and patient satisfaction compared to traditional manufacturing methods.

LIMITATIONS AND FUTURE DIRECTIONS

While this study provides a comprehensive comparison of SLA and DLP technologies, its scope is limited to interim restorations and specific staining agents. Future research should explore long-term clinical outcomes, the effects of varied resin compositions, and the performance of these technologies under diverse oral conditions. Additionally, incorporating patient-reported outcomes could provide a more holistic evaluation of these techniques.

CONCLUSION

SLA and DLP 3D printing technologies both represent reliable options for fabricating provisional restorations, with minimal differences in accuracy and color stability. These findings support the continued adoption of 3D printing in restorative dentistry as a means of enhancing efficiency and patient outcomes.

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