Educational Administration: Theory and Practice
2024, 30(5), 3016-3023
ISSN: 2148-2403
https://kuey.net/

Research Article

Chestx-Edge: An Integrated Approach For Outlier Detection In Chest X-Rays Using Dimension Reduction And Edge Detection

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Citation: Dr.Asha PNal. (2024), Chestx-Edge: An Integrated Approach For Outlier Detection In Chest X-Rays Using Dimension Reduction And Edge Detection *Educational Administration: Theory and Practice*, *30*(5), 3016-3023
Doi: 10.53555/kuey.v30i5.3381

ARTICLE INFO	ABSTRACT

The advancement of artificial intelligence technology has driven artificial intelligence research in many field s such as medicine. Medical intelligence focuses on co mputer-aided diagnosis , which uses signals from the human b ody to predict health problems and diagnose diseases t hrough medical examinations . However, processing a nd recognition of high- quality medical images requires expensive equipment and high energy consumption. To solve these problems, this paper proposes a new approach to detect outliers in chest radiographs using dimensionality reduction and edge detection techniques. The proposed method involves scanning X- ray images using a fixed-size window, performing differential imaging on adjacent segment images, and extracting edge information in binary format using AND operations. Subsequently, the extracted edge data is convolved using a detection filter to generate a series of lines that are divided into 16 types. The frequency of each line type is then summed to form a one- dimensional array for each segment image. This reduced data is used as input for a training model based on a recurrent neural network.To evaluate the effectiveness of the proposed model, se veral experiments were conducted using data showing COVID in chest X-ray. The results showed that the special education con solidation application achieved the highest accuracy a t 97.5%.

Keywords— Computer-aided diagnosis system, feature extraction, line feature analysis, RNN, deep learning.

I. Introduction

To address the shift towards preventive healthcare and the growing demand for efficient and personalized treatment, medical artificial intelligence has emerged as a promising avenue. By leveraging lifetime patient data, medical images, genetic information and literature, AI technologies aim to assist and sometimes replace human judgment in healthcare decision-making processes. This is particularly important given the variability in treatment approaches among health care providers and the importance of accurate diagnosis in health care. Medical imaging in particular has seen significant advances with AI, enabling more accurate and faster analysis of image data compared to traditional methods. The recent COVID-19 pandemic has further accelerated the adoption of artificial intelligence in disease detection and diagnosis, particularly in chest diseases.
Various studies have proposed artificial intelligence systems to detect lung nodules and abnormalities in medical images using techniques such as Convolutional Neural Networks (CNN) and Deep Learning frameworks. Despite these advances, the computational complexity of medical image diagnosis systems remains a challenge that requires significant time and resources for model training and inference.
To solve these problems, this work presents a chest x- ray outlier detection model using dimensionality reductio n and edge detection tools. The proposed line feature analysis algorithm aims to increase processing speed and acc uracy by reducing the size of high- resolution images. This study aims to evaluate the effecti veness of the algorithm and compare it with existing lear ning models.

The structure of this article is as follows: Section 2 discus ses breast cancer diagnostic programs based on artificial i ntelligence and medical image dimensionality reduction t echnology. Section 3 describes the data generation proces s using the dimensionality reduction method, RNN model , and chest x-ray system. Section 4 evaluates the effectiveness of the pr oposed method through experiments, and Section 5 descri bes the research.
By focusing on innovative techniques to enhance medical image analysis while providing a comprehensive overview of existing research and methodologies, this study aims to contribute to the advancement of AI in healthcare with a particular emphasis on chest disease detection.

RESEARCH

1. THE BEST DISEASE WITH AN AI-BASED SCORE DIAGNOSTIC SERVICES

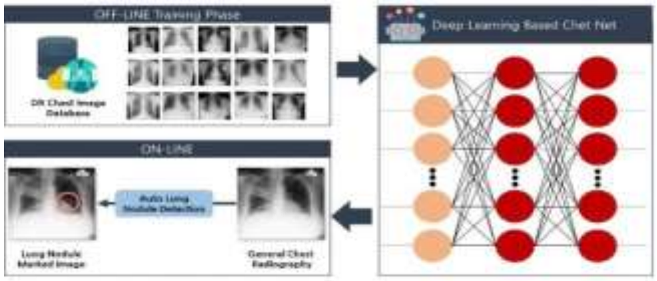


FIGURE 1. Auto lung nodule detection software of Samsung electronics.

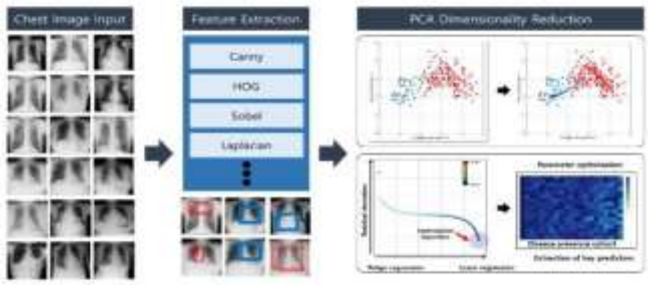


FIGURE 2. Dimensionality reduction process of PCA.

Conditions such as breast cancer, chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis, and lung cancer pose significant health challenges in everyday life. Given the expertise needed to detect them, research into AI-based methodologies for breast cancer diagnosis is actively underway. In addition, companies such as VUNO have developed AI solutions such as VUNO-med to diagnose lung nodules and assist in medical diagnosis with a high level of accuracy compared to trained doctors. VUNO-med uses a deep learning algorithm to accurately analyze X-ray images determine pediatric bone age, and facilitate lung disease diagnosis by identifying challenging areas for medical specialists, achieving high accuracy rates.
Despite the promising capabilities of AI-based diagnosis systems, the computational complexity of processing high- quality medical images necessitates dimension reduction techniques to enhance learning and recognition efficiency. By converting high-dimensional data into low-dimensional representations, these techniques optimize resource utilization and accelerate AI model training and inference processes.
In summary, ongoing research and technological advancements in AI-based chest disease diagnosis aim to improve accuracy, efficiency, and accessibility in medical imaging, contributing to better healthcare outcomes for patients.

2. IMAGE DIMENSION REDUCTION TECHNOLOGY

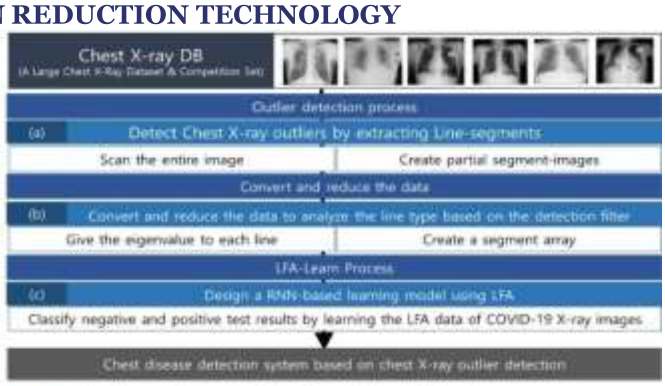


FIGURE 3. Processing of chest X-ray outlier detection model using dimension reduction and edge detection.

image dimension reduction technologies commonly utilized for smoother data interpretation in medical devices include Linear Discriminant Analysis, Independent Component Analysis , and Principal Component Analysis . Independent Component Analysis separates mixed independent signals, tending towards a Gaussian distribution with increased data volume. Principal Component Analysis, on the other hand, transforms high-dimensional space into a lower-dimensional one by identifying orthogonal axes while preserving data dispersion. The process, illustrated in Image 2, involves generating new features through linear combinations of original data features, with eigenvectors defined as principal components.
However, Principal Component Analysis application can be challenging due to difficulty in determining class identification and variability in the number of principal components based on input data. This discrepancy between learning and test data can hinder classifier usage. Additionally, changing classification criteria based on varying amounts of learning data requires reestablishing criteria, complicating real-life application.
To address these limitations, this study proposes an algorithm that preserves X-ray image line characteristics while reducing data size. It aggregates weak and strong lines, maintaining object shapes, and forms rough classification criteria based on strong line features. The model then conducts detailed object classification based on weak characteristics. Notably, this algorithm's applicability remains consistent regardless of data characteristics, allowing immediate use of additional learning data post-processing.
In summary, this work provides a solution that improves t he interpretation of reduced data while preserving import ant images, thus providing an easy way to diagnose chest diseases using eight treatments of the owner.

OUTLIER DETECTION USING DIMENSION DECREASE AND EDGE DISCOVERY

Nowadays, diagnostic methods based on medical images face problems such as the needs of artificial intelligence a nd long-
term cognitive models, which affect the timing and recog nition of good medical imaging. This article proposes a s olution by presenting a chest radiograph model using dim ension reduction and edge measurement techniques. This model combines a statistical algorithm to extract relevant features from chest X-
ray images to facilitate breast cancer diagnosis. Additiona lly, recurrent neural network .
architecture is also used to develop models for breast can cer detection based on image segmentation.

Image 3 shows the X-ray chest of the pipe processing model, including dimension reduction and edge detection. This process is divided into external identification, data transformation and reduction, and training.

In summary, this paper presents a novel approach to improve the efficiency and accuracy of breast cancer diagnosis by combining dimensionality reduction and edge detection techniques in medical image analysis.

1. X-RAY Exception Discovery THROUGH LINE-SEGMENT EXTRACTION COVID-

19 often shows shadows on the heart in some areas of the x-ray, and the left ventricle is large and clear, similar to pne umonia. Symptoms may include progressive leaks, conso lidation, minor right upper quadrant consolidation, and o pacification. To understand these symptoms, x- ray images are analyzed through a window of the same si ze to create a cross- sectional image. The image matching machine separates t he frontal area with computer vision, using half of the im age to identify three overlapping images. This is possible with high-resolution images because increasing the number of pixel s allows you to get closer to the field of view and get eno ugh foreground. Image 4 shows the segmentation process and Algorithm 1 shows its operation.
Scan the x- ray image through the M×N window, intersect and subtra ct the captured images, and use the AND function to crea te a binary image view to obtain the segmented image. A djacent sections are divided into pairs and different shape s are used. This tool extracts objects by comparing them with a previously captured foreground image. The VE fu nction further refines captured edges, sharpens focus and eliminates noise. Data created in binary format represent line features in the X- ray image and can be easily converted into models for cal culation**.**
In summary, this process enables precise extraction of object edges from X-ray images, facilitating analysis and interpretation of COVID-19 and pneumonia symptoms.

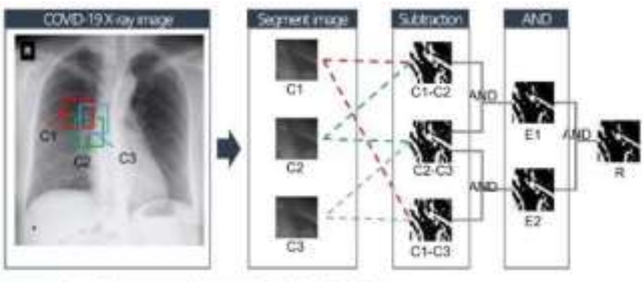


FIGURE 4. Three adjacent segment-image sets detected through windows.

2. DATA CHANGE AND DECREASE FOR DECTION

In the previous step, different images are used by intersec ting adjacent images and extracting the binary edge data by AND operation. However, since this information repre sents visual information, it is difficult to determine the sh ape of the line. To solve this problem, the lines of the obj ects in the image are converted into digital models that ca n be seen with the help of filters. Figure 5 shows the nor malization of the visible profile pattern using this filter.

Linear data is calculated by adding 2^n coefficients to eac h 2^2 exponential filter (*). This method determines the e igenvalues of each row in the graph section, as shown in Table 1. Ta ble 1 provides information about the row types identified by the decision filter, from binary engineering to mathem atics. Each element has a unique distribution value, and u seful filters remove these features.

Image6 shows the use of convolution-
based detection filters and image patch convolution to ex pand the visual image. This method generates reaction co efficients for each pixel, adds them to represent values, a nd creates an LSmap. The generated data is represented a s a number between 0 and 15, corresponding to the string type shown in Table 1. Use LSmap to convert each image fragment into a 1D file with 16 dimensions.

Equation 1 shows the process of using LSmap to create a n array. W and H represent the size of the LSmap, while LFA represents the 1D array collection line type n- segment image. In this case, I show the number of partiti ons as 16. Extract the LSmap coefficient values and use them as parameters for the LFA. Since each coeff icient value represents a characteristic value of the array, when the array expression is called, the number of rows i s calculated by incrementing the value of the array. This process reduces the amount of data, creating the final mat rix of size "number of image segments" × 16.

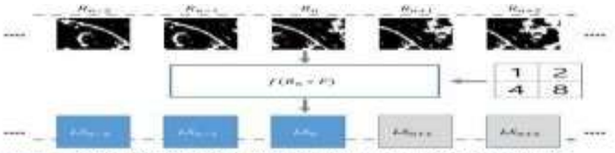


FIGURE 5. Standardization conversion of visual data patterns using detection filter.

TABLE 1. The eigenvalue for each line type.

Pattern	Line Type	Pattern	Line Type
0000 (0)	Non-Activity	8000 (8)	Point
0001 (1)	Point	8001 (9)	Verticality
0020 (2)	Point	8020 (10)	Diagonal
0021 (3)	Horizontality	8021 (11)	Curve
0400 (4)	Point	8400 (12)	Horizontality
0401 (5)	Diagonal	8401 (13)	Curve
0420 (6)	Verticality	8420 (14)	Curve
0421 (7)	Curve	8421 (15)	Activity

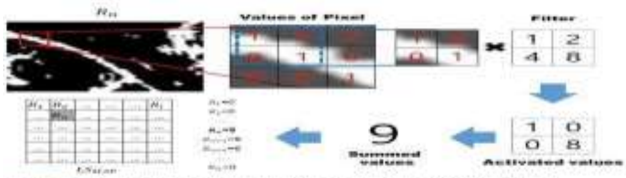


FIGURE 6. Visual image compression using a convolution-based detection filter.

3. Establishment AND DISPLAY DISEASE Discovery Framework

Based on the above experimental results, this study developed a breast cancer diagnosis system using chest X-rays. This system processes CT and X-ray images of lung cancer patients and sends them to a server for analysis and prognosis. To ensure accurate prediction, the system automatically repositions the image and checks the coverage of all areas of the patient's lungs. Chest x-ray systems are very effective and provide important information to medical professionals with limited diagnostic experience. It supports decision making byreducing false diagnosis rates and making accurate diagnoses. Figure 7 shows an X-ray-based breast cancer diagnosis system that analyzes data based on chest X-ray images tagged
Contains user ID, name and date. After the user enters the system, an xray is taken. , analyze data by expanding, re ducing, transforming and comparing. It provides informat ion about the general structure of the lungs and enables th e diagnosis of up to 15 diseases and related disorders bas ed on stable xrays. Figure 8 shows a chest In glass surger y (GGO), which determines lung laxity according to the t ype of aggregation and atelectasis, especially the analysis of the level of the transparent ball facilitates the detectio n of lung diseases.
Monitoring GGO patterns, which often show confusing p atterns of changes in patterns, is important for diagnosing COVID-19. However, early or mild cases of COVID- 19 may not show lung symptoms on x- ray and may require GGO- based chest CT for accurate diagnosis. Aggregation patter ns varying in severity and

presentation are common in C OVID- 19 patients, with many of the previously unchallenged as sociations. Other features such as persistent pleural thicke ning, overlapping septal thickening, and air bronchogram s aid diagnosis.
In summary, the advanced breast cancer diagnostic system based on chest x-rays offers a comprehensive approach to disease prediction and diagnosis, using advanced imaging analysis techniques to support medical professionals in providing appropriate and accurate treatment..

TABLE 2. Structure of proposed-RNN.

No.	Layer Name
1	Input Layer (*N*)
2	Convolution (64, *N*, std=1, pad="same," act="relu")
3	BatchNormalization
4	Reshape (64, N)
5	Bidirectional-GRU (64)
6	Bidirectional- GRU (32)
7	Dropout (0.2)
8	Output Dense Layer (act="sigmoid")

FIGURE 7. Chest disease detection system based on chest X-ray outlier detection.

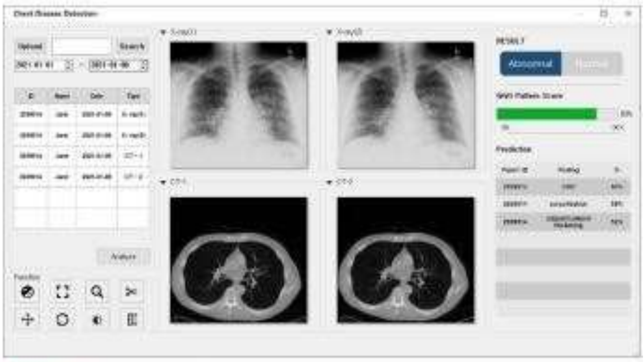


FIGURE 8. Chest X-ray outlier detection-based chest disease detection screen.

EVALUATING PERFORMANCE

In this section, an RNN-
based learning model using LFA was developed and its p erformance was evaluated. The design consists of reducin g the size of the learning-
oriented data structure with the LFA algorithm. There are a total of 8 layers in the model, including the input layer and the output layer. Table 2 shows the RNN model prop osed in this study. In the input process, the size of the inp ut data (such as N) follows a pre-
designed strategy to improve features through the convol utional process and use the "normalization process" to re duce redundancy during training. To enable the recycling process, the input data size is determined by the recycling process, and the data in each part of the input image is re duced by the bidirectional GRU.

The ratio model is analyzed based on input data from two clusters of 64 and 32 units each. After the recycling proc ess, the sample goes through the "Release" process and d ensity process before forming the final product. This mod el analyzes data containing reduced-size x- ray images of COVID-19 to classify negative or positive results.

The test consists of two parts to test the accuracy and reli ability of the algorithm. First of all, the accuracy is evalu ated by comparing the proposed detection algorithm with the famous Laplace, Sobel and Canney edge detection alg orithms

ACCURACY CHANGES OF THE line feature analysis MODEL ACCORDING TO EDGE DETECTION ALGORITHM

In this section, we evaluate the accuracy of the LFA algor ithm through experimentation and compare its performan ce with known edge recognition methods such as Laplace
, Sobel, and Canny. Now the edge search algorithm preset s many parameters and selects the best parameter values based on reality. When COVID-19 chest X-
ray data is used, 80% of the data is used for training and 20% for testing. Figure 9 shows actual measurements for edge indexing; where (a) denotes the accuracy and (b) de notes the loss for each algorithm. This algorithm has the highest accuracy at 98.9%, followed by Canny (97.9%), Sobel (97.6%), and Laplace (98.2%). These results are rel evant to the edge detection results because the request to reduce the index uses the extracted line to create a new i mage. The loss measurement results shown in Figure 9(b) show that the proposed algorithm has the lowest loss at 0.067, followed by Sobel (0.113), Canny (0.124) and Lapl ace (0.215) know the best edge performance. The propos ed algorithm makes it more efficient by calculating the st art of the season with a visible advantage, unlike existing algorithms that need to be changed.
The Laplace edge algorithm identifies edge points (zero c rossings) by dividing them into four and can complete ed ge detection from all directions. However, it is important in terms of noise causing incorrect area detection due to o ptical noise, which affects the accuracy of LFA-RNN. The Sobel edge algorithm performs well for centra l values of the output image but works harder for diagonal lines a nd provides greater accuracy in identifying exact edges, e specially in X- ray images. Although the Canny Edge algorithm shows g ood performance in terms of accuracy and low error, it is not suitable for real- time use due to its high usage time and long processing ti me. Additionally, due to the similarity between bone and skin, determining the appropriate classification in X-ray images may cause problems with contour profiles and reduce the accuracy of the LFA-RNN model.
The contour detection method introduced in this article le arns how to reduce light noise and complete edges before using the X- ray image edge detection method. This method avoids det ection errors caused by noise in adjacent areas and provid es greater accuracy than other algorithms.
Considering these factors, the proposed algorithm shows higher accuracy in edge detection compared to existing algorithms.

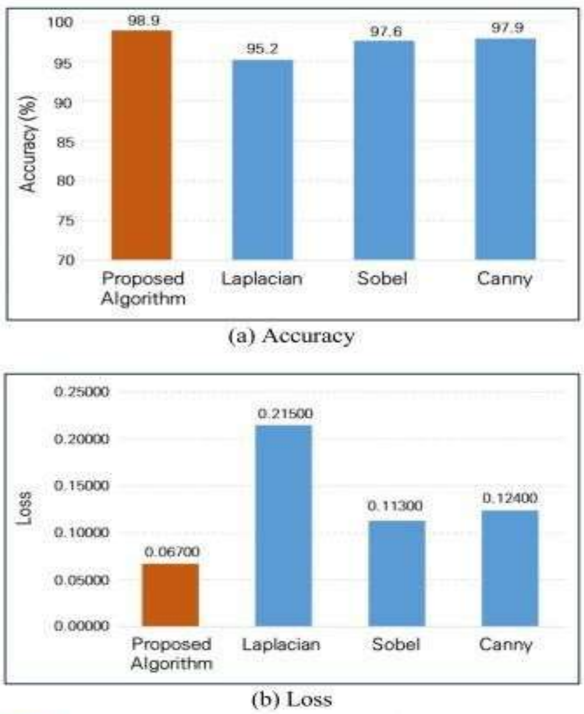


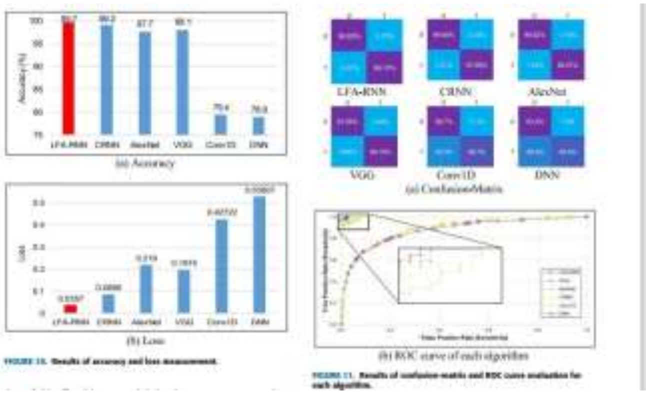
FIGURE 9. Results of measuring accuracy according to the edge detection algorithm.

1. EXACTNESS CHANGES OF THE LINE FEATURE ANALYSIS MODEL ACCORDING TO THE EDGE DISCOVERY CALUCLATION

The performance of the RNN model has been compared with CRNN, AlexNet, VGG, Conv1D and DNN models t hrough experiments. The data contains a total of 950 ima ges, including 482 normal images and 468 COVID-19 images; 70% is used for training (665 images), 10% fo r verification (95 images) and 20% for Exams (190 image s). Figure 10 shows the actual and measured loss. The pro posed LFA- RNN model achieved the highest accuracy of 99.7% with a loss of 0.0357. In comparison, the performance of othe r models is as follows: CRNN (99.2%), VGG (98.1%), A lexNet (99.7%), Conv1D (79.4%), and DNN (78.9%).

Furthermore, the Galau- Matrix curve and receiver operating characteristic (ROC) curve were measured as shown in Figure 11 to evaluate t he accuracy and reliability of the proposed method. for al l types of breast cancer. On average, the LFA- RNN model outperforms the baseline model with an accu racy of 99.7% for LFA-RNN, 98.6% for CRNN, 97.7% for AlexNet, and 98.1% f or VGG. The accuracy of Conv1D and DNN model is lo wer at 77.7% and 76.5% respectively. The LFA method c reates new data by compressing the original image and re duces the data size by focusing on strong features and re moving detailed information, thus obtaining more accurat e results.

During the experiments, the proposed line feature analysis model showed consistent learning and validation curves and achieved the highest performance with 99.7% accuracy on the experimental data. It also gives the lowest loss of about 0.0357 and more than other models in precision recall and accuracy tests.



CONCLUSION:

This paper presents a new method for chest X- ray examination using dimensionality reduction and edge detection techniques. Unlike existing methods, this algor ithm maintains consistency in reduction by using the data itself as a criterion, thus providing a good classification t est regardless of changes in the training data, class distrib ution or images. This algorithm focuses on preserving the unique features of the image based solely on the appeara nce of the object during classification while reducing artif act. To capture information about an object, it creates thre e different images by processing adjacent images to a spe cific size and using functions that extract binary edge dat a. This edge data is further processed using a 2x2 expone ntial filter to convert the seen data into a digital model, cr eating eigenvalues that represent different lines. Such results are calculated t o create 16- dimensional 1D data that refines the image while preservi ng the shape of the object.

The generated data is used as input for an RNN- based learning model where the reduced data for each uni que value is fed to the back layer for analysis. Abnormali ties in the X-ray image and diagnosis of COVID - 19 are classified as positive or negative. This method imp roves the dimensionality reduction process by splitting th e lines of the medical image, simplifying the reduction, e quation, and assembly.

Currently the LF algorithm only focuses on reducing ima ge size based on contours. However, future research aims to extend this approach to the color space because color i s important information in diagnosis. The aim of the LFA algorithm is to improve the detection of the disease by se arching for the color region.

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