THE X-RAY EUCLIDEAN SYNTHETIC IMAGE

Halah Ahmad AbdAlmeneem

Department of Mathematics, Darb University College, Jazan University, Jazan, 45142, Saudi Arabia

ABSTRACT

One of the most popular medical diagnostic tools ever is X-ray imaging, and that's saying something considering how far biomedicine has come.The amount of information that may be retrieved from images is significantly impacted by the characteristics that are already there.We propose to apply the Euclidean distance transform technique for image preprocessing to take the advantage of the image feature technology that makes it easier to identify pneumonia cases.The paper concurrently applya number of image preprocessing techniques, such as binarization, thresholding, scaling, normalization, and others, to the sampled image before the features are obtained. Then we extract the characteristics for image classification and recognition.The suggestion is verified and examined using the publicly accessible COVID-19, Pneumonia, and Normal image datasets.

The objective is to acquire the maximum level of identification that is practically possible.This would create an accessible and affordable diagnostic and illness management tool that medical professionals might utilize in the event of the COVID-19 pandemic and other future events.

The practical results showed that, given any query image of the three cases of X-ray images; Covid-19 case, Normal case and X-ray image of Pneumonia case the high precision is evident when correlating with the normal cases, which it negates the infection.

KEYWORDS

Chest X-ray, image pre-processing, Euclidean distance transform,COVID-19, pneumonia, deep learning, textural analysis, diagnosis, healthcare.

1. INTRODUCTION

To acquire fresh perspectives and tackle outstanding issues in image analysis, writers introduced several techniques that have been suggested in the literature to convert the image into a different representation [1].The procedure of generating new images from a pre-existing dataset is referred to as image creation or synthesis. Euclidean Distance Transform (EDT) is a technique in the image processing domain that helps in converting the input binary image into the distance map of numeric value.X-ray images, in general,is the initial screening technique that proved beneficial in diagnosing any infection.These images offer significantly lower costs [2], faster results, and enhanced accessibility in comparison to the less common and more expensive CT scan machines. Like all diseases, pneumonia inflames the lungs' alveoli, which exchange oxygen. The fact that SARS–CoV–2 is not the only pathogen that may cause pneumonia is something that should be brought to attention. Other bacteria, molds, fungi, and viruses are all capable of causing pneumonia itself. In severe instances, the patient may need to be admitted to the ICU for mechanical ventilation to assist with respiration[3]. Identifying pneumonia involves greater complexity.Kawecki, D. and A. Majewska [4] facilitate the automatic detection of bacterial and viral pneumonia through the analysis of digital X-ray images.Current trends in image analysis indicate that most recent methodologies for identifying pneumonia in X-ray images rely on various adaptations of CNN-based deep learning algorithms, recognized as the leading techniques in the field. Several CNNs have been developed for the detection of pneumonia, including those referenced in the works of[5].Boilerplate models developed from the DenseNet-121 architecture [6] served as the foundational basis for the research outlined in [7, 8].An ensemble learning process, incorporating numerous weak models alongside transfer learning, was employed for the detection of pneumonia utilizing X-ray images as referenced in [9]. The most recent developments in research focused on automatic pneumonia detection in X-ray images highlight the use of CNN-based deep learning algorithms, which have been referenced in various related studies [10]. Additionally, other methodologies discussed in these studies incorporate machine learning algorithms alongside handcrafted textural features, demonstrating significant advantages as image analysis tools [11]. The definition of textural characterization indicates that this concept encompasses a diverse array of techniques aimed at parameterizing alterations in texture features associated with pathologies that may differ from other pathologies across various medical imaging modalities [12].The presented methods in the field of characterizing textural images are very good at using computers because they take very little time to run and only need small amounts of training data.

Our work is interested in demonstrating the value of translating the X-ray image into a new representation toobtain powerful (sharprobust) features that enhance accuracy and expedite infection diagnosis.We apply an approach calleddistance transform thatprovides a measure of the separation of points in the image and to take the advantage of the image feature technology we apply the Histogram of Oriented Gradients (HOG) features. Figure 1 shows a rough outline of how the work is organized.

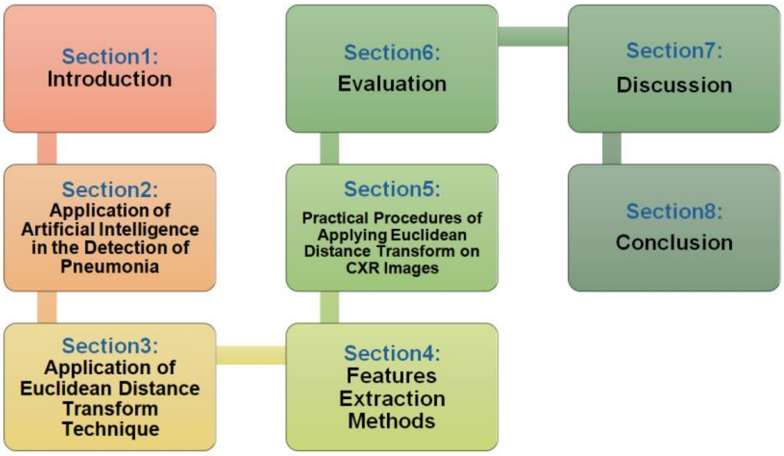

Figure 1. The exact plan of our paper structure.

1.1. Objectives

When considering expense, availability, and radiation exposure, Chest X-rays offer certain advantages over CT scans, making them potentially more suitable for routine use.

1- The primary goal of this work is to serve as an illustration of analyzing the image by high-level algorithms to exploit the feature structure of X-ray images in order to classify it as infected with viruses.
2- The second is to be more proactive in preventing future epidemics or new varieties by learning from and studying past experiences. To do this, we must first provide sound policies,

decision-making processes, and management practices that may aid others in strengthening their response to the epidemic.

2. Application of Artificial Intelligence in the Detection of Pneumonia

2.1. Introduction to AI-Based Solutions

The means used by AI in diagnosing ailments entail faster evaluation and interpretation of data than humans can accomplish on their own [13]. Regular diagnostic techniques for such imaging involve radiologists' analysis of the images, which takes quite a long time and still presents variability. While developing such AI-based solutions manually is very time-consuming, requires human diagnostic proficiency and tends to be rather unreliable due to the subjective nature of visual pattern identification [14], AI can be trained on a giant set of medical images marked with pneumonia symptoms, which it can then identify with high reliability. It enables the availability of fast and uniform diagnostic evaluations from the AI system, excluding the probabilities of human-produced errors[15].

This improved accuracy and efficiency of AI in diagnosing diseases by identifying patterns that humans may overlook makes AI a great tool in early diagnosis, which can help detect pneumonia at a stage that will certainly respond to treatment [16]. By making physicians' diagnostic functionalities more sophisticated, artificial intelligence can contribute to enhancing the quality of treatment and preventing pneumonia and its impact on the health sector.

2.2. Employing Archetype CNN-Based Deep Learning Algorithm for Pneumonia Diagnosis

The use of CNN-based algorithms for pneumonia detection has been established to receive much attention, much attention with several studies showing that its use can effectively help in identifying pneumonia from chest X-ray (CXR) images [17].

CNNs are typically constructed hierarchically, starting with layers like the convoluted layer and the pooling layer, followed by the fully connected layer [18]. The output layers of the neurons in each convolutional layer connect the neurons from the other layers and are in touch with the higher layers. In convolutional layers, an image is convolved zoom through filters to produce edges, textures, shapes and so on or other features in deep networks. The pooling operation is available and works on feature maps. It decreases the dimensions of the feature map, but it takes only the main distinctions. They are connected fully and make decisions concerning the presence or absence of pneumonia [19].

Similarly, recently, several studies have discussed the efficiency of using deep learning CNN-based models for diagnosing pneumonia. For instance, [20]propose a CNN approach for CXR images. Within this method, it was quickly realised that the results are, in fact, more precise at high levels than other strategies that have to use only converted machine learning methodologies for the basic detection of pneumonia. Likewise,Kaya and Gürsoy[21] reported a slightly more accurate CNN-based model for diagnosing pneumonia.They further expanded the view of deep learning models as groundbreaking in diagnostic medicine.

2.3. Recent Advances

Remzan et al. [22] utilised a more effective deep learning structure, which is DenseNet-121, has recently produced a great performance in the tasks involving the classification of medical image. In DenseNet-121 models, there are mainly several notable layers that are connected densely while aiming at learning intricate features as well as enriching the classification functionality [26].Figure 2 shows an algorithm to apply Artificial Intelligence in the Detection of Pneumonia.

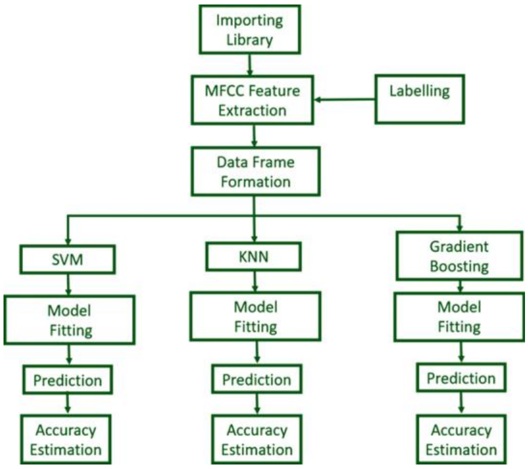

Figure 2. Application of Artificial Intelligence in the Detection of Pneumonia [24].

3. APPLICATION OF EUCLIDEAN DISTANCE TRANSFORM TECHNIQUE

3.1. Introduction to the Technique

The Euclidean Distance Transform (EDT) is a technique in the image processing domain that helps in converting the input binary image into the distance map of numeric value.Applied in various domains such as vision and robotics systems, patterns and shape recognition, and practices of medical image analysis [25]. From the perspective of the EDT's use in the selection and transformation of feature maps for machine learning models in diagnosing an important role in enhancing features that signify pneumonia in the context of medical diagnosis, notably in preprocessing CXR images for the identification of pneumonia, is evident[26]. Euclidean Distance Transform can also be defined as the procedure of approximating the distance of a feature belonging to the object to the feature of the object's boundary. Distance transformation can be best explained by relating it to the technique used by the shortest distance transform algorithm & can be described as the estimation of the foreground against the nearest background point in terms of Eros Distance Transform [27].

3.2. In Relation to the Pre-Processing of Images

As indicated in the literature, it is understood that noise and artefact structures are present in many CXR images and can interfere with the features of the pictures that are important in diagnosis [28]. With such adaptations, we are able to obtain distance maps that highlight edges and the general morphology of the organs of interest, such as the lungs, for accurate detection of pneumonia.The distance maps produced by the EDT can provide supplementary information for deep learning models, alongside the input intensity-based images. This would also enhance the model's feature sensitivity, particularly on aspects like the presence of infiltrates or consolidations within the lungs. Additionally, the EDT can assist in making the distribution of various shapes in space more standardised to make the models more stable and less sensitive to patient and imaging variability [29].

3.3. Explanation of Euclidean Distance Transform

EDT applied to CXR images entails numerous steps, from image acquisition to the incorporation of distance maps in the machine learning model.

3.3.1. Image Pre-processing

CXR image database that includes good quality images or, in other words, ‘normal’ CXR images are collected [30]. On the other hand, images are converted to binary form.

3.3.2. Distance Transform Computation

The Euclidean Distance Transform process is performed on the binary images to obtain the distance maps [31]. The distance maps used in the calculation of similarity and dissimilarity to the standardised range are scaled and can be conveniently used for input in the machine learning model.

Using the distance transform, one can determine the degree to which points in the image are separated from one another. This function determines the distance between each pixel that has been set to off (0) and the pixel that is closest to it that is not zero for binary pictures. Several different distance measures are supported by the function.

- Euclidean distance is the distance between two dots that can be drawn in a straight line, as shown in Figure 3.
- The city block distance metric measures the path between the pixels based on a 4-connected neighborhood. As shown in Figure 4, pixels that touch diagonally are two units apart, while pixels whose edges touch are one unit apart.
- According to an eight-connected neighborhood, the chessboard distance is a measurement that determines the path that connects the pixels. The pixels that are one unit apart from one another are those that have edges or corners that contact, shown in Figure 5.
- The quasi-Euclidean measures the total Euclidean distance along a set of horizontal, vertical, and diagonal line segments as shown in Figure 6.

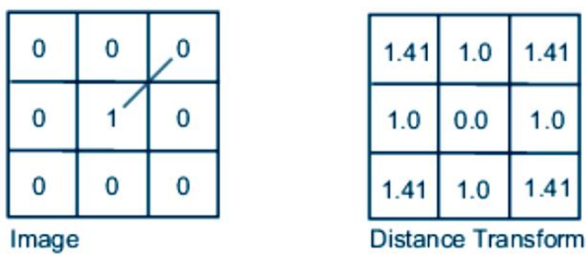

Figure 3. 2-D Image Example and its Euclidean distance Transform.

In 2-D the Euclidean distance between $(x_1, y_1) and (x_2, y_2)\ is$:

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}.$$ Adopted from (MATLAB).

3.3.3. Model Integration

Convolutionally, the distance maps with the CXRs are integrated into a multi-channel input for feeding into the machine learning model [32]. The augmented dataset on the diagnostic accuracy of the model and the robustness of the augmented data on the trained model are evaluated [33].

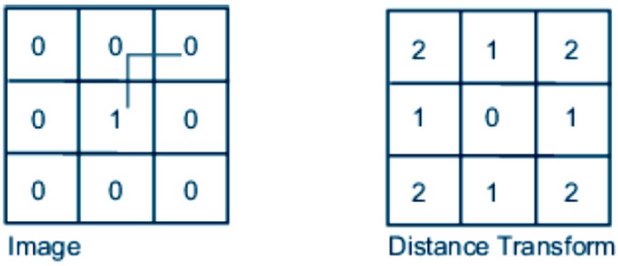

Figure 4. 2-D Image Example and its cityblock distance Transform.

In 2-D the cityblock distance between $(x_1, y_1) and (x_2, y_2) is: |x_1 - x_2| + |y_1 - y_2|$. Adopted from (MATLAB).

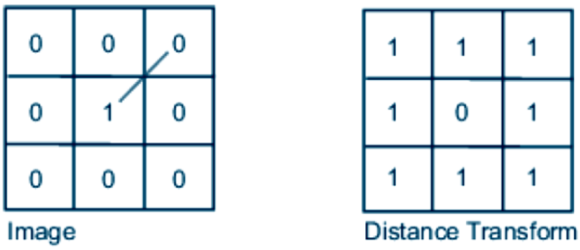

Figure 5. 2-D Image Example and its chessboard distance Transform.

In 2-D the chessboard distance between $(x_1, y_1) and (x_2, y_2) is: max|x_1 - x_2| + |y_1 - y_2|$. Adopted from (MATLAB).

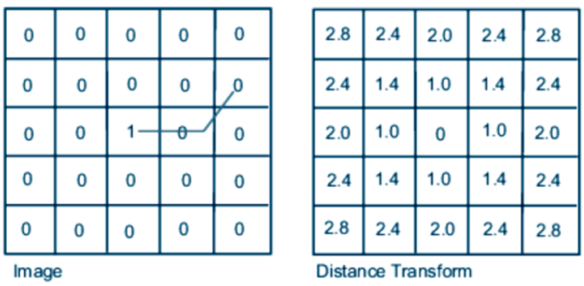

Figure 6. 2-D Image Example and its quasi-Euclidean distance Transform.

In 2-D the quasi-Euclidean distance between $(x_1, y_1) and (x_2, y_2)\ is$:

$$|x_1 - x_2| + (\sqrt{2} - 1)|y_1 - y_2|, |x_1 - x_2| > |y_1 - y_2|$$
$$(\sqrt{2} - 1)|x_1 - x_2| + |y_1 - y_2|, otherwise.$$ Adopted from (MATLAB).

4. FEATURES EXTRACTION METHODS

Thus, the textural features that have to be extracted must be carefully chosen and have a significant meaning, which can enhance the medical analysis for the identification of diseases and their future evolution [34].

4.1. Feature

An image is a function that uses pixel values for representation. Represent it using a separate coordinate system, known as features extraction/selection, which focuses on rates of change.

A feature is a piece of data regarding the content of an image, usually pertaining to whether a certain area of the image possesses particular attributes. Features in an image could be particular structures like edges, points, or objects. Features detection is performed to the picture or to shapes that are described by boundaries or curves separating various image regions.More widely, any piece of data that is pertinent to resolving the computational problem associated with a particular application is referred to as a feature.

4.1.1. Feature Extraction

Transforming the input data into a calculated set of features is called feature extraction. The calculated set of features will extract the relevant information from the input data in order to perform the desired task

4.2. Radiomics

In oncology, the term radionics defines what comprises radionics, which entails obtaining numerous quantitative characteristics of an image from a digital picture [35]. The radiomics process is usually divided into two processes: the object of interest (for example, lung fields) and statistical analysis of the collected radiomic features, which is performed to investigate the corresponding associations with the clinical phenotypes of interest.

The strength of radiomics is the information that makes it possible to obtain numerous quantitative imaging biomarkers which could be unnoticed by the human look [36]. With the use of multiple textural features, the usefulness of a radiomics approach has been reported within numerous CXR-based applications focused on tuberculosis, pneumonia, and lung carcinoma [37].

4.3. Fractal Dimension

It is actually a mathematical term that represents the degree of complexity of the texture and the extent of similarity between the larger and the smaller image [38]. Looking at the interpretation of the CXR image, the fractal dimension has emerged as a versatile textural feature for quantifying lung distortions [39]. Researchers have also published methods that involve calculating the fractal dimension of the lung regions and, hence, the ability to come up with models that distinguish normal images and abnormal images in a CXR with an acceptable level of accuracy[40].

4.4. Super Pixel-Based Textural Feature Extraction

Apart from radiomic and fractal dimensions, the use of superpixels has turned out to be fruitful as it considers the approach to extracting textural features from the CXR images [41]. Superpixels are groups of connected pixels that are perceptually similar, and they are used as a medium for texture analysis. The superpixel concept or based strategy starts with dividing the CXR image into a set of superpixel regions and then evaluating textural measures (for example, GLCM, LBP) in each superpixel [42]. This method has the advantageof improving spatial localisation: Instead of working with individual pixels, the method involves considering the textural characteristics of superpixels, which allows the information about the image's spatial organisation to be used [43].

Advances in performance can be owed to several reasons, the biggest of which is the capacity of superpixels to describe the intricate and diverse features found in lung tissue.

5. Practical Procedures of Applying Euclidean Distance Transform on CXR Images

Figure 7 showsthe detailed steps involved in applying the Euclidean Distance Transform to CXR images.

5.1. A Simple Practical Pre-processing for Image Dissimilarity

Using image technology and the Euclidean distance transform technique for preprocessing in order to take advantage of the image feature technology that makes it easier to identify cases in X-ray images.

5.1.1. Case Detection

The American College of Radiology (ACR) has recently updated its recommendations regarding the use of imaging for screening or primary diagnostic procedures [44, 45]

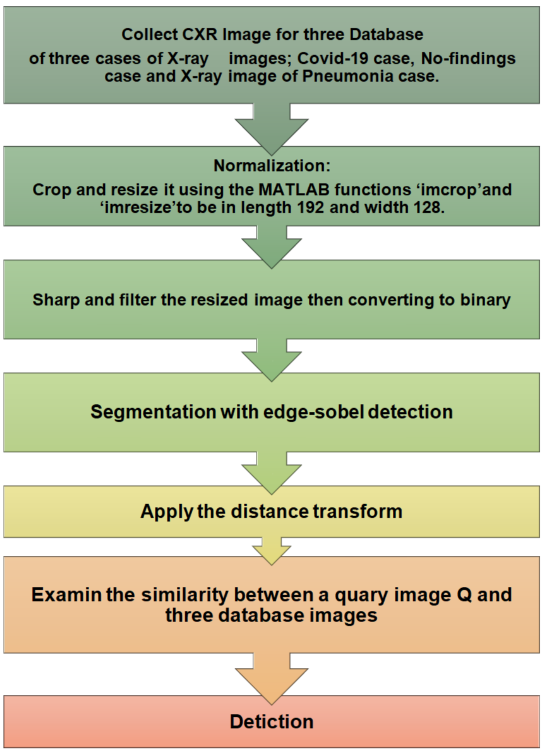

Figure7. Practical Procedures of Applying Euclidean Distance Transform on CXR Images.

Compared to chest radiography, there are significantly more papers in the literature describing chest CT in acute COVID-19 pneumonia. Chest CT has a higher sensitivity for finding problems that a chest radiograph could miss. Bilateral multifocal peripheral ground-glass opacities, with or without consolidation that might be spherical and exhibit "crazy paving" (ground-glass opacity with intralobular lines), are usual findings in adults.

5.1.2. Data Resources

Data on X-ray images, one can be accessed here: this https URL and also numerous datasets were located, data available in [46].

5.1.3. Euclidean Distance and Dissimilarity

Using MATLAB;it is usual practice to use data augmentation to create artificial images (Euclidean Distance image) using the following methods: (1) Flip either vertically or horizontally ;(2) rotate a certain amount;(3) scale inward or outward;(4) crop at random;(5) translate; and(6) add Gaussian noises to reduce overfitting. Our process can be broken down into the following steps:

Get the image by ‘imread’ MATLAB function.

i- Crop and resize it using the MATLAB functions ‘imcrop’and ‘imresize’to be in length 192 and width 128.

ii- Sharp and filter the resized image using the MATLAB function ‘imgSharp’. After every sharped image is converted to greyscale, we are left with an array that contains values ranging from 0 to 255 in a single array element then converting to binary using the MATLAB functions ‘graythresh’ , ‘histeq’ and ‘im2bw’.

iii- Segmentation with edge-sobel detection using the MATLAB functions ‘imfill’, and ‘edge’.

iv- Apply the distance transform.The distance transform is one method for extracting relevant features from an image that show internal patterns

v- Implement the confirmation of infection by examin the similarity between a quary image Q and three database images; the confirmed infected database images I, the no-finding (normal) database images and the Pneumonia database images.

vi- In order to determine the degree of similarity between query image Q and database image I, the following criteria are used:

For each image I features vector and image Q features vector, the common distance measure used is the Euclidean distance which is defined as follows:

$D = \sqrt{\sum_{i=1}^{n} (f_{I_i} - f_{Q_i})^2}$, where n is the quantity of features; the vector's length.

vii- Only the image I with smaller distance, under an arbitrary suitable threshold t, will be chosen to match the query, i.e. if D < t, then I is similar to Q and classify it.

The classification is completely controlled by adjusting the threshold t. We discovered that for a very big threshold, many database images are of the same class, even if the images are dissimilar, and for a very tiny threshold, practically one image corresponds to the class that is used as a query.

5.1.4. Results

As a result, a transformation must be discovered in order to produce an accurate depiction of the internal patterns. One idea is to crop each image to show the chest.Figure 8shows an image with data augmentation techniques. Binary transformation shows pixel distribution and reduces dimensionality.

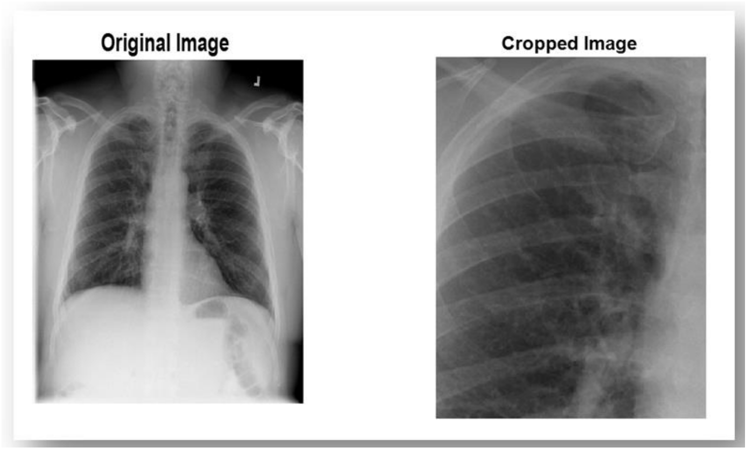

Figure 8. Representative images with data augmentation techniques, such cropping, rescaling and sharping processed by MATLABsoftwar.

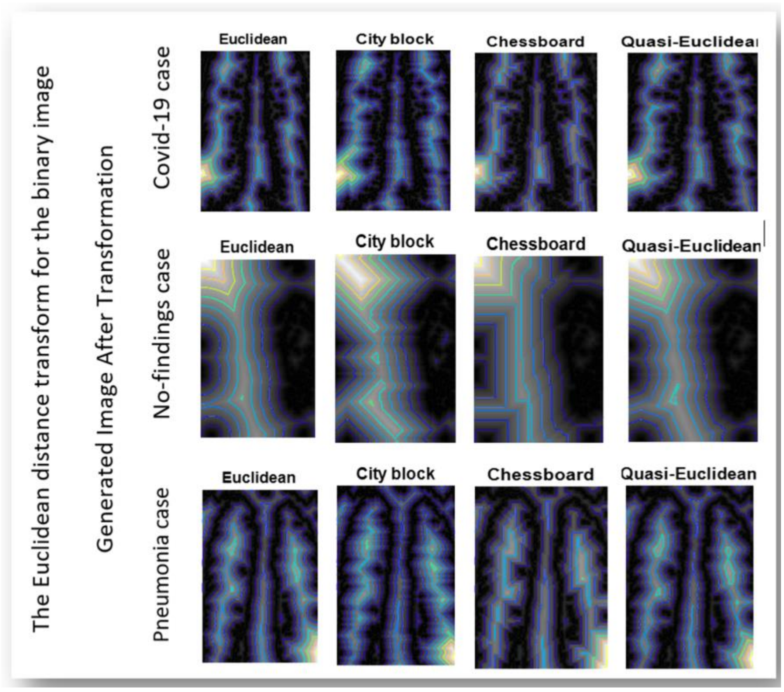

Figure 9. The Euclidean distance transform for the binary image of three cases of X-ray images; Covid-19 case, No-findings case and X-ray image of Pneumonia case. (processed by MATLAB softwar).

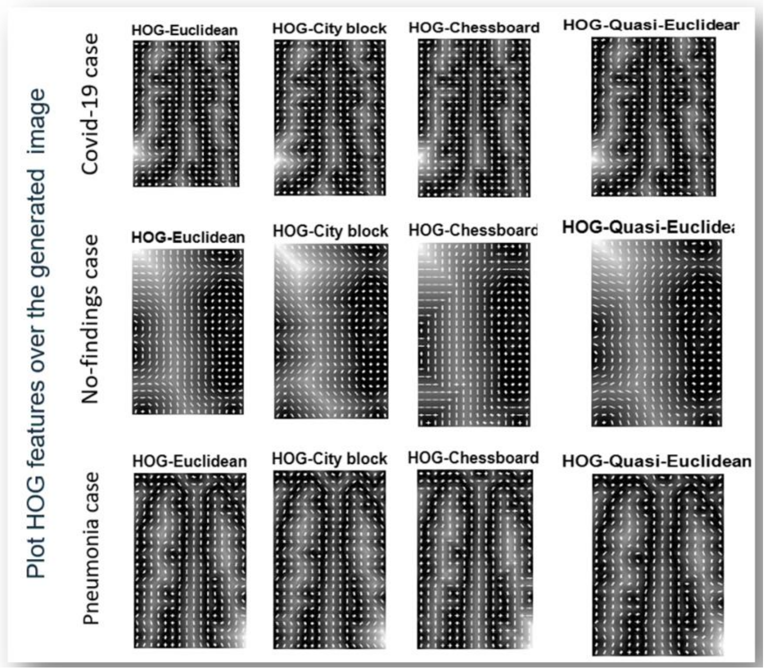

Figure 10. The same privious generated Image with A Histogram of Oriented Gradients (HOG) features is plotted over it. The edge directions, which are normal to the gradient directions, are shown in the plot. Graphing the plot with edge directions helps to recognize the contours and pattern that HOG encodes processed by MATLAB softwar.

We apply the distance transform to get the transformed image. Subsequently, features are extracted using a Histogram of Oriented Gradients (HOG) while taking texture analysis into account. Figure9 shows samples of the produced images of the 2-D distance transformations for the supported distance methods and which provide a decent illustration of the internal patterns. Figure 10 shows samples of the produced images with A Histogram of Oriented Gradients (HOG) features is plotted over it.

6. EVALUATION - INFLUENCE AND IMPLICATIONS OF HYPERPARAMETER TUNING

6.1. Accurate Detection

Deep learning was specifically used to identify and distinguish between viral and bacterial pneumonia in pediatric chest radiographs [47,48]. Additionally, attempts have been undertaken to identify different chest CT imaging findings. By employing chest CT, Lin Li et al. [49] developed and tested a fully automatic framework to identify COVID-19. To assess the model's sturdiness, community-acquired pneumonia (CAP) and additional non-pneumonia examinations were incorporated. This computer-aided diagnostic tool, according to [50], can considerably increase the speed and accuracy of diagnosing COVID-19 cases. In a pandemic situation where disease load and the need for preventive measures conflict with available resources, this might be very helpful.

6.2. Comparison of Application Methods

The organization of elements is crucial for obtaining important information and achieving goals. Table 1 compares some Textural Features Extraction Methods. Table 2 summarizes various results and advantages of several applied techniques.

Table1. Comparison of Textural Features Extraction Methods

Method	**Description**	**Advantages**
Radiomics	Extracting large sets of quantitative imaging characteristics from digital images	1. Provides numerous quantitative imaging biomarkers that may be overlooked by human observation 2. Features can be integrated with other patient data for more comprehensive models
Fractal Dimension (FD)	Mathematical measure of the degree of complexity and self-similarity in the texture	1. Quantifies complexity and disorder in lung texture that may not be captured by standard image analysis 2. Relatively robust to changes in image resolution and contrast
Super pixel-Based Textural Features	Dividing the image into perceptually similar groups of pixels (super pixels) and extracting textural features from each super pixel	1. Improved spatial localisation of textural information 2. Reduced computational complexity compared to per-pixel feature extraction 3. Increased robustness to noise and variations in the image

.

Table 2.Several applied techniques offer various advantages.

S/N	Reference	Description /Goal	Advantages and results
1	Abiyev, R. H. and M. K. S. Ma'aitaH [5].	They demonstrate the ability to classify chest diseases in chest X-rays using conventional and deep learning methods. The research introduces convolutional neural networks (CNNs) for diagnosing chest illnesses. The CNN architecture and design principle are shown. Comparatively, BPNNs with supervised learning and CpNNs with unsupervised learning are used to diagnose chest illnesses. This research shows that chest diseases may be classified in chest X-rays using conventional and deep learning methods. The research introduces convolutional neural networks (CNNs) for diagnosing chest illnesses. They present CNN's architecture and design principle. Comparatively, BPNNs with supervised learning and CpNNs with unsupervised learning are used to diagnose chest illnesses.	CNN demonstrated superior generalization capacity compared to BPNN and CpNN, despite higher computation time and recurrenceIt was found that CNN had stronger generalization capability than BPNN and CpNN, but required more computing time and iterations.
2	Kawecki, D. and A. Majewska [4].	This paper aims to facilitate the automatic detection of bacterial and viral pneumonia through the analysis of digital X-ray images. The document offers a comprehensive report on the progress achieved in the accurate detection of pneumonia and subsequently outlines the methodology employed by the authors. This study presents three classification schemes: normal versus pneumonia, bacterial versus viral pneumonia, and a categorization of normal, bacterial, and viral pneumonia.	Classification accuracy for normal, bacterial, and viral pneumonia pictures was 98%, 95%, and 93.3%, respectively. Comparing this approach to the accuracy recorded in the literature, it is the most accurate. Consequently, the suggested study may facilitate expedited pneumonia diagnosis by radiologists and assist in the rapid screening of pneumonia patients at airports.
3	Chouhan, V., et al. [9].	They suggest a new deep learning approach that uses the idea of transfer learning to find pneumonia. Image features are retrieved using neural network models pretrained on ImageNet and input into a classifier for prediction. Five models were created and evaluated.	Using unknown data from the Guangzhou Women and Children's Medical Center dataset, the ensemble model achieved 96.4% accuracy and 99.62% recall.
4	Moujahid, H., et al. [11].	They suggest utilizing CNN-based classification models with transfer learning to diagnose pneumonia. Results are compared to choose the optimal model for the task based on specific criteria.	Similar to accuracy curve analysis, their technique demonstrates that the VGG16 model is the most effective for detecting pneumonia. NasNetMobile model yields the worst performance for this assignment. In a manner similar to accuracy curve

S/N	Reference	Description /Goal	Advantages and results
			analysis, this tool confirms that the VGG16-based model is the most effective in accomplishing the pneumonia detection task. The NasNet Mobile model yields the worst results for this challenge.
5	Hammoudi, K., et al. [17]	To diagnose viral pneumonia, tailored deep learning models are suggested. Viral pneumonia cases during a COVID-19 outbreak are thought to indicate infection. Also, simple health markers are suggested for evaluating infection status and forecasting patient status from pneumonia cases.To diagnose viral pneumonia, tailored deep learning models are suggested. Viral pneumonia cases during a COVID-19 outbreak are thought to indicate infection. Also, simple health markers are suggested for evaluating infection status and forecasting patient status from pneumonia cases.	Training deep learning models on publicly available chest X-ray images can screen viral pneumonia, according to experiments. COVID-19-infected individuals' chest X-rays are diagnosed using performed detection models.
6	idhya, B., et al. [24].	A software is being developed to diagnose pneumonia from the lung sound using a gradient enhancing algorithm in the proposed work. For pneumonia diagnosis, lung sounds suffice. The Electronic Stethoscope records lung sounds for doctors. Lung noises are treated with audacity. This software separates needed and undesirable sounds. For algorithm training, healthy audio recordings are labeled 0 and pneumonia patient audio files are labeled 1.	During diagnosis study and performance evaluation with support vector machine and k-nearest neighbors (KNN) algorithms, gradient boosting showed good identifying property with 97% accuracy.

S/N	Reference	Description /Goal	Advantages and results
7	Nneji, G. U., et al. [32]	This study introduces a multi-channel image processing approach for the automatic extraction of features and identification of pneumonia in chest X-ray images. The proposed approach aims to tackle the issue of low quality and to identify pneumonia in chest X-ray images. Three channels of chest X-ray (CXR) images—Local Binary Pattern (LBP), Contrast Enhanced Canny Edge Detection (CECED), and Contrast Limited Adaptive Histogram Equalization (CLAHE)—are analyzed using deep neural networks. LBP CXR features are extracted using shallow CNN, CLAHE's using pre-trained inception-V3, and CECED's using pre-trained MobileNet-V3. Three channel feature weights are combined and softmax classification is used to produce the final identification result.	The suggested network accurately classifies pneumonia based on experimental results. The proposed technique achieved 98.3% accuracy, 98.9% sensitivity, and 99.2% specificity on a publically available dataset. Compared to single and state-of-the-art models, our suggested network performs similarly.
8	Lin Li et al. [49].	The objective is to create a comprehensive automated system for the detection of COVID-19 through chest CT imaging and to assess its effectiveness.	On lung CT scans, COVID-19 could be found with a deep learning method (area under the receiver operating characteristic curve, 0.96). Deep learning to detect community-acquired pneumonia on chest CT (AUC, 0.95).
9	Ortiz-Toro, C., et al.[51]	Employed textural characteristics to automatically identify pneumonia in chest X-ray image.	Recognize pneumonia in chest X-ray images automatically.
10	Çinkooğlu, A., et al.[53]	Compared CT scans using a simplified scoring system developed for emergency room triage.	Chest X-ray effectiveness in diagnosing COVID-19 pneumonia
11	Yang, W., et al. [54]	Introduced the role of imaging in 2019 novel coronavirus pneumonia (COVID-19).	Imaging helps doctors make earlier diagnoses, which lets them limit and respond to this contagious disease faster. This way, the outbreak can be stopped as soon as possible by working together.
12	Vidhya, B. et al. [59]	An investigation into diagnostic and performance testing with different machine learning algorithms, such as the support vector machine and k-nearest neighbours (KNN) algorithms.	This proposed method showed that the gradient boosting algorithm is very good at identifying things, with a 97 percent success rate also demonstrates superior diagnostic capabilities for pneumonia compared to other artificial intelligence and deep learning

S/N	Reference	Description /Goal	Advantages and results
			techniques. This approach can additionally be utilized to forecast the lung sounds of individuals affected by COVID.

7. DISCUSSION - COMPARISON OF CONTRAST-ENHANCED DIAGNOSTIC IMAGING BETWEEN PNEUMONIA PATIENTS AND HEALTHY CONTROLS

7.1. Common Diagnostic Methods

Proper diagnosis and therapy are needed for pneumonia. The chest X-ray (CXR) and the computed tomography (CT) scan are the two principal imaging modalities that are used for diagnostic purposes. CXRs are cheap and easy to find, showing the chest's architecture and opacities quickly. CT scans provide improved clarity and resolution on the pulmonary parenchyma, which enables a more comprehensive and accurate evaluation of abnormalities in the lungs. CT is better than quantum dot imaging for detecting microlesions and lung disorders.

7.2. Advantages of CXR

Pneumonia diagnosis is best started with a chest X-ray (CXR) due to its cost-effectiveness, availability, and low-resource requirements. CXRs provide less radiation than CT scans, making them safe for children and pregnant women. Repeated imaging is possible if needed. In acute wards, where prognosis is critical, CXRs are faster. Fast results enable speedier treatment, improving healing and lowering the risk of deterioration. The price, radiation-free nature, and quick results of CXRs make them an effective and safe pneumonia diagnostic tool [51-53].

7.3. Challenges in Pneumonia Detection

Due to their varied imaging appearances, pneumonia radiographic symptoms are hard to spot. Identifying lung consolidation X-ray findings might be difficult and delay or prevent diagnosis. The imaging pattern of pneumonia resembles tuberculosis, lung abscesses, and bronchitis. Also use microbiological tests or high-level imaging to diagnose. Clinical history and physical examination can also help diagnose. The assignments of chest X-rays are opaque, thus training, experience, and subjective treatment goals affect diagnosis [54-58].Vidhya, B. et al. [59] investigated that the gradient boosting algorithm is very good at identifying things, with a 97 percent success rate also demonstrates superior diagnostic capabilities for pneumonia compared to other artificial intelligence and deep learning techniques.

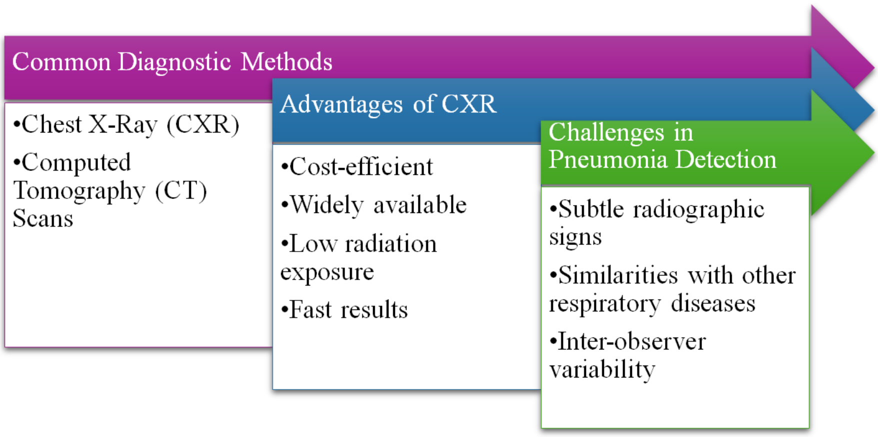

Figure 11. Comparison of Contrast-Enhanced Diagnostic Imaging between Pneumonia Patients and Healthy Controls.

7.4. Experimental Results

In the experiment, we present a small example that examines the performance of the matching procedure using various thresholds across three distinct datasets. We reported three schemes of matching: (i) normal query image vs normal dataset, normal query image vs pneumonia dataset and normal query image vs COVED-19 pneumonia dataset. (ii) pneumonia query image vs normal dataset, pneumonia query image vs pneumonia dataset and normal query image vs COVED-19 pneumonia dataset.(iii) COVED-19 pneumonia query image vs normal dataset, COVED-19 pneumonia query image vs pneumonia dataset and COVED-19 pneumonia query image vs COVED-19 pneumonia dataset.

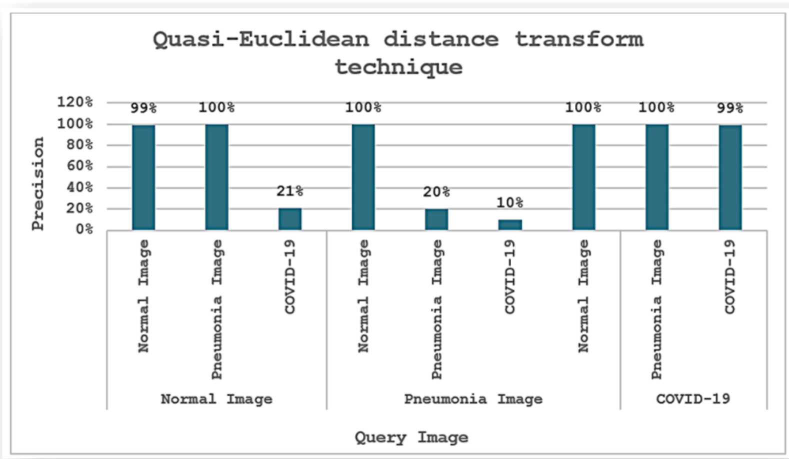

Figure 12.The precision achieved with applying the quasi-Euclidean distance transform technique.

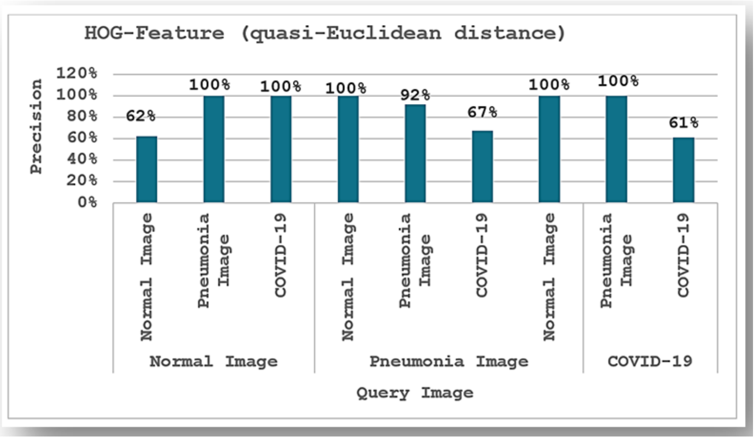

Figure 13. The precision achieved with applying the HOG Features after quasi-Euclidean distance transform technique.

Figures12 and 13 show the precision achieved with various thresholds when applying the quasi-Euclidean distance transform technique and HOG feature. The similarity quantifies the extent of the difference between the features of the query image and those of the database feature image. We employ precise metrics to evaluate the performance of the matching system, which are defined as follows:

$$\text{Precision} = \frac{\text{Number of images matched}}{\text{Total number of all images in dataset}}$$

The precision refers to the ratio of true positive matches to the total number of dataset cases. From the precision achieved, we can summaries;the high precision is evident when correlating with the normal cases, which it negates the infection.

8. CONCLUSION

In this present paper, the Euclidean distance transform technique has been discussed while analysing the image preprocessing for the chest X-ray images where COVID-19 and pneumonia cases were identified. This study was set to get the maximum sensitivity of COVID-19 pneumonia in comparison to other types of pneumonia and normal lung pathology as the chest X-ray images are cost-efficient, easily available and have minimal radiation exposure, unlike CT scans.

Euclidean distance transform was introduced as a preliminary step with the assumption that it could facilitate the differentiation between various types of pneumonia in the chest X-ray images through simplification of the input data and emphasising important features to help deep learning algorithms.

The introduced quick small experiment demonstrated that, the Euclidean distance transform helps in finding important patterns and making detection more accurate.

Future work seeks to present a strategy that involves preparing the input image or time series data using various techniques to highlight the critical components of the data, resulting in precise outcomes. Due to the data's comprehensiveness and complexity, this endeavor may prove to be difficult.

ACKNOWLEDGEMENTS

Appreciation

1. Thanks and admiration to the Dean of the College for working hard and encouraging faculty members to submit and publish more scientific research.
2. Thank you to the coordinator of scientific research in the college and math department for helping faculty and overcoming challenges.

Use of AI tools declaration

The author affirms that she has not utilized artificial intelligence (AI) tools in the creation of this article.

REFERENCES

[1] Mhamd, Halah. (2024). Mutual and Common Utility between data representation variations. International Journal of Applied Science and Research. 10.56293/IJASR.2024.6208.

[2] Vliegenthart, R., et al. (2022). "Innovations in thoracic imaging: CT, radiomics, AI and x-ray velocimetry." Respirology 27(10): 818-833.

[3] Musher, D. M. and A. R. Thorner (2014). "Community-acquired pneumonia." New England journal of medicine371(17): 1619-1628.

[4] Kawecki, D. and A. Majewska (2021). "Pneumonia in the Covid-19 era–emergency room physician's perspective.Part I–etiology and epidemiology." Emerg. Med. Serv 8: 32-38.

[5] Abiyev, R. H. and M. K. S. Ma'aitaH (2018). "Deep convolutional neural networks for chest diseases detection." Journal of healthcare engineering 2018(1): 4168538.

[6] Huang, G., et al. (2017). "Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition."

[7] Rajpurkar, P., et al. (2018). "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists." PLoS medicine 15(11): e1002686.

[8] Cohen, J. P., et al. (2019). "Chester: A web delivered locally computed chest x-ray disease prediction system." arXiv preprint arXiv:1901.11210.

[9] Chouhan, V., et al. (2020). "A novel transfer learning based approach for pneumonia detection in chest X-ray images." Applied Sciences 10(2): 559.

[10] Abbas, A., et al. (2021). "Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network." Applied Intelligence 51: 854-864.

[11] Chattopadhyay, A. and M. Maitra (2022). "MRI-based brain tumour image detection using CNN based deep learning method." Neuroscience informatics 2(4): 100060.

[12] Zhou, S. K., et al. (2021). "A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises." Proceedings of the IEEE 109(5): 820-838.

[13] Kumar, Y., et al. (2023). "Artificial intelligence in disease diagnosis: a systematic literature review, synthesising framework and future research agenda." Journal of ambient intelligence and humanised computing 14(7): 8459-8486.

[14] Abdel-Karim, B. M., et al. (2023). "HOW AI-BASED SYSTEMS CAN INDUCE REFLECTIONS: THE CASE OF AI-AUGMENTED DIAGNOSTIC WORK." MIS Quarterly 47(4).

[15] Gehrmann, S., et al. (2023). "Repairing the cracked foundation: A survey of obstacles in evaluation practices for generated text." Journal of Artificial Intelligence Research 77: 103-166.

[16] Zicari, R. V., et al. (2021). "Co-design of a trustworthy AI system in healthcare: deep learning based skin lesion classifier." Frontiers in Human Dynamics 3: 688152.

[17] Hammoudi, K., et al. (2021). "Deep learning on chest X-ray images to detect and evaluate pneumonia cases at the era of COVID-19." Journal of medical systems 45(7): 75.

[18] Basha, S. S., et al. (2020). "Impact of fully connected layers on performance of convolutional neural networks for image classification." Neurocomputing 378: 112-119.

[19] Gholamalinezhad, H. and H. Khosravi (2020). "Pooling methods in deep neural networks, a review." arXiv preprint arXiv:2009.07485.

[20] Rajaraman, S., et al. (2020). "Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays." Ieee Access 8: 115041-115050.

[21] Kaya, Y. and E. Gürsoy (2023). "A MobileNet-based CNN model with a novel fine-tuning mechanism for COVID-19 infection detection." Soft Computing 27(9): 5521-5535.

[22] Remzan, N., et al. (2024). "Advancing brain tumor classification accuracy through deep learning: harnessing radimagenet pre-trained convolutional neural networks, ensemble learning, and machine learning classifiers on MRI brain images." Multimedia Tools and Applications: 1-29.

[23] Chhabra, M. and R. Kumar (2022). A smart healthcare system based on classifier DenseNet 121 model to detect multiple diseases. Mobile Radio Communications and 5G Networks: Proceedings of Second MRCN 2021, Springer: 297-312.

[24] idhya, B., Nikhil Madhav, M., Suresh Kumar, M. et al. AI Based Diagnosis of Pneumonia. Wireless Pers Commun 126, 3677–3692 (2022). https://doi.org/10.1007/s11277-022-09885-7

[25] Elyan, E., et al. (2022). "Computer vision and machine learning for medical image analysis: recent advances, challenges, and way forward." Artificial Intelligence Surgery 2.

[26] Hajipour Khire Masjidi, B., et al. (2022). "[Retracted] CT-ML: Diagnosis of Breast Cancer Based on Ultrasound Images and Time-Dependent Feature Extraction Methods Using Contourlet Transformation and Machine Learning." Computational Intelligence and Neuroscience 2022(1): 1493847.

[27] Baniasadi, P., et al. (2020). "A transformation technique for the clustered generalised traveling salesman problem with applications to logistics." European Journal of Operational Research 285(2): 444-457.

[28] VanBerlo, B., et al. (2024). "A survey of the impact of self-supervised pretraining for diagnostic tasks in medical X-ray, CT, MRI, and ultrasound." BMC Medical Imaging 24(1): 79.

[29] Ebert, M. A., et al. (2021). "Spatial descriptions of radiotherapy dose: normal tissue complication models and statistical associations." Physics in Medicine & Biology 66(12): 12TR01.

[30] Giełczyk, A., et al. (2022). "Pre-processing methods in chest X-ray image classification." Plos one 17(4): e0265949.

[31] Liang, D., et al. (2022). "Focal inverse distance transform maps for crowd localisation." IEEE Transactions on Multimedia.

[32] Nneji, G. U., et al. (2022). "Multi-channel based image processing scheme for pneumonia identification." Diagnostics 12(2): 325.

[33] Moreno-Barea, F. J., et al. (2020). "Improving classification accuracy using data augmentation on small data sets." Expert Systems with Applications 161: 113696.

[34] Ali, H., et al. (2020). "A survey of feature extraction and fusion of deep learning for detection of abnormalities in video endoscopy of gastrointestinal-tract." Artificial Intelligence Review 53: 2635-2707.

[35] Rogers, W., et al. (2020). "Radiomics: from qualitative to quantitative imaging." The British journal of radiology 93(1108): 20190948.

[36] Scapicchio, C., et al. (2021). "A deep look into radiomics." La radiologia medica 126(10): 1296-1311.

[37] Varghese, B. A., et al. (2021). "Predicting clinical outcomes in COVID-19 using radiomics on chest radiographs." The British journal of radiology 94(1126): 20210221.

[38] Bianconi, F., et al. (2021). "Colour and texture descriptors for visual recognition: A historical overview." Journal of Imaging 7(11): 245.

[39] Pinto-Coelho, L. (2023). "How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications." Bioengineering 10(12): 1435.

[40] Shaik, Karimullah & Wheeb, Ali & Shaik, Dr. Fahimuddin. (2024). Detection and Classification of Brain Tumor from MRI And CT Images using Harmony Search Optimization and Deep Learning. 11. 31-49.

[41] Riaz, M., et al. (2022). "Metaheuristics based COVID-19 detection using medical images: A review." Computers in biology and medicine 144: 105344.

[42] Ghalati, M. K., et al. (2021). "Texture analysis and its applications in biomedical imaging: A survey." IEEE Reviews in Biomedical Engineering 15: 222-246.

[43] Derksen, D., et al. (2020). "Geometry aware evaluation of handcrafted superpixel-based features and convolutional neural networks for land cover mapping using satellite imagery." Remote Sensing 12(3): 513.

[44] Foust AM, Phillips GS, Chu WC et al (2020) International expert consensus statement on chest imaging in pediatric COVID-19 patient management: imaging fndings, imaging study reporting, and imaging study recommendations. Radiol Cardiothorac Imaging 2:e200214

[45] American College of Radiology (2020) ACR recommendations for the use of chest radiography and computed tomography (CT) for suspected COVID-19 infection. https://www.acr.org/Advoc acy-and-Economics/ACR-Position-Statements/Recommenda tions-for-Chest-Radiography-and-CT-for-Suspected-COVID 19-Infection. Accessed 26 Oct 2021.

[46] Cohen JP, Morrison P, Dao L, Roth K, Duong TQ, Ghassemi M (2020) Covid-19 image data collection: Prospective predictions are the future. arXiv:2006.11988

[47] Ye H, Gao F, Yin Y, et al. Precise diagnosis of intracranial hemorrhage and subtypes using a threedimensional joint convolutional and recurrent neural network. European Radiology, 2019, 29: 6191–6201.

[48] Kermany DS, Goldbaum M, Cai W, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell 2018, 172, 1122–1131.

[49] Lin Li, Lixin Qin, Zeguo Xu, Youbing Yin, Xin Wang, Bin Kong, Junjie Bai, Yi Lu, Zhenghan Fang, Qi Song, et al. Artificial intelligence distinguishes covid-19 from community acquired pneumonia on chest ct. Radiology, page 200905, 2020.

[50] Anas Tahir, Yazan Qiblawey, Amith Khandakar, Tawsifur Rahman, Uzair Khurshid , Farayi Musharavati , Serkan Kiranyaz, Muhammad E. H. Chowdhury,Coronavirus: Comparing COVID-19, SARS and MERS in the eyes of AI. Available at: https://www.researchgate.net/publication/341639961

[51] Ortiz-Toro, C., et al. (2022). "Automatic detection of pneumonia in chest X-ray images using textural features." Computers in biology and medicine 145: 105466.

[52] Withers, P. J., et al. (2021). "X-ray computed tomography." Nature Reviews Methods Primers 1(1): 18.

[53] Çinkooğlu, A., et al. (2021). "Efficacy of chest X-ray in the diagnosis of COVID-19 pneumonia: comparison with computed tomography through a simplified scoring system designed for triage." Egyptian Journal of Radiology and Nuclear Medicine 52: 1-9.

[54] Yang, W., et al. (2020). "The role of imaging in 2019 novel coronavirus pneumonia (COVID-19)." European radiology 30: 4874-4882.

[55] Sergi, C. M. and C. M. Sergi (2020). "Lower Respiratory Tract." Pathology of Childhood and Adolescence: An Illustrated Guide: 139-253.

[56] Cook, A. E., et al. (2022). Imaging Patterns of Pneumonia. Seminars in Roentgenology, Elsevier.

[57] Newman-Toker, D. E., et al. (2021). "Rate of diagnostic errors and serious misdiagnosis-related harms for major vascular events, infections, and cancers: toward a national incidence estimate using the “Big Three”." Diagnosis 8(1): 67-84.

[58] Quinn, L., et al. (2023). "Interobserver variability studies in diagnostic imaging: a methodological systematic review." The British Journal of Radiology 96(1148): 20220972.

[59] Vidhya, B. & Madhav, M. & Kumar, M. & Kalanandini, S.. (2022). AI Based Diagnosis of Pneumonia. Wireless Personal Communications. 126. 1-16. 10.1007/s11277-022-09885-7.

AUTHOR

Halah Ahmad Abd AlmeneemMhamd, Department of Mathematics, Darb University College, Jazan University, Jazan, Saudi Arabia; previously, Department of Mathematics, Faculty of Science, Minia University, Minia, Egypt.

She was associated with the Dept. of Mathematics, Minia University, received her B.Sc. , M.Sc. and Ph.D degrees in Mathematics and Computer Science from Minia University and her area of interest includes feature extraction, and image searching in large databases.