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The Empowerment of Healthcare Technology to Achieve Universal Health Coverage

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2021 IEEE International Biomedical Instrumentation and Technology Conference (IBITeC)

“The Improvement of Healthcare Technology

To Achieve Universal Health Coverage”

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WELCOME MESSAGE FROM DEAN

Distinguished guests and participants,

Assalamu'alaikum warahmatullahi wabarakatuh

Firstly, let us thank Allah Almighty, who has given us His blessings and mercies so we can gather today, in good health and spirits.

On behalf of the Faculty of Industrial Technology, Universitas Islam Indonesia (UII), I welcome our speakers and participants.

The development of technology has become very rapid with the advent of Industry 4.0, and almost all aspects of our lives have been influenced by it.

In the field of health, technology and information systems have become vital tools to discuss. The demands of the health community must be followed by the development of the technology used. Healthcare technology is one of the technologies most affected by global regulations. Because technology is the only instrument to generate added *value,* mastery and the ability to create technology becomes a crucial problem.

Also, the application of information technology in the field of health is believed to provide various benefits for health care providers. With the support of these technologies, the benefits that can be obtained include the availability of accurate and comprehensive patient health information so that professionals can provide the best possible treatment.

To develop health technology, scientific meetings are needed as a means for sharing, disseminating, and communicating between practitioners, researchers, government agencies, non-governmental institutions, and industry.

On this occasion, the Electrical Engineering Department, Faculty of Industrial Technology, Universitas Islam Indonesia held The International Biomedical Instrumentation and Technology Conference, IBITeC 2021. This seminar is the second conference organized by the Electrical Engineering Department and co-organized by Diponegoro University (UNDIP) and Universiti Teknologi Malaysia (UTM). We hope this activity can provide a change of knowledge for researchers, practitioners, students, and lecturers to improve their abilities.

To our speakers and all those who support the seminar, we thank you for your cooperation in conducting this seminar. Finally, our congratulations on attending the seminar. Hopefully, what we achieve here will benefit institutions and society as a whole.

Wassalamu'alaikum warahmatullahi wabarakatuh

Dean,

Faculty of Industrial Engineering

Prof. Dr. Ir. Hari Purnomo, M.T

WELCOME MESSAGE FROM CONFERENCE CHAIR

Distinguished guests, respected colleagues, ladies, and gentlemen,

Assalamu'alaikum. All praise is for Allah, who guided us to do good deeds and gave us the health bounty. On behalf of the 2nd International Biomedical Instrumentation and Technology Conference (IBITeC) 2021 Committee, I would like to welcome you to this biannual conference held by the Department of Electrical Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia, Yogyakarta. This conference is co-sponsored by IEEE Communication Society Indonesia Chapter, and co-organized by the Center for BioMechanics, Bio-Materials, Bio Mechatronics, and Bio Signal Processing (CBIOM3S) of Diponegoro University (UNDIP), Universiti Teknologi Malaysia (UTM), and UII IEEE Student Branch. The goal of this conference is to facilitate researchers, practitioners, students, and lecturers around the world to publish, explore and share their latest research in Biomedical Engineering and related fields in Biomedical Sensors Development, Biomedical and Informatics, Biomedical Imaging, Internet of Things (IoT) and Healthcare Information System with its associated topics. This year's theme is "The Empowerment of Healthcare Technology to Achieve Universal Health Coverage."

The committee is delighted with the positive response of researchers to this conference. We received 50 submissions from Germany, France, Portugal, Morocco, Malaysia, Vietnam, China, India, Pakistan, Iraq, and our own Indonesia. The papers were peer-reviewed by our reviewers from several countries to maintain the quality of this conference. The acceptance rate of the 2nd IBITeC 2021 is 58%. All accepted and presented papers will be forwarded for consideration to be published in the IEEE Xplore Digital Library and indexed by Indexing Service Partners (Scopus, INSPEC, Semantic Scholar, EBSCO, and others that are available/eligible).

We are grateful for the contributions of our invited speakers. We will have three keynote speakers that we believe could spread the new insight for biomedical engineering disciplines to follow the industry 4.0 needs. The organization of a conference is very much a team effort. I want to thank all committees, editorial team, event-organizer, reviewers, and other parties who have carried a vast and complicated workload. The 2nd IBITeC 2021 strives to offer plenty of opportunities, especially networking. Authors and participants have the chance to meet and interact with each other to share and transfer their knowledge in similar fields. We hope that you can benefit from this conference during discussions and, most importantly, networking among our peers. We hope that this conference will be unforgettable moments and experiences. Thank you. *Wassalamu'alaikum.*

Yogyakarta, October 2021

Firdaus, Ph.D

Conference Chair of The 2nd IBITeC 2021

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----- CONFERENCE PAPERS-----

Texture Analysis of Ultrasound Images to Differentiate Pneumonia and Covid-19

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***Abstract*— Lung ultrasound can potentially diagnose lung abnormalities such as pneumonia and covid-19, but it requires high experience. Covid-19, as a global pandemic, has similar common symptoms as pneumonia. The proper diagnosis of covid-19 and pneumonia necessitates clinicians' high expertise and skill to classify Covid-19 disease. This paper presents an approach to differentiate pneumonia and covid-19 based on texture analysis of ultrasound images. The proposed scheme is based on the Gray Level Co-occurrence Matrix (GLCM) features computing with Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma transformation for image enhancement. The results of the feature extraction analysis for lung ultrasound images suggest that differentiating pneumonia and Covid-19 is possible based on image texture features.**

***Keywords*— GLCM, CLAHE, gamma transformation, pneumonia, covid-19, texture analysis, lung ultrasound**

I. Introduction

Pneumonia is one of the world's leading health sector problems, including in Indonesia, especially pneumonia in children. Pneumonia is an infectious disease, the leading cause of death in children under five, with more than 800,000 cases, or about 2,200 every day worldwide [1].

In some situations, the radiological evaluation included the chest X-ray (CXR) is needed for the initial imaging step in diagnosing pneumonia in children [2]. CXR as a standard imaging mode can be found easily in almost all hospitals or health centers, making CXR the most popularly used to diagnose lung disease. Another X-ray-based imaging mode that is the gold standard with the highest level of accuracy used to diagnose abnormalities in the lungs is Computed Tomography (CT). Although its availability is still limited, CT has played an essential role in diagnosing lung diseases. Despite its excellent accuracy, computed tomography (CT) cannot be employed as a first-line radiological evaluation due to high ionizing radiation exposure, availability, and expense [2].

One alternative medical imaging method apart from using CXR and CT suggested to apply is lung ultrasound (LUS). It is considered safe, especially for pediatric patients, because it is easily performed by clinicians at the point of care, inexpensive, avoids exposure to radiation [3], [4], and is portable. It can be performed at the bedside [4], [5]. LUS has higher sensitivity compared to CXR [3], [5]–[9]. Lung ultrasound is also safe for routine and repeated examinations with high frequency[4]. Lung ultrasonography is a powerful tool for identifying and evaluating lung consolidation [6].

Recently, in the massive spreading of Covid-19 globally, the use of traditional imaging is significantly more challenging to do in this situation than lung ultrasonography in the case of a significant spread. In this case, children with COVID-19 will be safely investigated by ultrasound imaging, and the use of a chest CT scan is not recommended [10].

Covid-19 has common symptoms that are similar to pneumonia [4]. On a lung ultrasound image, some image artifacts such as a glass rocket, confluent B-lines, thick irregular pleural lines, and subpleural may arise on the COVID-19 patient as same as the symptoms on pneumonia patients [4], [9], [11]. Diagnosis based on direct visual inspection of lung ultrasound images requires highly experienced clinicians to differentiate pneumonia and covid-19.

To reduce the inconsistent diagnosis of lung abnormalities, extracting specific features methods on the lung ultrasound image has been extensively investigated. The feature extraction based on pleural lines analysis has been proposed in [13]. Based on its features, normal lung and pneumonia based on ultrasound images can be identified.

In the other studies in [12], the features extraction using the GLCM specific on the pleural lines has been proposed. The method tested to differentiate normal lung and acute respiratory distress syndrome (ARDS) or acute cardiogenic pulmonary edema (CPE). In [12], the GLCM feature-based correlation and homogeneity were reported as the potential texture features.

This study proposes analyzing the texture of ultrasound images based on GLCM as mentioned in [12]. In our work, extracting features calculation is not specific only on the pleural lines reported in [12]. This work investigated the whole area of images to consider some potential signs of lung abnormalities, such as A-lines, B-lines, thick irregular pleural lines, or subpleural consolidations.

For normalization contrast range dynamic, pre-processing is proposed based on Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma transformation. The proposed scheme in this work evaluated the covid-19-positive lungs and pneumonia lesions with healthy tissues.

II. Method

The proposed method for analyzing texture features of LUS images is summarized on the block diagram as shown in

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Fig.1. This work approach is divided into three major stages: image acquisition, texture feature extraction, and analysis. We use the images in this work by converting a video LUS file. Histogram equalization and gamma transformation were applied for the contrast enhancement process. The analysis stage uses GLCM feature extraction to distinguish labeled pictures into three categories: covid-19, pneumonia, and regular. Spyder v4.1.5 and Jupiter Notebook v6.1.4, both based on Python, were used to perform feature extraction and analysis on an MSI laptop with an Intel(R) Core (TM) i5-10200H CPU @ 2.40GHz, 16 GB RAM, and an NVIDIA GeForce RTX 3060 Laptop GPU. The explanation of each stage description is below.

A. *Converting LUS Video Files to Images*

The freely available online lung ultrasound images and videos in this work were obtained from the POCOVID-Net dataset [14] for covid-19, pneumonia, and regular labeled data and have various frame sizes, framerate, and format files. The initial process started by converting the LUS video to images before the image processing process. The image resizes of an image frame are needed to allow for improved comparability of condition datasets with each video frame.

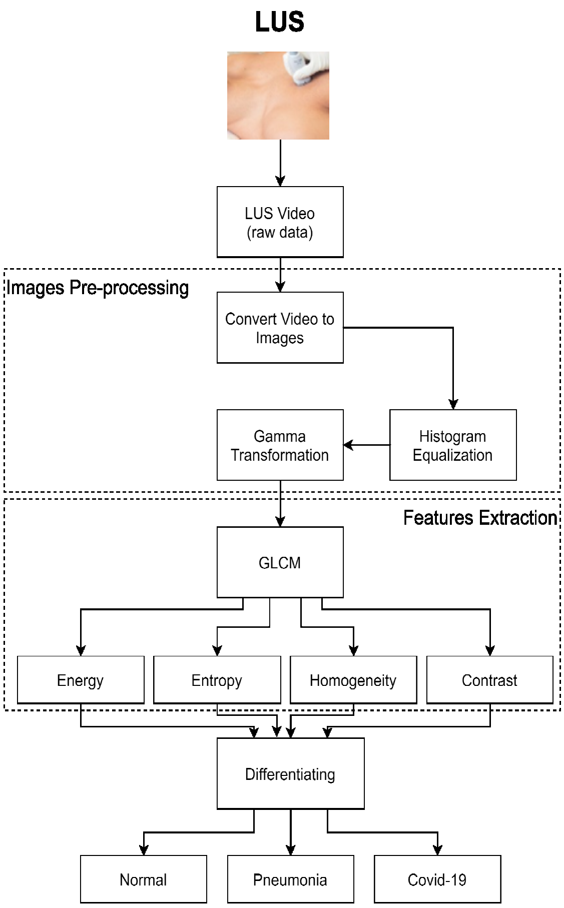


Fig. 1 Block diagram of the image processing stages

This work analyzes the image from the [14] dataset downloaded on Jan. 5, 2021. The dataset consists of 129 total LUS videos with 122 videos recorder using a convex transducer and seven videos using a linear transducer with various frame sizes (between 139x139 and 1080x1080), different framerate (between 12 and 60 frames/sec) and stored in AVI, MP4, MOV, GIF and MPEG files format. The LUS videos dataset has covid-19 (33 videos), pneumonia (37 videos), and regular/normal lung (59 videos) labels. Fig.2 shows a sample of the images we use in this study.

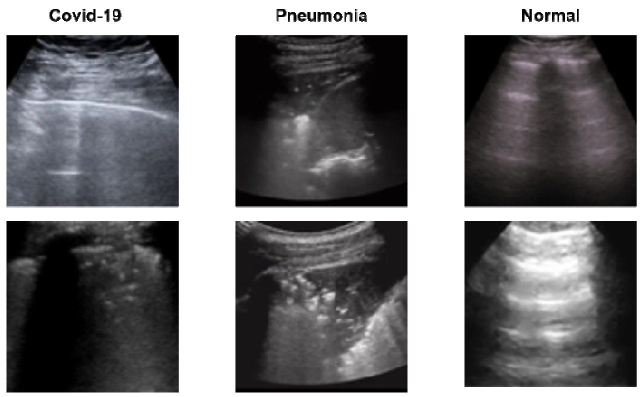


Fig.2 Sample of the images of lung diseases: covid-19, pneumonia, and normal/regular lung

B. *Image Pre-processing*

In the image pre-processing stages, as shown in Fig.1, each video file is converted to image files with frequency 2Hz and randomly selected by 100 images for each labeled data (covid-19, pneumonia, and regular/normal). For pre-processing, an image enhancement and following gamma correction is done before the step of feature extraction.

For image enhancement purposes, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied. For medical image, the excellent performance of CLAHE has been reported in [15], [16]. Specific for ultrasound images, CLAHE could reduce blurring resulting from the speckle filtering [16].

CLAHE works on a specific small area of an image (tile) rather than the complete image. The neighboring tiles are merged using bilinear interpolation to remove imaginary boundaries. The parameters size of tiles and the histogram's clip level could be set as CLAHE parameters to optimize the image enhancement process. CLAHE work is based on partitioning the image into numerous non-overlapping, nearly equal-sized areas [17]. The histogram of each region is calculated initially in this method. After that, a clip limit for clipping histograms is calculated based on a specified contrast expansion limit. The height of each histogram is redistributed so that it does not exceed the clip limit. Finally, cumulative distribution functions (CDF) of the resultant contrast constrained histograms for grayscale mapping are determined. Pixels are mapped using the CLAHE technique by linearly integrating the mappings of the four closest regions [17].

Furthermore, to optimize contrast range dynamic of image resulting from CLAHE process, Power law transformations has used [18]. Its transformations can be formulated as

$$s = c\, r^{\gamma} \qquad (1)$$

In equation (1), s and r represent the pixels' gray levels in the output and input images, respectively, and c is a constant.

The value of c =1 was selected in this work. Because the symbol γ is gamma, this transformation is also known as gamma transformation. When γ >1, the input's narrow range of high grayscale is mapped to a wide output, enhancing the contrast of high gray areas. When γ <1, the input's narrow range of low grayscale is mapped to a wide output range, increasing the contrast in the low gray area. The value of γ =1.5 was selected in this work.

C. Features Extraction

The gray-level co-occurrence matrix (GLCM) has been frequently employed to characterize textures in LUS images [19], [20]. As defined by Haralick and Shanmugam in [17], this method counts pairs of horizontally adjacent pixels in a grayscale version of the image. The properties collected by this approach have specific characteristics that are detailed in-depth elsewhere. The GLCM was computed using four adjacency directions (0^0, 45^0, 90^0, and 135^0), and eight gray levels with four out of 28 textural elements in [21] were used. Table I shows the selected features for GLCM computing.

TABLE I. COMPUTED GLCM FEATURES [21]

Computed Features	Description
Energy	Known as the angular second moment, it is a measure of the global homogeneity of an image.
Contrast	A measure of the local variations in an image
Entropy	A measure of information content. It measures the randomness of the intensity distribution. A homogeneous scene has a high entropy
Homogeneity	A measure of a local homogeneity of an image, also known as inverse difference moment

In this study, the extraction of texture features was computed using Eqs. (2), (3), (4), and (5) were for energy, contrast, entropy, and homogeneity features [21].

$$Energy = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \left(p(i,j)\right)^2 \quad (2)$$

$$Contrast = \sum_{n=0}^{N_g-1} (|i-j|)^2 \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \quad (3)$$

$$Entropy = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \, . log\left(p(i,j)\right) \quad (4)$$

$$Homogeneity = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \left(\frac{1}{1+(i-j)^2} p(i,j)\right) \quad (5)$$

Notations:

Ng : Number of distinct gray levels in the quantized image

p(i, j) : (*i, j*)th entry in a normalized gray-tone spatial-dependence matrix

III. RESULT

This study utilizes the feature extraction of gray level co-occurrence matrix (GLCM) ultrasound imagery to differentiate between covid-19 disease, pneumonia, and regular/normal. Ultrasound imagery data was taken as much as 300 data, with each composition consisting of 100 images for the label covid-19, pneumonia, and regular/normal. The images from each data resized to 128x128 pixels size and then followed by pre-processing of the images. The next process is to determine the GLCM matrix in a directional formation of 0°, 45°, 90°, and 135° and the calculated feature extraction characteristics for energy, contrast, entropy, and homogeneity.

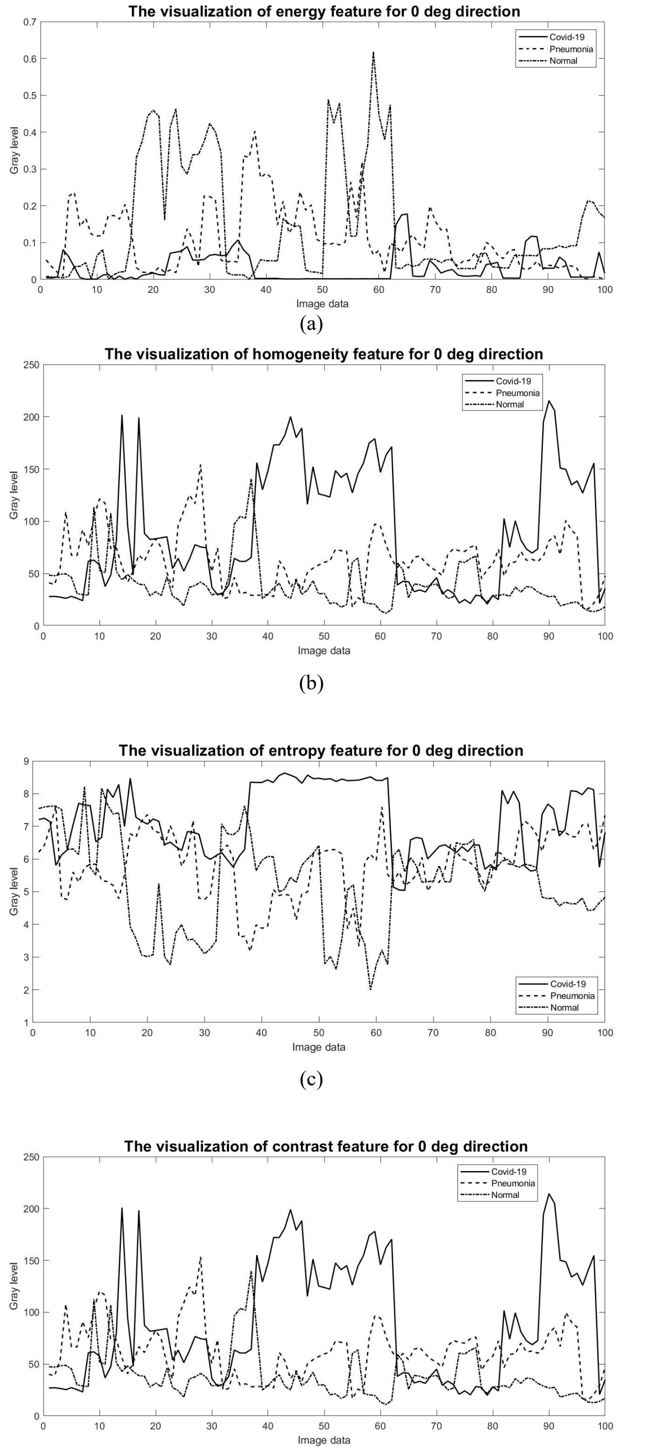
The mean values and standard deviation values of the feature extraction characteristics of energy, contrast, entropy, and homogeneity for all formations of the GLCM matrix direction are given in Table II.

TABLE II. COMPARISON OF TEXTURE FEATURES (MEAN ± SD) BETWEEN PATIENTS WITH COVID-19, PNEUMONIA, AND REGULAR

GLCM Features	Covid-19 (n=100)	Pneumonia (n=100)	Regular (n=100)
energy_0	0.03 ± 0.04	0.11 ±0.09	0.15 ± 0.16
homogeneity_0	90.96 ± 58.07	63.00 ± 26.03	39.44 ± 22.91
entropy_0	7.17 ± 1.04	5.81 ± 0.99	5.26 ± 1.46
contrast_0	89.96 ± 58.07	62.00 ± 26.03	38.44 ± 22.91
energy_45	0.03 ± 0.04	0.11 ± 0.09	0.14 ± 0.16
homogeneity_45	91.50 ± 58.46	63.33 ± 26.20	39.71 ± 23.03
entropy_45	7.18 ± 1.04	5.83 ± 0.99	5.28 ± 1.47
contrast_45	90.50 ± 58.46	62.33 ± 26.20	38.71 ± 23.03
energy_90	0.03 ± 0.04	0.11 ± 0.09	0.14 ± 0.16
homogeneity_90	266.67±187.41	144.91±64.19	88.97 ± 63.10
entropy_90	7.42 ±1.10	5.92 ± 1.05	5.42 ± 1.55
contrast_90	265.67±187.41	143.91± 64.19	87.97 ± 63.10
energy_135	0.03 ± 0.04	0.10 ± 0.09	0.14 ± 0.16
homogeneity_135	287.01±194.78	171.12±79.56	106.06 ±77.05
entropy_135	7.50 ± 1.08	6.08 ± 1.03	5.54 ± 1.57
contrast_135	286.01±194.78	170.12± 79.56	105.06±77.05

There were statistically significant changes in 4 gray-level co-occurrence matrix features between covid-19, pneumonia, and regular lung imaging. The covid-19 subgroup had the highest cluster homogeneity, entropy, and contrast but lowest cluster energy than pneumonia and regular/normal subgroup. For another comparison, the pneumonia subgroup had higher cluster homogeneity, entropy, and contrast but lowest cluster energy than the normal subgroup.

Fig.3 shows the visualization of feature extraction characteristics of energy, contrast, entropy, and homogeneity for 0 deg direction. Using 100 sample images for the labeled data as covid-19, pneumonia, and regular/normal, extraction characteristics of energy, contrast, entropy, and homogeneity for 0 deg direction in Fig. 3 generally show that the covid-19 data have the highest value than pneumonia and regular/normal. In contrast, the energy feature has the lowest value. These figures in Fig.3 could differentiate the covid-19, pneumonia, and regular/normal.



(a) (b) (c) (d)

Fig. 3 The visualization of computed feature results in 0^0 direction for (a) energy, (b) homogeneity, (c) entropy, and (d) contrast with labeled data are covid-19, pneumonia, and regular/normal.

While the maximum values of the four GLCM features for covid-19, pneumonia, and regular lung imaging in Table III had the highest values for cluster contrast, homogeneity, and entropy for the 135^0 direction, the covid-19 subgroup has the lowest cluster energy than pneumonia and normal subgroup.

TABLE III. THE MAXIMUM VALUE OF GLMC FEATURES

GLCM Features	**Maximum Value**		
	Label '0' (Covid-19)	**Label '1' (Pneumonia)**	**Label '2' (Normal)**
contrast_0	214.348	153.389	139.612
contrast_45	215.641	154.596	140.454
contrast_90	735.274	428.949	341.402
contrast_135	787.464	522.624	385.744
energy_0	0.178	0.403	0.618
energy_45	0.176	0.405	0.627
energy_90	0.175	0.404	0.625
energy_135	0.171	0.394	0.619
entropy_0	8.630	7.605	8.213
entropy_45	8.630	7.631	8.224
entropy_90	8.974	7.803	8.484
entropy_135	9.016	7.852	8.520
homogeneity_0	215.348	154.389	140.612
homogeneity_45	216.641	155.596	141.454
homogeneity_90	736.274	429.949	342.402
homogeneity_135	788.464	523.624	386.744

The GLCM-based extraction features method with our pre-processing proposed could differentiate pneumonia, Covid-19, and normal lung. It can be combined with machine learning classification approaches to create a decision support system for diagnosing and classifying covid-19, pneumonia, and normal lung.

IV. CONCLUSION

The analysis for lung ultrasound images suggests that differentiation of pneumonia and Covid-19 is possible based on image texture features. The covid-19 subgroup had the highest cluster homogeneity, entropy, and contrast but lowest cluster energy than pneumonia and normal subgroup. The covid-19 subgroup had the highest cluster contrast, homogeneity, and entropy, and the lowest cluster energy than pneumonia and normal subgroup in the 135^0 direction.

For further research, GLCM extraction features can be combined with machine learning classification approaches to create a decision support system for diagnosing and classifying covid-19, pneumonia, and normal lung.

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"The Empowerment of Healthcare Technology to Achieve Universal Health Coverage"

Held by Department of Electrical Engineering, Faculty Industrial Technology, Universitas Islam Indonesia at Yogyakarta, 20-21 October 2021

CONFERENCE CHAIR

FIRDAUS, S.T., M.T., PH.D

Reviewer Comments:

IBITeC 3rd Period 1

Detailed comments: Please justify your recommendation and suggest improvements in technical content or presentation.

The manuscript in LUS analysis is well written. There are several improvements: Eq 1, c is constant, please provide a number used for this study. Please improve Eq 2-Eq 5. Please improve the x-y axis caption of Fig 3 (a)-(d). The Authors may use the three types of lines instead of color to improve readability.

IBITeC 3rd Period 2

Detailed comments: Please justify your recommendation and suggest improvements in technical content or presentation.

1 Please check the following:

- Abstract: The proposed scheme is base on the ... -> based on ??
- I. Introduction: ... the chest X-ray (CXR) needed ... -> ... is needed ??
- II. Method We use the mages in this work .. -> images ???
- B. Image Pre-processing In the image processing stages, as shown in Fig. 1, ... -> do you mean "the image pre-processing stage ..." ??
- C. Features Extraction ... texture features computed using (2), (3), (4), and (5) ... -> should be "Eqs. (2), (3), (4), and (5)"

2 Related Work

I think it is better to cite similar works that also use "Ultrasound Images" to classify or differentiate between COVID19 and Non-COVID19. Then, you need to explain the difference between your approach and other recently published works is.

3 Equations

It is better not to display equations as images. Eqs. 2, 3, 4, and 5 are not clear.

4 Figures

- Fig. 3 is NOT CLEAR. A resolution of at least 300 dpi is normally used by the IEEE. Please check it.
- There is no detailed explanation about Fig. 3.

Discussion

In my opinion, the discussion part related to the results obtained is very little.

IBITeC 3rd Period 3

Detailed comments: Please justify your recommendation and suggest improvements in technical content or presentation.

Authors have classification of normal, pneumonia or COVID-19 using lung ultrasound images. Texture features like energy, contrast, entropy and homogeneity have been used for classification. Prior to calculating these features, Gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) have been applied for enhancing the images.

Authors are suggested to re-write the equations (2) to (5) for better clarity/ readability.

Authors Responses to Reviewer's Comments

(Paper ID: 1570754268)

IBITeC 3rd Period 1 (Reviewer 1)

The manuscript in LUS analysis is well written. There are several improvements: Eq 1, c is constant, please provide a number used for this study. Please improve Eq 2-Eq 5. Please improve the x-y axis caption of Fig 3 (a)-(d). The Authors may use the three types of lines instead of color to improve readability.

Authors Responses:
Thank you for your advice and correction of our manuscript. We have appreciated all your concern and comments on our manuscript. We have corrected our manuscript based on your suggestion. Here is the improvement and correction in our revised manuscript:

- The c constant we used in our work is c=1. We wrote it in the last line of the 1st paragraph below Eqs. (1).
- We have improved the clarity of the writing of Eqs. 2 – Eqs. 5.
- We've improved the visualization and the caption on each axis in Figure 3(a)-(d), and we've used three different line types for each category of data labels. We used a multiline chart to improve the readability to show the differences between the image label covid-19, pneumonia, and normal that we only present in one line before.

IBITeC 3rd Period 2 (Reviewer 2)

1 Please check the following:

- *Abstract: The proposed scheme is base on the ... -> based on ??*
- *I. Introduction: ... the chest X-ray (CXR) needed ... -> ... is needed ??*
- *II. Method We use the mages in this work .. -> images ???*
- *B. Image Pre-processing In the image processing stages, as shown in Fig. 1, ... -> do you mean "the image pre-processing stage ..." ??*
- *C. Features Extraction ... texture features computed using (2), (3), (4), and (5) ... -> should be "Eqs. (2), (3), (4), and (5)".*

Authors Responses:
Thank you for your advice and correction of our manuscript. We have appreciated all your concern and comments on our manuscript, and we agree with your suggestion. We have corrected our revised manuscript based on your recommendation.

2 Related Work

I think it is better to cite similar works that also use "Ultrasound Images" to classify or differentiate between COVID19 and Non-COVID19. Then, you need to explain the difference between your approach and other recently published works is.

Authors Responses:
Thank you for your advice and correction of our manuscript. We have corrected our revised manuscript based on your recommendation. We have added two similar works that use ultrasound images.

1. To reduce the inconsistent diagnosis of lung abnormalities, extracting specific features methods on the lung ultrasound image has been extensively investigated. The feature extraction based on pleural lines analysis has been proposed in [13]. Based on its features, normal lung and pneumonia based on ultrasound images can be identified.
2. In the other studies in [12], the features extraction using the GLCM specific on the pleural lines has been proposed. The method tested to differentiate normal lung and acute respiratory distress syndrome (ARDS) or acute cardiogenic pulmonary edema (CPE). In [12], the GLCM feature-based correlation and homogeneity were reported as the potential texture features.

The difference between our approach and other recently published works is:

In our work, extracting features calculation is not specific only on the pleural lines reported in [12]. This work investigated the whole area of images to consider some potential signs of lung abnormalities, such as A-lines, B-lines, thick irregular pleural lines, or subpleural consolidations.

The added similar work on the revised article are written in 6th and 7th paragraph in the introduction part and the explanation of the difference between our approach and other recently published works we wrote in 8th paragraph in the introduction part.

3 Equations

It is better not to display equations as images. Eqs. 2, 3, 4, and 5 are not clear.

Authors Responses:
Thank you for your advice and correction of our manuscript. We have corrected our revised manuscript based on your recommendation. We have changed the clarity of the writing of Eqs. 2, 3, 4, and 5.

4 Figures

- *Fig. 3 is NOT CLEAR. A resolution of at least 300 dpi is normally used by the IEEE. Please check it.*
- *There is no detailed explanation about Fig. 3.*

Authors Responses:
Thank you for your advice and correction of our manuscript. We have corrected our manuscript based on your suggestion. The improvement and revisions in our revised manuscript are:

- We've improved the image resolution in Figure 3(a)-(d). We have used higher resolution and utilized three different line types for each category of the data label. We use a multiline chart in Figure 3 to improve the readability to show the differences between the image labeled covid-19, pneumonia, and normal that we only present in one line before.

- We have added the explanation for Fig. 3 in the 4th paragraph in the Result part:
  Fig.3 shows the visualization of feature extraction characteristics of energy, contrast, entropy, and homogeneity for 0 deg direction. Using 100 sample images for the labeled data as covid-19, pneumonia, and regular/normal, extraction characteristics of energy, contrast, entropy, and homogeneity for 0 deg direction in Fig. 3 generally show that the covid-19 data have the highest value than pneumonia and regular/normal. In contrast, the energy feature has the lowest value. These figures in Fig.3 could differentiate the covid-19, pneumonia, and regular/normal.

5 Discussion

In my opinion, the discussion part related to the results obtained is very little.

Authors Responses:
Thank you for your advice and correction of our manuscript. We have appreciated all your concern and comments on our manuscript. We have corrected our manuscript based on your suggestion. The improvement and correction in our revised manuscript were written in the last paragraphs in the Result part.

IBITeC 3rd Period 3 (Reviewer 3)

Authors have classification of normal, pneumonia or COVID-19 using lung ultrasound images. Texture features like energy, contrast, entropy and homogeneity have been used for classification. Prior to calculating these features, Gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) have been applied for enhancing the images.

Authors are suggested to re-write the equations (2) to (5) for better clarity/ readability.

Authors Responses:
Thank you for your advice and correction of our manuscript. We have appreciated all your concern and comments on our manuscript. We have corrected our revised manuscript based on your recommendation. We have changed the clarity and the readability of the writing of Eqs. (2) to (5).