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Tuberculosis detection using deep learning and contrast-enhanced canny edge detected X-Ray images

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ABSTRACT

Tuberculosis (TB) is a disease that causes death if not treated early. Ensemble deep learning can aid early TB detection. Previous work trained the ensemble classifiers on images with similar features only. An ensemble requires a diversity of errors to perform well, which is achieved using either different classification techniques or feature sets. This paper focuses on the latter, where TB detection using deep learning and contrast-enhanced canny edge detected (CEED-Canny) x-ray images is presented. The CEED-Canny was utilized to produce edge detected images of the lung x-ray. Two types of features were generated; the first was extracted from the Enhanced x-ray images, while the second from the Edge detected images. The proposed variation of features increased the diversity of errors of the base classifiers and improved the TB detection. The proposed ensemble method produced a comparable accuracy of 93.59%, sensitivity of 92.31% and specificity of 94.87% with previous work.

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1. INTRODUCTION

The bacteria that causes Tuberculosis is called Mycobacterium Tuberculosis. The World Health Organization states that about ten million individuals were infected with TB in 2018, with approximately 25,387 cases reported in Malaysia [1]. Among them, about 1.5 million died from TB in 2018.

TB is a treatable infection, and it can be detected by examining the chest x-rays of the patients. Therefore, early diagnosis of TB is essential for raising the likeliness of recovery [2]. Nevertheless, there are two main challenges for TB detection. First, lung cancer and TB look similar, this causes difficulties for a radiologist to differentiate between these two [3]. Second, there is an insufficiency of expert radiograph readers in high-TB-burden areas [4]. Therefore, a semi-automated TB detection system that can support medical diagnosis is necessary to provide better healthcare to society [5].

Several works on semi-automated TB detection using machine learning can be found in the literature. Lately, features from medical images were analyzed using deep learning techniques [6]. Deep learning can identify features hierarchically. The lower level features help generates the higher-level features. The ability of deep learning to identify high-level features is shown to produce better classification results [7]. Numerous works using deep learning for TB detection on chest x-rays can be found in [8-19].

Some studies used ensemble techniques, whereby more than one classifier was selected, to make predictions. The ensemble classifiers can perform more accurate classification than any single classifier [20]. More work on TB detection using ensemble techniques were presented in [21-23].

According to the literature, it is shown that deep learning performed well in TB detection. The works presented in the literature mostly utilized features extracted from the original chest x-ray images [11-12, 14-19, 22]. The performance of the classifier is influenced by the features used. Therefore, using a variety of features to train the classifiers may generate better TB detection models and this should be investigated. An ensemble of classifiers perform well when the base classifiers have a diversity of errors [24], which means the errors of the base classifiers have a low correlation. One method to achieve such a condition is by having diverse classifiers. If two classifiers make different errors on new values, they are said to be diverse. For example, if there is an ensemble of three classifiers, namely f_1, f_2 and f_3, and a new image x. If these classifiers are not diverse, then when $f_1(x)$ misclassify, $f_2(x)$ and $f_3(x)$ will also misclassify. Conversely, if the errors made by the classifiers are uncorrelated, then when $f_1(x)$ misclassify, $f_2(x)$ and $f_3(x)$ might be correct. Diverse classifiers could be achieved either by using different classification techniques or different sets of features. Most of the works on ensemble classifiers in the literature focus on the former.

The process of identifying the boundaries of objects in an image is known as edge detection. The discontinuities in brightness were detected to define edges. Edge detected images provide essential features for image analysis [25-26]. There are many edge detection methods reported in the literature. Traditional gradient-based operators like Sobel, Robert and Prewitt were first constructed for edge detection, but they are susceptible to noise and did not produce sharp edges [27]. Laplacian operators', another method to detect edges, tend to detect false edges and severe localization errors of curved edges [25]. John F. Canny proposed an algorithm known as canny edge detection in 1986, and his technique is considered as the optimum edge detection technique for images that are degraded by noise [28]. However, the conventional canny edge detection technique suffers from a few weaknesses. One of them is that the use of Gaussian filtering smoothed the important edges while removing the noise [29]. As a result, the edges are weakened.

This paper presents an approach to TB detection using deep learning and contrast-enhanced canny edge detected (CEED-Canny) x-ray images. CEED-Canny is a modified Canny algorithm to detect the edges of the x-ray images and was used to generate the edge detected images. Previous work extracted features from the original chest x-ray images only. Our method extracted features from the enhanced original chest x-ray images and the edge detected images. The aim is to increase the diversity of errors in the base classifiers of the ensemble classifiers. We hypothesized that by using different types of features and ensemble classifiers will produce higher TB detection accuracy, sensitivity and specificity. The contributions of this paper are thus:

a. Using the CEED-Canny technique that combines canny edge detection and local morphological contrast enhancement to detect edges in chest x-ray images.
b. Generate ensemble CNN classifiers for TB detection using two sets of images, namely the Enhanced images of chest x-rays and the chest Edges images detected from the Enhanced x-rays.

2. RESEARCH METHOD

There are three main phases in our research work:

a. Image preparation,
b. Classifiers generation,
c. Ensemble classification.

In the image preparation phase, resizing, contrast limited adaptive histogram equalization (CLAHE) and CEED-Canny were performed and this produced two sets of images - the enhanced images and the edge images. These images were used for training. In the classifiers generation phase, several selected CNN architectures were used to generate classifiers. Each classifier extracted features from the Enhanced and Edge images and learned to recognize TB-infected lungs and healthy lungs. In the ensemble phase, the predictions made by individual classifiers were combined using average probability scoring. Details of each phase are described in sub-sections 2.1 to 2.3. Sub-section 2.4 presents the performance measure.

2.1. Image preparation phase

There are three operations involved in the image preparation phase. First, resizing was performed on all the images such that they are all 250 x 250 pixels. The reason for doing this was to reduce computational workload, as the computational cost increases with image size. It was also to make sure all images are of the same size and match the CNNs' input size. Second, CLAHE was performed on the original x-ray images to produce the Enhanced dataset. This operation improves the quality of the x-ray images. Third, CEED-Canny, described in detail in section 2.1.1, was applied to the Enhanced dataset to generate the Edge dataset.

The Edge dataset was used as we conjectured that images of TB infected lungs might contain more uncommon edges compared to healthy lungs. At the end of this phase, two sets of images were generated, namely the Edge images and Enhanced images. Both sets of images were used to generate classifiers.

2.1.1. Contrast-enhanced canny edge detection for chest X-Ray images

The CEED-Canny method combines local morphological contrast enhancement and the Canny edge detection technique. Morphology is an image processing technique that processes images based on shapes known as structuring elements. In morphological operations, a structuring element is applied to an input image, and then an output image with the same size as the input image is produced. The intensity value of each pixel in the output image is decided by a comparison of the corresponding pixel in the input image with its neighbors. For morphological contrast enhancement, its filter replaces the central pixel by the local maximum if the original pixel value is closest to the local maximum; otherwise, minimum local will be used. The Canny edge detector consists of a few steps. The first step is noise reduction. Noise contained in the image is reduced by convolving the input image with the Gaussian filter. The second step is finding gradients to detect edges where the change in grayscale intensity is maximum. The third step is non-maximum suppression that retain all local maxima in the gradient image and eliminates any undesirable pixels that may not be a part of an edge. The final step is the hysteresis thresholding. This stage determines which detected edges are true edges and which are false. More information about Canny edge detection can be found in [29-30].

Figure 1 shows the pseudocode of the CEED-Canny. For a grayscale image, morphological contrast enhancement was first performed, followed by Canny edge detection. Morphological contrast enhancement replaces the central pixel by the local maximum if the original pixel value is closest to the local maximum, otherwise by the local minimum. Then, Canny edge detection was applied to detect the edges present in the image. Figure 2 displays samples of a chest x-ray image before and after the application of CEED-Canny.

```
Input
      - Load grayscale image
Process
      - FOR all pixels
            - Get original pixel value, P_o
            - Find local maximum, P_max
            - Find local minimum, P_min
            - Compute difference between original pixel value and local maximum, D_1
            - Compute difference between original pixel value and local minimum, D_2
            IF D_1 < D_2
                  P_o = P_max
            ELSE
                  P_o = P_min
      - Perform noise reduction using Gaussian filter
      - Compute Intensity Gradient of the image
      - Perform non-maximum Suppression
      - Set double threshold value
      - Apply hysteresis thresholding
Output
      - Edge image
```

Figure 1. Pseudocode for CEED-Canny

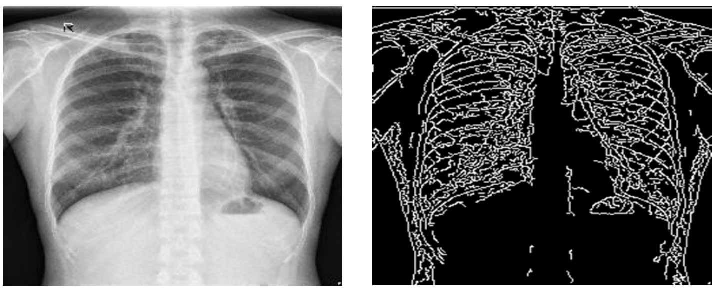

Figure 2. Chest x-ray image (left) before CEED-Canny is applied and (right) after CEED-Canny is applied

2.2. Classifiers generation phase

The process of generating a classifier using CNN is as follows. First, the image dataset was divided into two subsets, namely the training set and testing set. Next, CNN was used to extract features from the training set images and learn to recognize Normal and TB lungs. After the training was completed, a classifier was produced. This classifier was used to make predictions on every image in the test set, and the results were recorded. The performance of the classifier was evaluated using a confusion matrix, which was used to determine the sensitivity, specificity and accuracy of the classifier.

2.3. Ensemble phase

When a classifier predicts the label of an image, it outputs a probability score in the range of 0 to 1. If the score is lower than 0.5, then the image was labeled as Normal. Else, it was labeled as TB. For ensemble classification, average probability scoring was used. The probability scores of individual CNN classifiers were averaged, and the subsequent average probability score defines the final label of the images [10]. The following formula was used to determine the ensemble's final score:

$$final\ score = \frac{\sum x}{n}$$

where x is the probability score of a classifier and n is the number of the classifier.

2.4. Performance measure

The presented work requires two types of performance measures. The first is to evaluate the effectiveness of the CEED-Canny in detecting the chest edges from a chest x-ray image. The second is to measure the performance of TB detection.

The effectiveness of the CEED-Canny was evaluated using the mean square error (MSE). MSE was used because it provides an impartial assessment of the perceptual quality of images [31]. Most previous work used MSE to evaluate their proposed image processing technique [29, 32-33]. The MSE is the average of the squares of the errors between the original image and the noisy image. The error is the amount by which the values of the original image differ from the noisy image. To calculate MSE, the errors between the original image and the noisy image are squared, then averaged. The lesser the MSE, the better the restoration of the noisy image to match the original image, thus demonstrating the performance of the restorative algorithm. MSE is defined as follow:

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

where f denotes the matrix data of the original image, g denotes the matrix data of the degraded image, m denotes the numbers of rows of pixels of the images, i denotes the index of that row, n denotes the number of columns of pixels of the image and j denotes the index of that column.

The metrics selected to evaluate the performance of this approach were sensitivity, specificity and accuracy. Sensitivity calculates how well the classifier identifies positive cases. On the other hand, specificity calculates how well the classifier identifies negative cases. Accuracy measures how well the classifier predicts both labels. In this paper, TB was treated as a positive case and non-TB was treated as a negative case.

3. RESULTS AND ANALYSIS

This section describes the datasets used, the experimental setups, results and the discussions of results.

3.1. The datasets

Two public TB chest x-ray image datasets were selected in this paper. They are the Montgomery and Shenzhen datasets [34]. The Montgomery dataset contains 138 images, in which 58 images were TB-infected lungs and 80 images were healthy lungs. The image resolution was either 4020×4892 pixels or 4892×4020 pixels. The Shenzhen dataset contains 662 images, in which 336 images were TB-infected lungs and 326 images were healthy lungs. The image resolutions were approximately 3000×3000 pixels. Both datasets provide images in PNG format. Both datasets were combined, which provides a total of 394 TB-infected lungs and 406 healthy lungs. Twelve healthy lung images were randomly discarded, so that the number of images in each category is the same. For training, 90% of the images were allocated. The remaining 10% was allocated for testing. This train-test split proportion is identical to the works done in [18] and [35].

3.2. Experimental setup

Three experiments were conducted to measure the performance of the proposed approach. The first experiment aimed at the performance evaluation of the proposed CEED-Canny method, while the second experiment was to evaluate the performance of TB detection using the features extracted from the Enhanced images and Edge detected images. These features were used to train CNN classifiers, and later, these classifiers made predictions on the test images. In this paper, two CNN architectures were used, the VGG16 [36] and InceptionV3 [37]. VGG16 will be trained on the Enhanced dataset and Edge dataset, producing two classifiers. Likewise, InceptionV3 will also be trained on these two datasets and produced another two classifiers. The third experiment aimed at the performance comparison of individual classifiers and the ensemble of classifiers. Here, the Keras [38] implementation of VGG16 and InceptionV3 was used. These CNNs were also pre-trained using the ImageNet dataset.

3.3 Performance of contrast-enhanced canny to detect edges

In this set of experiments, we compare the performance of the proposed CEED-Canny and the original Canny. Four sample images were selected for the tests. The first two images were Lena and Cameraman. These two images are standard test images in the image processing community. The third and fourth images were taken from the Shenzen dataset. Table 1 shows the result of the MSE test. Based on the MSE test results, it shows that the CEED-Canny produced lower MSE values than those of the Canny. The results indicate that the edge image produced by CEED-Canny is more accurate than the original Canny.

Table 1. Result of MSE Test for Canny and CEED-Canny methods

Sample	Canny MSE	CEED-Canny MSE
1	239.88	232.51
2	214.32	208.35
3	216.49	197.33
4	244.82	230.98

3.4. Individual classifier test results

Two sets of images were used; the enhanced images and the edge images. All the test images were classified into either TB or non-TB in this experiment. The learning rate of the classifiers was set to 0.0001 and the number of epochs was 2000. Preliminary tests were conducted to determine the optimum learning rate and number of epochs, which were not reported in this paper due to space constraints. Table 2 displays the experimental results. Based on Table 2, the highest accuracy and specificity of 91.03% and 92.31% were achieved using VGG16 and the Enhanced images. VGG16 records the best sensitivity of 89.74% on the Enhanced and Edge images; InceptionV3 produced a similar result when applied on the Edge images.

Table 2. Performance of different CNN classifiers to detect TB on enhanced and edge images

Image type	CNN Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
Enhanced	VGG16	89.74	92.31	91.03
	InceptionV3	84.62	79.49	82.05
Edge detected	VGG16	89.74	89.74	89.74
	InceptionV3	89.74	74.36	82.05

3.5. Ensemble classifier test results

In the third experiment, classifications were done using ensembles of the classifiers. All available combinations were tested. Table 3 displays the results obtained from the test data. (A represents VGG16 trained on the Enhanced dataset, B represents VGG16 trained on the Edge dataset, C represents InceptionV3 trained on the Enhanced images, D represents InceptionV3 trained on the Edge images).

Based on Table 3, all the ensemble combination produces at least the same, if not better, accuracy than any individual InceptionV3 classifier. The ensemble combination that produced the highest accuracy is ABC, at 93.59%, with sensitivity and specificity of 92.31% and 94.87%, respectively. There were two combinations of the ensemble that produced the same highest sensitivity, at 92.31, which are ABC and ABCD. Sensitivity is considered pertinent in medical image analysis as we want to reduce false negatives.

Table 3. The Performance of Ensemble CNN to Detect TB

Ensemble	Sensitivity (%)	Specificity (%)	Accuracy (%)
AB	89.74	92.31	91.03
AC	79.49	89.74	84.62
AD	87.18	84.62	85.90
BC	84.62	79.49	82.05
BD	87.18	84.62	85.90
CD	89.74	76.92	83.33
ABC	92.31	94.87	93.59
ABD	89.74	92.31	91.03
ACD	92.31	89.74	91.03
BCD	87.18	87.18	87.18
ABCD	89.74	89.74	89.74

3.6. Discussion of results

From the MSE Test, it is shown that the MSE values produced by CEED-Canny are lower than the MSE values produced by Canny. It indicates that the edge images produced by CEED-Canny are more accurate than the traditional Canny and subsequently produced more informative features for classifier generation. The individual classifier test results show the potential of using the edge features detected by the CEED-Canny in detecting TB. From the Ensemble Test, we have shown that the combined predictions of multiple classifiers, generated from different datasets, outperformed the predictions of single classifiers. The results show that higher sensitivity, specificity and accuracy can be achieved when using more than one type of image. Extracting features from different types of images can produce better TB detection performance. The ensemble of ABC produced the best performance with the accuracy, sensitivity and specificity of 93.59%, 92.31% and 94.87%, respectively.

There is no direct comparison that can be conducted with other works in the literature. For example, the TB detection on the Shenzhen and Montgomery datasets was performed separately in [9], whereby the accuracies recorded for each dataset were 95.57% and 78.3%, respectively. In [11], the sensitivity of 97.3% was recorded but with an additional dataset used and excessive augmentation, including random cropping of pixels, mean subtraction, mirror images, rotations and CLAHE. The other works [10, 16, 22] produced accuracies lower than that of the work presented in this paper.

4. CONCLUSION

This paper presents Tuberculosis detection using deep learning and Contrast-Enhanced Canny edge detected x-ray images. The problem is that previous ensembles only combine CNNs trained on similar features and thus limited the performance of the classifiers. We present ensembles that combine CNNs trained on different features extracted from a different set of images, the Enhanced and Edge images. We used CEED-Canny to produce edge images. VGG16 and InceptionV3 were selected and employed as classifiers. The results indicate that using ensembles of classifiers trained on multiple types of features extracted from various types of images improved the detection accuracy, sensitivity and specificity. Consequently, it supports the hypothesis of the work presented in this paper. For future works, we would like to extend the scope to classify chest x-ray images based on TB severity and investigate more features that would further improve the performance of the classifiers.

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