

Development of hybrid convolutional neural network and autoregressive integrated moving average on computed tomography image classification

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ABSTRACT

One of the deadliest diseases in humans is lung cancer. Radiologists and experienced doctors spend much more time investigating the pulmonary nodules due to the high similarities between malignant and benign nodules. Recently, the computer-assisted diagnosis (CAD) tool for nodule detection can provide a second opinion for the doctor to diagnose lung cancer. Although machine learning technologies are extensively employed to identify lung cancer, the process of these methods is complex. The numerous researches have sought to automate the diagnosis of pulmonary nodules using convolutional neural networks (CNN) to aid radiologists in the lung screening process. However, CNN still confronts some challenges, including a significant number of false positives and limited performance in detecting lung cancer from computed tomography (CT) images. In this work, we proposed a hybrid of CNN and auto-regressive integrated moving average (ARIMA) for lung nodule classification using CT images to address the classification issue. The proposed hybrid CNN-ARIMA can classify CT images successfully with test accuracy, average sensitivity, average precision, average specificity, average F1-Score, and area under the curve (AUC) of 99.61%, 99.71%, 99.43%, 99.71%, 99.57%, and 1.000, respectively.

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1. INTRODUCTION

The most common cause of mortality worldwide is lung cancer. In comparison to other cancers, lung cancer is responsible for roughly 1.8 million fatalities (18.0% of all cancer deaths) in 2020 [1]. If lung cancer is detected earlier, it can be treated effectively and even cured. The pulmonary nodules are the abnormal development of lung tissue and are generally the first sign of lung cancer. As a result, it is critical to detect and diagnose lung nodules earlier to reduce lung cancer mortality [2]. Radiologists utilize a variety of diagnostic techniques to detect lung cancer, including magnetic resonance imaging (MRI), computed tomography (CT), chest X-ray, and other methods. However, a CT scan is the most reliable screening approach due to its low noise and robustness in determining tumor size [3]. With the widespread use of CT scanning technology, the need for medical image analysis has risen and causes an increased workload for radiologists [4]. Traditionally, achieving an accurate radiologic diagnosis requires the expertise of the radiologist throughout the analysing process. The emergence of computer-aided tools has relieved the burden on radiologists and offered a second opinion for doctors to diagnose lung cancer [5]. In traditional methods, there exist various techniques for feature

extraction and classification in the diagnosis of lung cancer. Among feature extraction techniques are the threshold method, the region growth method, the morphology approach, and so on [6]. Machine learning technologies, such as support vector machines (SVM) and k-nearest neighbor, are extensively employed to distinguish the false-positive nodules [6]. However, the process of these traditional methods is complex, which leads to poor generalization. This issue is due to the pulmonary nodule features needing to be extracted manually, which causes the automation degree to be limited [7]. Motivated by the lung nodule analysis 16 (LUNA16) challenge [8], numerous research has sought to automate the diagnosis of pulmonary nodules using deep learning, particularly convolutional neural networks (CNN), to aid radiologists in the lung screening process [9]. These techniques have substantially enhanced the treatment's quality and dependability, particularly the early detection of lung cancer. While lung cancer is slow and unreliable in survival rates compared to other cancers, CNN techniques show promising performance. The computer-aided diagnosis (CAD) systems that focused on CNN strategies can reduce lung cancer death rates by a factor of 25% in the last five years [10]. Despite the advancements in using CNN for lung cancer detection, there are still several issues that need to be addressed. These include a high false-positive rate that limits its clinical application and the challenge of surpassing the performance of conventional CAD systems in detecting lung cancer from CT images [11]. Moreover, the approach of adding more training data or fine-tuning hyperparameters to improve CNN's performance faces three main challenges. Firstly, there is observer variability among radiologists, which can significantly affect the interpretation of the images. Secondly, detection networks may miss nodules that are under-represented in the training set. Finally, neural networks are susceptible to unanticipated image distortions [9].

To address the challenges of lung nodule classification, we propose a hybrid approach that combines CNN and auto-regressive integrated moving average (ARIMA) for lung nodule classification using CT scan images. This approach was motivated by previous research that used the hybrid CNN-ARIMA model for skin cancer classification, which demonstrated promising results [12], [13]. In this approach, the CNN algorithm serves as a feature extractor, while the ARIMA model functions as a classifier. The aim of this study is to assess the performance of the hybrid CNN-ARIMA model for lung cancer classification.

2. RELATED WORKS

Several deep learning approaches have been effectively applied in medical domains to address classification problems [12]–[15]. A recent study showed that deep learning methods outperform conventional CAD systems in detecting lung cancer with CT scans [11]. As a result, deep learning algorithms become beneficial for nodule detection and classification, with very intriguing results.

Haiying *et al.* [16] proposed a new deformable convolutional neural network (DCNN) architecture to address the problem of the similarity between true and false-positive nodules in early morphology in China. The efficacy of the DCNN model was evaluated on the Lung Nodule Analysis 2016 dataset, achieving an average competitive performance metric score of 0.835 and a high sensitivity of 0.941 and 0.958 to 4 and 8 false positives per scan, respectively. Sheng *et al.* proposed a method for detecting and diagnosing lung nodules using two networks: Prediction network (PredNet) and diagnosis network (DiagNet). The PredNet uses convolutional networks to predict the growth of nodules between consecutive CT scans through spatial transformation. The DiagNet categorizes nodules based on their growth and previous diagnosis. The model was tested on a dataset of 615 low-dose computed tomography (LDCT) images of 153 early-stage lung nodules from 125 individuals. The proposed method demonstrated promising performance with a classification accuracy of 90%. Many researchers have also shown interest in hybridization techniques due to their outstanding performance in addressing cancer problems by enhancing algorithm performance in recent times [10], [12], [13], [17]–[19]. Agarwal *et al.* [10] proposed a method to classify lung cancers as either malignant or benign by combining a CNN with the AlexNet network model whereas Ardimento *et al.* [17] suggested a novel ensemble-based method for classifying lung cancer more accurately using CT scan images. Saleh *et al.* [20] developed an approach for classifying CT images of the lung using a hybrid of CNN and SVM algorithms. The goal was to effectively detect the presence of cancer cells. The results showed that the proposed CNN-SVM approach achieved an accuracy of 97.91% and had the ability to accurately classify lung cancer in CT scans.

3. METHODOLOGY

This section discusses the study's methodology. The proposed approach in this study does not require any prior techniques because the CNN can classify lesions based on high-level features without the need for low-level nodule visual information and segmentation steps as required in traditional methods [10], [19]. Figure 1 depicts the image classification algorithm used in this study to detect lung cancer.

3.1. Dataset

In this study, the doctor from Sarawak General Hospital provided the dataset for the experiment. These datasets contain 1,286 digital imaging and communications in medicine (DICOM) images divided between normal lung and lung cancer images. There were 890 images of lung cancer and 396 images of normal lung. These DICOM-format datasets need to convert to JPEG format for deep learning applications. Furthermore, all images have a resolution of 512×512 pixels. Figure 2(a) shows the examples of normal lung. Meanwhile, Figure 2(b) illustrates the lung cancer images and the red circle indicates the nodules.

3.2. Image pre-processing

Most of the collected images are not clear. Therefore, the pre-processing process needs to perform. To enhance image clarity, the contrast limited adaptive histogram equalization (CLAHE) method was used via OpenCV as the pre-processing technique [20]. CLAHE is also often used to improve the intensity of the lung image by adding smoothing filters [21]. The final pre-processed images will generate after the CLAHE method. Figure 3 summarizes the process of the CLAHE technique on lung cancer images.

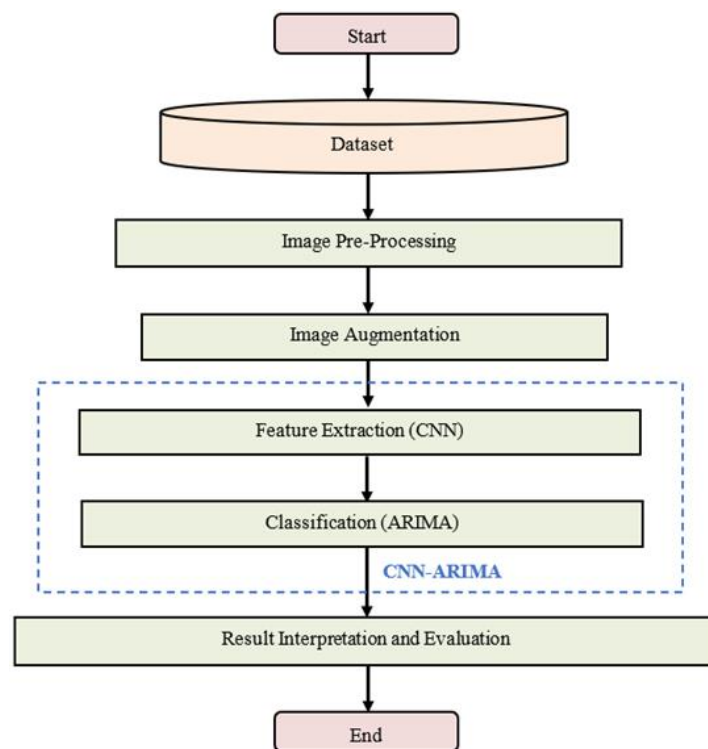


Figure 1. The proposed lung cancer diagnostic CAD system

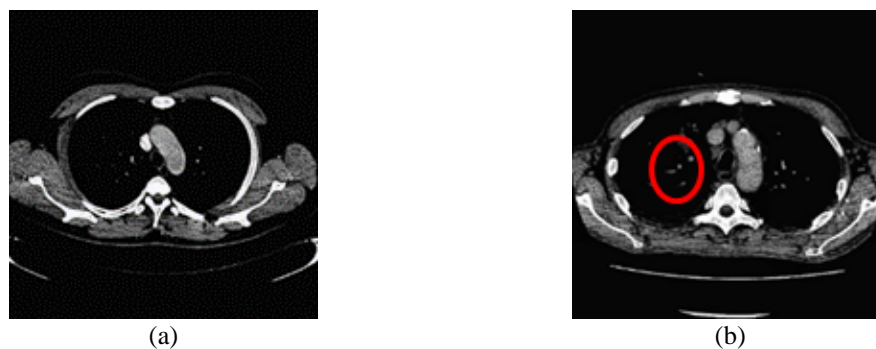


Figure 2. Type of lungs: (a) Normal lung and (b) Lung cancer – red circle indicates the nodules

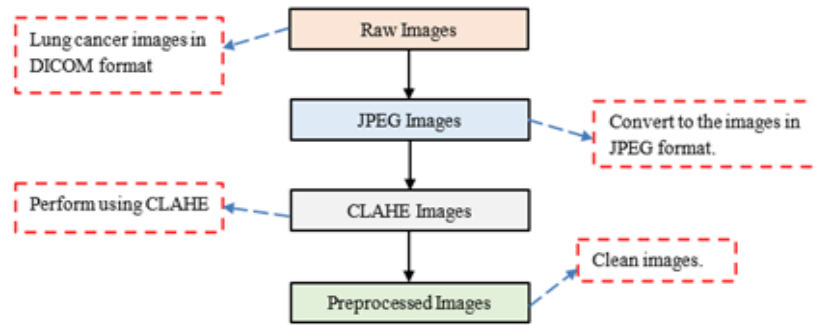


Figure 3. CLAHE using OpenCV framework

3.3. Image Augmentation

An augmentation technique used in this study is an affine transformation [22]. This technique aims to avoid overfitting issues and improve neural network accuracy in this study. This process can map an object from one affine space to another while preserving its structures [23]. In this study, various affine transformation techniques were used, such as width shift, height shift, zoom, stretch, and rotation. Table 1 provides a detailed overview of the chosen parameters for data augmentation through affine transformation on the skin cancer dataset.

Table 1. Parameters and values of selected affine transformation techniques

Parameters	Value of Parameter	Action
width_shift_range	0.1	Shifts the image size horizontally by 10% at random.
height_shift_range	0.1	Shifts the image size vertically by 10% at random.
zoom_range	0.2	Zoom out by 0.2 from the middle.
shear_range	10	Extend the image by a factor of 10.
rotation_range	10	Rotate from -10 to 10 degrees.

3.4. CNN-ARIMA

The aim of this study was to combine the CNN and ARIMA algorithms to extract image features and classify them. The CNN algorithm was used as a feature extractor, while the ARIMA algorithm acted as a classifier by being integrated into a fully connected layer, which transformed the extracted features non-linearly. To output two classes (normal lung and lung cancer), the traditional CNN algorithm was modified by placing the ARIMA model between the flatten and dense layers of the fully connected layer. This hybridization also evaluated the similarity between images of different categories by calculating the performance evaluation for all classes when the proposed CNN-ARIMA model predicted a new image. Based on the approach presented in [13], the decision-making process of the CNN-ARIMA model proposed in this study is achieved through the implementation of a modified ARIMA algorithm in the fully connected layer.

$$ARIMA(9, (p, d, q)) \quad (1)$$

The value 9 was used as the average out-shape value in the fully connected layer, which showed the best performance in [13]. In addition, p , d , and q are the auto-regressive, differencing, and moving average values, respectively. However, the performance in this experiment was not affected by the specific values chosen for p , d , and q . Therefore, these p , d , and q set to a value of 1. Figure 4 illustrates the architecture of CNN-ARIMA.

The datasets are resized to a 32×32 shape and converted into feature maps, which are arrays of every pixel in the images, before being pre-processed and augmented for use in the model. The CT image, represented as a 2D array, is then input into three components, each consisting of two convolutional layers with 64, 32, and 16 filters, respectively. After each convolutional layer in the feature extractor, a rectified linear unit (ReLU) is applied as an activation function, and dropout with a ratio of 0.5 is utilised.

In the classification stage, the output obtained from the last dropout layer in the feature extraction stage is flattened into a single array. Then, the ARIMA layer is used to improve the classification accuracy. A dense layer with 512 units and a dropout ratio of 0.5 is added, followed by a final layer with two nodes for classifying the CT images into two categories: lung cancer and normal lung. The SoftMax activation function is used in the last three layers for classification.

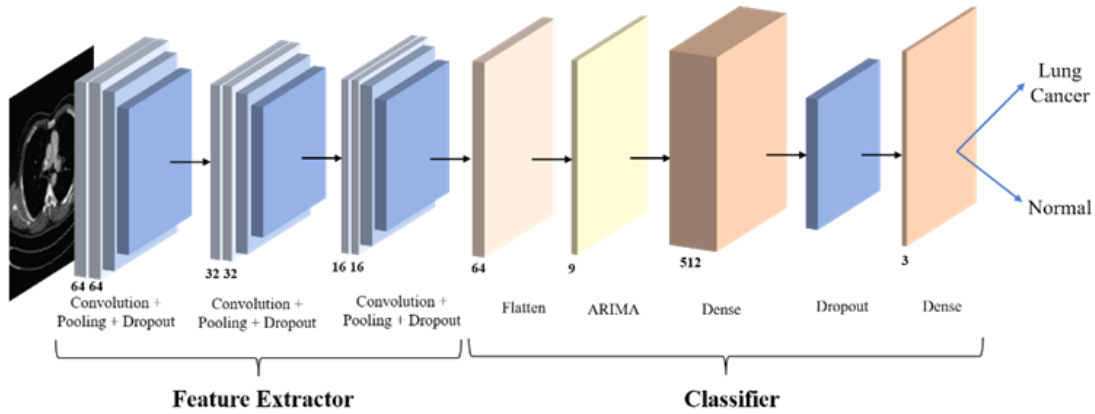


Figure 4. CNN-ARIMA architecture

3.5. Parameters and considerations

The model's accuracy was evaluated on a test set comprising 20% of the overall dataset, while the remaining data was split randomly into training and validation sets in a ratio of 80:20 to prevent overfitting. A learning rate of 0.0001 was used to assess overall accuracy performance, and other key parameters such as batch size and epoch values were carefully chosen for model training. A batch size employed in this research is 64 to perform model training because this batch size could result in faster training progress [24]. Furthermore, epochs values used in this work are 30 for model training. If the value of the epoch is too large, the training process takes too long [25]. The model training was also carried out with 2,000 steps per epoch since this parameter value could provide an excellent classification performance [26]. The optimizer used in this study is Adaptive Moment Estimation (Adam) for neural work optimization. Adam is considered a famous optimizer in the deep learning field due to its ability to perform faster and more reliably to reach a global minimum of the objective function during the optimization [27]. Adam was chosen as the optimizer in this study because it is highly suited to the classification problems, which involve vast amounts of data. Furthermore, this optimizer also has high computational efficiency with a low memory demand [25]. Therefore, this optimizer can reduce the loss in the model training.

3.6. Implementation requirements

In this work, Keras (2.3.1) [28] and TensorFlow (2.2.0) [29] are used to train the model. Keras is a simple, flexible, and robust framework for deep learning applications in Python language. This framework is also on top of TensorFlow, which provides an abstraction layer to give the configuration for the neural network for building the deep learning model. The Python environment allows the user to create a deep learning model using external Python libraries. Additionally, the model is trained using an Intel Core i5 10th Gen processor with 16 GB of memory and NVIDIA GeForce RTX 2060 GPU support with 6 GB of memory. This graphics processing unit (GPU) can train the model faster and more effectively.

3.7. Result interpretation and evaluation

The analysis performance of the CNN-ARIMA model on CT image will provide the test accuracy and then compute the confusion matrix, performance metrics, receiver operating characteristic (ROC) curve, and prediction performance to evaluate the classification performance in this work. The confusion matrix is a tool used to evaluate the performance metrics such as sensitivity, precision, specificity, and F1-score. It is a table that reports the number of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions. These four categories can be used to calculate four performance metrics, namely sensitivity, precision, specificity, and F1-score, using the following formulas [30],

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (2)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (3)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \quad (4)$$

$$F1 - score = \frac{2TP}{(2TP+FP+FN)} \tag{5}$$

after that, the ROC curve will show the performance of the binary classification model at all classification thresholds due to their decision-making ability in the classification issues. The prediction performance will show the output of an algorithm after being trained on the dataset.

4. RESULTS AND DISCUSSIONS

The method used for image pre-processing in this work is the CLAHE technique through OpenCV. The CT images collected were subjected to this technique to produce pre-processed images. This CLAHE technique can apply to lung skin cancer images to enhance the contrast of the images. Figure 4 illustrates the process of the CLAHE technique from CT image to pre-processed image that applies on the sample of lung cancer image, which is unclear. Based on Figure 4, the contrast of raw lung cancer images can enhance effectively using the CLAHE method. Compared to the lung cancer image in Figure 5(a), the pre-processed image in Figure 5(b) after implementation of CLAHE is much clearer.

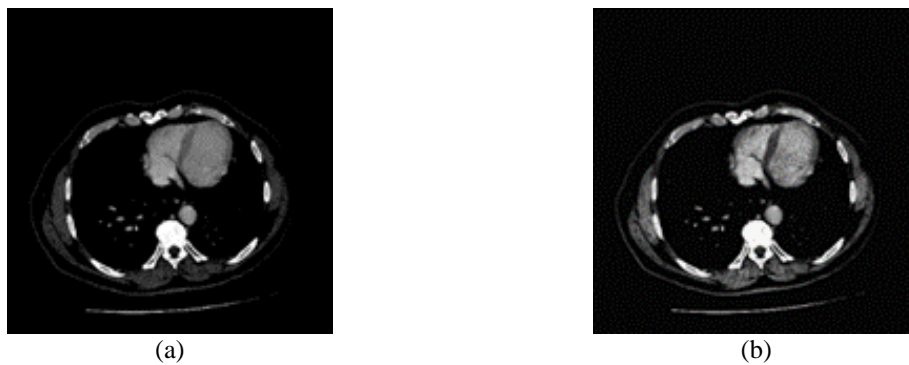


Figure 5. CLAHE implementation: (a) Sample of lung cancer image and (b) Clean image after CLAHE

This study achieved a test accuracy performance of 99.61% for CT image classification using the CNN-ARIMA model. The loss performance decreased exponentially while the accuracy performance increased exponentially for training and validation, as shown in Figure 6(a) and Figure 6(b), respectively, leading to high accuracy. The results demonstrated that the training and validation performance of the CNN-ARIMA on CT image classification were almost identical at every epoch, as illustrated in Figure 6. This condition can deliver high classification accuracy in the proposed method.

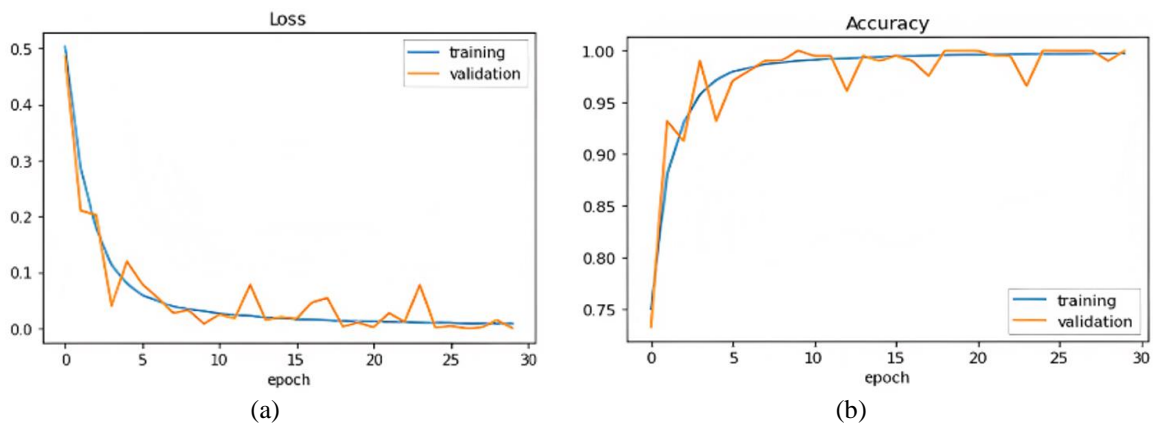


Figure 6. Performance during training and validation: (a) Loss and (b) Accuracy

According to Figure 7(a), the test datasets are labelled as “True label” in the confusion matrix. A total of 258 test images (20% of the overall dataset) are distributed randomly, of which 172 images were distributed in lung cancer and 86 images distributed in normal lung. Moreover, Figure 7(a) also shows the outstanding confusion matrix performance in CT images classification, in which 171 images categorize as lung cancer and 86 images categorize as normal lung. According to the results presented in Table 2, the performance metrics for CT image classification using the CNN-ARIMA model achieved an average sensitivity of 99.71%, an average precision of 99.43%, an average specificity of 99.71%, and an average F1-score of 99.57%. Furthermore, the ROC curve, as shown in Figure 7(b), demonstrated excellent performance with an area under the curve (AUC) of 1.000.

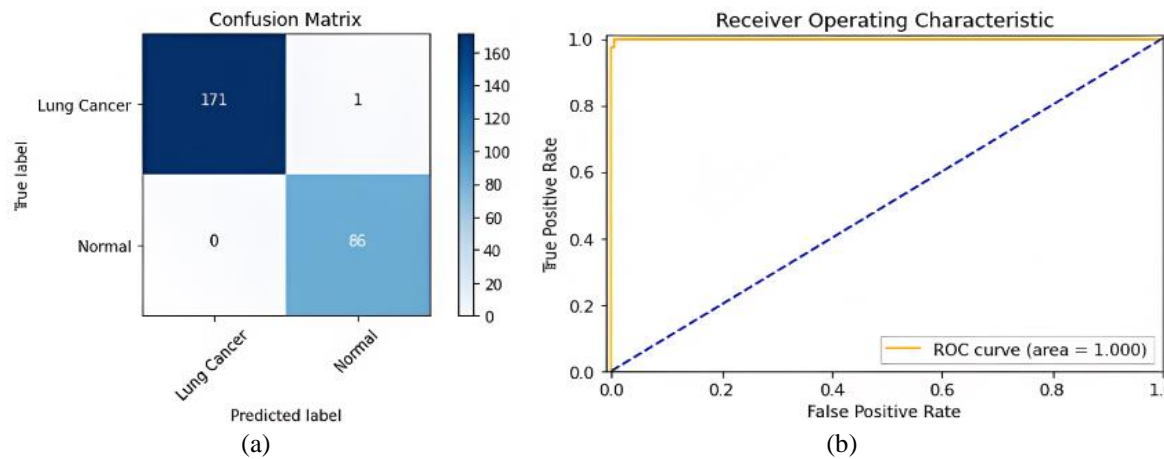


Figure 7. Performance: (a) confusion matrix and (b) ROC

Table 2. Performance measures

Type of CT images	Sensitivity	Precision	Specificity	F1-Score
Lung cancer	99.42%	100.00%	100.00%	99.71%
Normal	100.00%	98.85%	99.42%	99.42%
Average	99.71%	99.43%	99.71%	99.57%

The prediction performance of the proposed work on the testing dataset shows remarkable performance with accurate prediction. Figure 8(a) and Figure 8(b) show the examples of predicted lung cancer and normal lung images from the testing dataset respectively. The comparative analysis in Table 3 demonstrates that the performance of the proposed CNN-ARIMA model surpasses that of the existing techniques. Only work from Saleh *et al.* [20] obtained a similar result with the proposed work in terms of AUC.

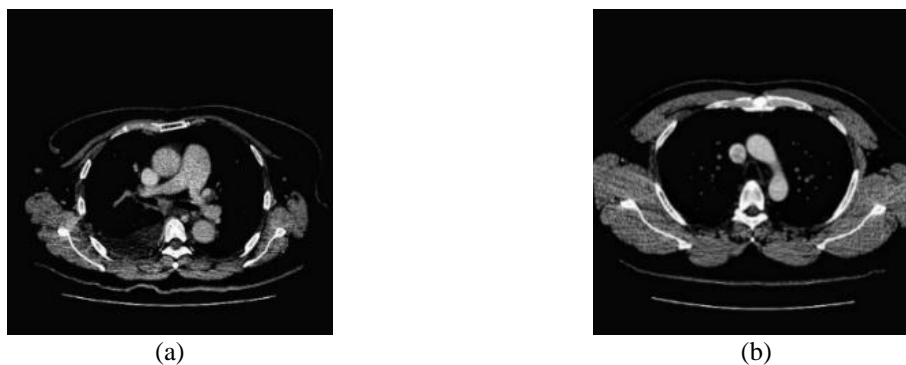


Figure 8. Detection Performance: (a) Predict: Lung cancer, Actual: Lung cancer and (b) Predict: Normal lung, Actual: Normal lung

Table 3. Comparative studies

Works	Method	Accuracy	Sensitivity	Precision	Specificity	F1-Score	AUC
Haiying <i>et al.</i> [16]	DCNN	-	95.80% at 8 false positive per image	-	-	-	-
Sheng <i>et al.</i> [18]	DiagNet	90.00%	-	-	-	-	-
Agarwal <i>et al.</i> [10]	Alexnet CNN	96.00%	-	-	-	-	-
Ardimento <i>et al.</i> [17]	Ensemble learning (VGG, Xception, and ResNet)	96.49%	98.73%	80.62%	-	-	-
Saleh <i>et al.</i> [20]	Hybrid CNN and SVM	97.91%	97.90%	97.96%	99.32%	-	1.000
Proposed Work	CNN-ARIMA	99.61%	99.71%	99.43%	99.71%	99.57%	1.000

5. CONCLUSION

This study presented the results of using a hybrid approach of CNN and ARIMA for CT image classification. The hybrid of CNN and ARIMA shows better performance than the state-of-art deep learning method. This study can further establish a CAD system, which assists radiologists and doctors in automatically detecting and predicting lung conditions effectively. Nevertheless, this proposed work did not localize and classify the pulmonary nodules in lung cancer image in depth. To further enhance the performance, the segmentation step will consider as a future work because the efficiency of segmentation performance will increase the diagnosis performance.

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