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DeePNeu: Robust Detection of Pneumonia Symptoms using Faster R-CNN

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Abstract
Every year, more than 150 million people, primarily children under five, develop pneumonia. Various articles present various methods for detecting pneumonia. However, to accurately analyze chest X-ray images, radiologists need expertise field. The traditional techniques remain shortcomings, including the availability of experts, maintenance costs, and expensive tools. Thus, we present a new intelligence method to detect pneumonia images quickly and accurately using the Faster Region Convolutional Neural Network (Faster R-CNN) algorithm. To build our detection model, we collect data, process it first, train it with various parameters to get the best accuracy, and then test it with new data. Based on the experimental results, it was found that this model can accurately detect pneumonia x-ray images marked with bounding boxes. In this model, it is possible to predict the bounding box that is more than what it should be, so NMS is applied to eliminate the prediction of the bounding box that is less precise to increase accuracy.

Keywords:
Detection, Pneumonia, Deep Learning, Faster R-CNN

1. Introduction

According to the World Health Organization (WHO), respiratory disorders are medically defined as abnormalities in the function of the pulmonary system. One is pneumonia caused by various microbes such as bacteria, viruses, and fungi. Aspiration of food and infection-related chemicals are two more causes of pneumonia. Pneumonia develops when bacteria induce inflammation in the lungs, leading the alveoli to fill with fluid or pus, reducing carbon dioxide exchange (CO2). And between the blood and the lungs, breathing is difficult for the sick person [1].

According to WHO, 4 million people die every year caused by pneumonia which comes from household air pollution. Pneumonia affects almost 150 million people each year, primarily children under the age of five. The risk of pneumonia is exceptionally high for many people, especially in developing countries where billions of people live in energy poverty and rely on polluting energy sources. The problem can be exacerbated due to a lack of medical resources and people [2].

Technology has an essential role for humans, especially in the development of algorithms that can make work easy so that it helps humans in providing employment. For diagnosing and detecting pneumonia, image processing is critical. The primary purpose of imaging tests is to validate the diagnosis of pneumonia. As a result, if the patient has a cough or a fever, pneumonia might be diagnosed. In analyzing treatment effects, including visuals in the review might be helpful. Imaging examinations are essential because they assist doctors in determining the best course of treatment for pneumonia. Imaging tests

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can help doctors differentiate between infected and non-infectious pneumonia. Doctors may also use chest X-rays to determine the location and amount of infection [3].

To overcome the problem of identifying pneumonia, some communities propose procedures such as chest X-ray, sputum culture, blood culture, fluid sampling, pulse oximetry. And bronchoscopy. The most common and reliable method of diagnosing pneumonia is a chest X-ray. A radiologist with skill and experience in the target issue is required to examine chest X-ray pictures appropriately. On the other hand, human-assisted approaches have several limitations, such as expert availability, treatment costs, and diagnostic tool availability. As a result, an intelligent and automated system is required to operate X-ray pictures to diagnose pneumonia. [4].

Detecting Pneumonia is a difficult task in many developing countries due to a lack of medical resources. Several previous papers proposed automatic categorization of pediatric pneumonia based on ultrasound and vector patterns processed using standard neural networks [5]. Another study also predicted in-hospital mortality in septic shock-associated pneumonia patients, using a classification tree model and regression methods to accurately predict clinical outcome, specificity, sensitivity, and area under the curve. Results The total mortality (51%) in pneumonia patients with complications of septic shock was high [6]. Another study suggested laboratory diagnosis of pneumonia at molecular age, with targeted antibiotic selection and more effective de-escalation and better care for pneumonia patients [7].

In the current study, some traditional classification methods still have weaknesses. However, their use still fails to produce accurate classification results [8][9]. To create effective results with large data sets, deep learning has an essential role in classifying and detecting pneumonia from a collection of chest X-ray images. A study has developed the detection of pneumonia infection in the lungs from chest X-rays using Convolutional Neural Network (CNN) and content-based imaging techniques [10]. Another study used the DL model to compare the model's performance with single learning and classify pneumonia with ensemble learning [11].

Another study analyzed and classified deep Convolutional Neural Network (DCNN) based chest X-ray pictures for COVID-19 pneumonia detection by explaining the behavior of learning training models to improve prediction accuracy. The method can achieve an average accuracy of more than 96% [12]. Viral Pneumonia Screening on Chest X-Rays Using Self-Confidential Anomaly Detection was also proposed in another study [13]. Another model has also been proposed for the chest X-ray-based pneumonia framework, which shows results with more than 91% inaccuracy, recall, F1 score, precision, and Area Under the Curve (AUC) [14]. In the study, a CNN model for COVID-19 pneumonia was proposed. When using radiographic patterns on chest CT scans, CNN screening has higher sensitivity and specificity than RT-PCR detection [15]. A Deep Learning model was also applied to classify chest X-ray images using DenseNet. Based on experimental results, this model shows an increased AUC for detecting nodules and cardiomegaly compared to methods already in use [16].

In this paper, we propose a model for pneumonia detection using Faster R-CNN to detect pneumonia symptoms quickly and accurately. The Faster R-CNN method extracts helpful pictures and organizes them into regular and pneumonia classes. In detection pneumonia symptom images using Faster R-CNN, we present several significant contributions to this research as follows:

1. We introduce a novel technique for detecting pneumonia images, using the Faster R-CNN algorithm to train the data set to develop a viable model. In this study, the dataset we used was in the form of pneumonia images.
2. We build a model that can detect cases of pneumonia symptom images. This detection model can be a solution to distinguish between standard and

pneumonia images. Moreover, the proposed technique can be a promising solution to improve the conventional model achievement.

3. We test the proposed model to achieve high accuracy results to predict positive cases in the next few days quickly and accurately based on features. We set the parameters to achieve high accuracy values and get the best results.

Organization: The following is a breakdown of the journal's structure: Part II delves further into past findings. Part III discusses the study's issue description. Section IV explains the experimental design, including a feature learning algorithm, a dataset, and pre-processing, while Section V gives the study's findings and extensive analysis. Finally, section VI discusses the results of the conclusions.

2. Related Works

Several researchers recommend conducting research using various methods to develop a classification model. Another study used the Haralick texture feature method to extract distinct texture features and identify pneumonia-infected lungs from normal lungs from x-ray pictures, resulting in a new system for detecting and classifying pneumonia-infected lungs from normal lungs. According to the data, the proposed approach has an accuracy of 86 % [17]. Another study used the area under the receiver operating characteristic, specificity, sensitivity, and kappa curves to assess the model's overall performance using accuracy. To develop a model that can predict hospital-acquired pneumonia. The outcome of a predictive model can help clinicians treat patients [18].

A paper explored a new technique using Transfer Learning In research presented using profound transfer studies to classify pneumonia between chest X-ray images. According to experimental results, deep transfer learning offers performance advantages from training from the outset with a little fine-tuning. ResNet-50, Inception V3, and DensetNet121 are three models introduced individually via transfer learning and from scratch. The former can achieve an AUC of 4.1 % to 52.5 %, which is higher than the latter, demonstrating that deep transfer learning successfully identifies pneumonia on chest X-ray pictures [19].

Identifying COVID-19 is a challenging task that requires regular attention to the patient's clinical picture; COVID-19 is similar to a lung infection due to viral pneumonia. Lungs are needed to add COVID-19 image data, the paper on implementing transfer learning methods on Chest X-Ray (CXR) and Cycle threshold (CT). COVID-19 is described as a bio-image of various lung disorders. The primary goal is to use CXR, and CT scans to classify Covid-19, pneumonia, and healthy lungs. The learning transfer method allows researchers to learn about COVID-19, a novel disease, utilizing the same unique architecture designed to detect viral pneumonia and must now be used to detect COVID-19. The proposed architecture can distinguish between healthy, pneumonia, and COVID-19 lungs. Therefore improvements to the Haralick texture feature enable automatic COVID-19 recognition of segmented and problematic lung images. All processes can be reliable using this technique [20].

Another study used X-ray images to test the performance of single and ensemble learning models to identify cases of pneumonia. For this study, a new data set of 6087 chest X-ray images were obtained and categorized into four categories: bacterial, covid-19, regular, and viral. With an F1 score of 94.84%, the three ResNet50 models made with the MobileNet V2 and InceptionResNet V2 ensembles were more accurate than the other ensembles [11].

Traditional machine learning was used to classify pneumonia symptoms in several communities. Due to solid contrast characteristics such as ground-glass opacities (GGO), consolidation, and pleural effusion in CoP patients, an Artificial Intelligence (AI) model correctly identified CoP against New Car Assesment Program (NCAP). Methodology Two models are based on classical machine learning k-Nearest Neighbor (k-NN) and rheumatoid factor (RF), and two are based on transfer learning (TL) (VGG19 and InceptionV3). The last two are the specially constructed Deep Learning (DL) Convolutional Neural Network (CNN) and CNN, which were created for the classification of COVID pneumonia (CoP) and non-COVID pneumonia Nutrition Care Process (NCP) New Car Assessment Program (NCAP). Results DL-based CNN and CNN architectures had high accuracy of 99.690.66 % and 99.531.05%, respectively, according to the study's results employing the K10 protocol, making them the two most accurate models among the six examined models [21].

In previous studies, the learning e-learning algorithm was also used to detect pneumonia. related to the level of accuracy of a study using the method Support Vector Machine (SVM) to detect the severity of COVID-19. The final SVM model was trained using 28 features and achieved an overall accuracy of 0.8148 [31]. The research also uses the Local Binary Pattern (LBP) and Support Vector Machine (SVM) method to classify the X-ray results whether there is pneumonia or normal. based on experimental results the model produces an accuracy of 65.63% [32].

The current research explored deep learning techniques to achieve good results in various fields [22]. A paper proposes CNN for pneumonia classification using the ResNet-50 and DenseNet-161 models, increasing the accuracy of total pneumonia classification. To develop the deep network architecture, the ResNet-50 and DenseNet-161 models were applied and pre-adjusted to improve the accuracy of pneumonia classification. The model mobilizes and combines augmented data with standard data sets to assess the proposed model. Based on experimental results, denesnet-161 outperforms ResNet-50 in all considered performance measures [2].

A study presented the CNN method to handle the challenge of identifying and classifying pneumonia. A set of chest X-ray pictures is used to detect and classify the existence of pneumonia. When working with medical experts, this model can assist reduce the reliability and interpretation issues. The model has an accuracy of 85.73% based on experimental results [23]. Another study used CXR images to investigate a light DL strategy based on DenseNet-121 that combined a Deep Neural Networks (DNN)-based method with a fine-tuning random search mechanism. The DenseNet-121 NS model was chosen to depict lung properties the most accurately. The use of random search speeds up the setup process and improves the DNN model's efficiency and accuracy. The model demonstrates that the strategy achieves a 98.90% accuracy based on the experimental results [24].

As a result, we present a model to handle pneumonia picture detection by proposing a new strategy for training the important features utilizing the Faster Region-based Convolutional Neural Network (R-CNN). We used the pneumonia image feature to build our dataset and trained the model to develop excellent detectability in this experiment.

3. Proposed Method

This section will provide a formal definition of the research problem and some of the concepts in this journal

A. Problem Definitions

The region proposal network (RPN) based Faster RCNN is a DL network model. RPN is utilized to go to the desired place. The obtained feature mapping is used to generate prospective target regions in the RPN network, then inputting the mapping features and potential target areas into the Return on invesment (ROI) network. The faster RCNN network accepts photos of any size as input before entering Faster RCNN, such as M×N to scale image normalization. After that, we can upload the P×Q size image. This image will be scaled if P×Q is bigger than M×N., and the image margin will be filled with 0 if P×Q is smaller than M×N [28].

B. Proposed Method

This study focuses on classifying pneumonia symptoms based on the features of the X-Ray image dataset, which consists of two classes, namely regular images and pneumonia images using the Faster R-CNN Algorithm [25]. Fast R-CNN is a descendant of R-CNN. [26]. By inserting an RPN layer, this model is intended to overcome the problem of slower R-CNN performance [27].

The faster RCNN is an RPN-based deep learning network model (Regional Proposal Network). To obtain the image mapping feature, RPN is first applied to reach the target position. The RPN network is used to construct a target region candidate once the model acquires a feature mapping (Proposal). Then, using the ROI network, it enters the feature mapping and the target candidate region (Region of Interest Pooling). Finally, it obtains each feature's feature expression Mapping of candidate target areas [29]. Figure 1 shows the structure of faster R-CNN as a whole

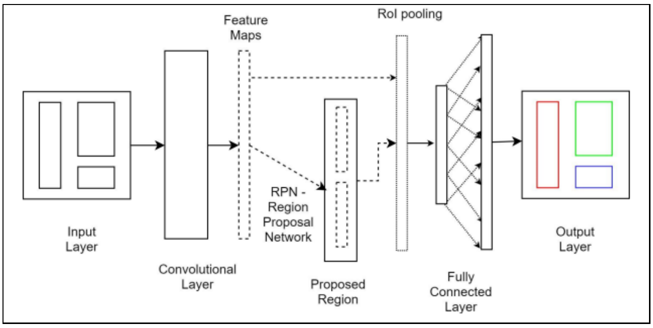

Fig 1. Faster Regional-based CNN Architecture.

The loss function is the multitasking loss which is the sum of the target frame prediction loss and the regression loss derived from the structural aspect of the faster RCNN network [26].

Equation (1) In Faster RCNN, an image's objective function is specified as:

$$L(\{P_i\}),\{t_i\} = \frac{1}{N_{cls}} \sum_i L_{cls}\ (P_i, P_i^*) + \lambda \sum_i P_i^*\ \ L_{reg}\ (t_{i,} t_i^*) \quad (1)$$

Equation (2) The probability that the anchor will be predicted as a target is P_i .

$$P_i^* = \begin{Bmatrix} 0 & negative\_lable) \\ 1 & positive\_lable \end{Bmatrix} \quad (2)$$

Equation (3) is a vector representing the coordinates of the four prediction bounding box parameters. In the truth bounding box. t_i^* is the positive anchor coordinate vector.

$$t_i = \{t_x, t_y, t_w, t_h\} \quad (3)$$

Equation (4) is a binary classification cross-entropy loss (target & non-target).

$$\begin{aligned} &L_{cls}\ (P_i, P_i^*) \\ &L_{cls}\ (P_i, P_i^*) = -\log\,[P_i^* P_i + (1 - P_i^*)(1 - P_i)] \\ &L_{reg}\ (t_i, t_i^*\ ) = R(t_i - t_i^*\ )\ \text{is used to}\ L_{reg}\ (t_i, t_i^*\ ) \end{aligned} \quad (4)$$

Equation (5) which is the regression loss, R is the smooth function L1

$$\text{smoothL1}(x) = \begin{cases} 0.5x^2 \times 1/\sigma^2 & |x| < 1/\sigma^2 \\ |x| - 0.5 & otherwise \end{cases} \quad (5)$$

Table 1. Mathematic notation of the Faster R-CNN

Notation	Description
P_i^*	Probability that the anchor is predicted to be target.
t_i^*	The coordinate vector of the ground truth bounding box corresponding to the positive anchor.
t_i	The vector, which represents the four parameter coordinates of the predict bounding box.
L_{cls}	The cross-entropy loss of binary classification (target & non-target)
L_{reg}	the regression loss
R	Smooth L1 function.
L1	Function.

R-CNN is slow because the regions overlap in any substantial part of the image, thus requiring a forward pass from the CNN. Then the feature extraction model, classification model, and regression model must be run in an independent order.

To solve this problem, a fast R-CNN is proposed, and improvements are made regarding the bigger picture and the extraction stage. Therefore, there are two elements to make Fast R-CNN better. First, Faster R-CNN, unlike R-CNN, integrates all models into a single network between detection, feature extraction, and classification. Second, the number of times a regional CNN must be run per picture has been decreased to one. The term "faster" refers to the Fast R-CNN algorithm's advancement, which is more efficient in delivering the desired outcomes [27].

4. Experimental Setup

A. Main Idea

The main goal of this study is to construct a detection model based on the results of X-Ray images of pneumonia using the Faster R-CNN algorithm. A supervised learning strategy was utilized to detect labeled data using a faster R-CNN, with training data and targeted variables used to categorize the data. The purpose of this method is to organize data into pre-existing categories. Faster R-CNN is often used to identify an item or object and group it due to the high accuracy achieved by faster R-CNN is very suitable for handling detection difficulties [29].

B. Dataset

We collected a dataset of X-Ray pneumonia features to detect fluid present in the lungs. Dataset taken from kaggle.com with a total dataset of 4,032 X-Ray images. The training dataset is used to develop or train the model, while the test dataset is used to evaluate the model's performance. In another study, we collected 4,032 samples and divided the dataset by 80% for training, 20% for testing. Table 1 shows the details of the distribution of the datasets in the study, as follows:

Table 2. Details distribution of the dataset

Dataset	Sample
Data Training (80%)	3.226
Data Testing (20%	806
Total	4.032

C. Data Preprocessing

In this pre-processing, we perform several steps that need to be performed on the input image. First, we perform scaling, which is used to reduce the digital appearance so that the number of pixels to be processed is not too much. After that, the image is transformed to grayscale before being denoised. After denoising, contrast normalization is used to boost the image's contrast. The prices of each sample are then sorted by size. The sample median in the window, which can be the filter output, is the middlemost value. Finally, the essential properties of the image need to be segmented into several segments to determine changes in image properties. Following segmentation, pixel-by-pixel analysis is undertaken, with each pixel labeled based on whether the grey level pixel is more significant or less than the threshold value. Segmented images are thus simple to examine [30].

D. Detection Method

In this study, we adopted Faster R-CNN to construct a pneumonia symptom classification model. To conduct our study, we collected datasets clustered into 2 classes of pneumonia and standard X-Ray images. After the data was collected, we divided the data into two parts, namely training and testing data. During the training procedure, we divided the dataset into two types of data: pneumonia and normal data.

In the next stage, we do preprocess by performing several steps that need to be done on the input image. First, we perform scaling, which is used to reduce the digital display so that the number of pixels to be processed is not too much. Then, we convert the image to grayscale, and then the converted image will be denoised. After denoising, contrast normalization is performed, increasing the picture's contrast. After segmentation, image analysis is performed, and each pixel is labeled according to the image. Thus, segmented images are easy to analyze.

In the testing phase of the process, we use the training dataset to develop or train the model. Instead, test data sets are utilized to assess the model's performance or correctness. Subsequently, a valid model was obtained and then tested using vector test data, which assessed the model's effectiveness in classifying pneumonia and normal symptoms. We changed many parameters to get the best accuracy value to achieve the best detection performance. Finally, after several stages, we obtained Faster R-CNN, which can classify normal and pneumonia categories.

5. Result & Analysis

In this study, we collected data in the form of X-Ray images of pneumonia. then, we built a model that could detect the spots present on X-ray pneumonia images.

In this experiment, we detect accuracy and performance time by adjusting various hyperparameters to get the best network performance. Based on detection tests, our model can detect more strongly. Based on the training results, the model made is good enough to help detect the location of pneumonia strongly. Fig.2 shows the results of training loss and epochs.

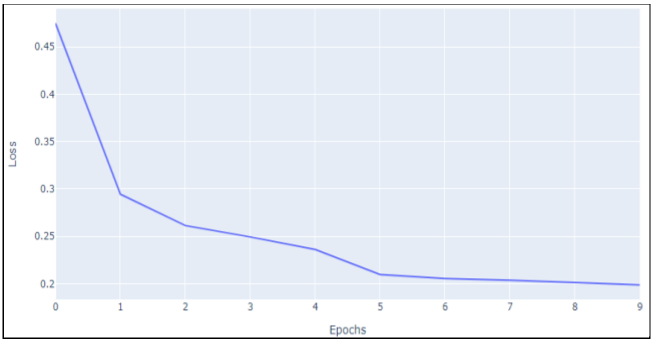

Fig. 2 Loss and Epochs graph

In the training process, we calculate loss and epochs to 0 until 9. To conduct the process, we set 10 epochs to train the model using pneumonia from X-Ray features. At epoch 0, the training model can produce loss = 0.45, while at epoch 9 produces loss = 0.2. Based on the training process, the more epoch, the smaller the training loss. The low train loss value indicates that the model is better and more accurate.

In the testing process, Fig.3 shows the actual location results and the pneumonia prediction box from X-Ray. Fig.4 shows the test process for calculating the actual vs. model ratio graph prediction. The proposed model can produce a better detection result than the actual detection technique after training the pneumonia x-ray image features.

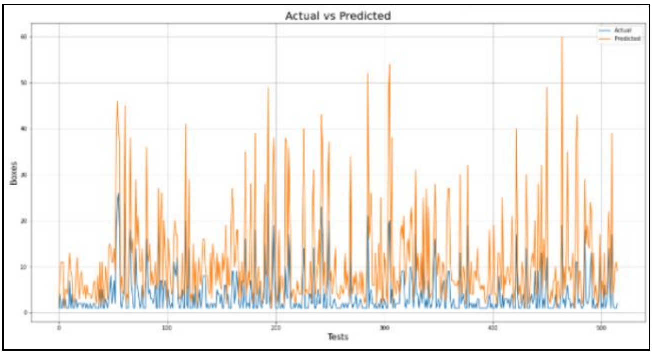

Fig. 3 Actual vs. Predicted graph

Fig.3 shows a graph of the results of testing the actual location of pneumonia and a prediction location using the Faster R-CNN. The blue line indicates the actual X-ray pneumonia image detection test. In contrast, the orange line indicates the prediction or detection of pneumonia using the model. Therefore, our model can detect X-ray pneumonia more accurately than conventional detection models in training a large dataset.

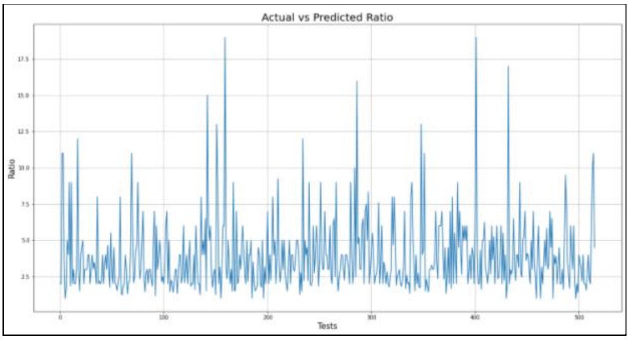

Fig. 4 Actual vs. Prediction Ratio graph

In the testing process, we calculate a graph of the actual vs. predicted model ratio on the X-ray image. We utilize 561 annotate data to test the model, while the percentage represents the detection results. In this study, the detection model helps measure the predictive quality of the detection algorithm. Our model marks a bounding box to enable location detection of the pneumonia spot. Fig. 5A depicts the actual location of pneumonia, and Fig. 5B shows the predict location of pneumonia using the proposed model.

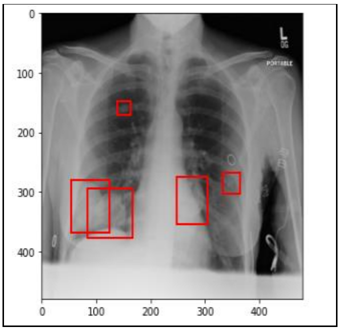

Fig. 5A Real

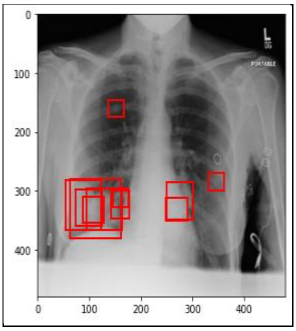

Fig. 5B Predicted

Fig.5A shows the actual image before entering the model, where 5 red squares indicate the location of pneumonia. Figure 5B shows pneumonia detection using the Faster R-CNN model can produce more red squares as the location of pneumonia. Our model provides better detection than the actual detection technique after training pneumonia x-ray image features.

In the testing process, we also utilize the Non-Maximum Suppression (NMS) method to reduce the redundant bounding boxes to achieve accurate bounding boxes. Fig.6 shows the output of the NMS calculation in the testing process.

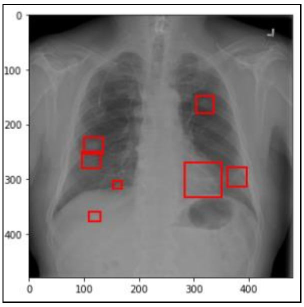

Fig. 6 MNS Model Output

Fig. 6 depicts NMS's detection result to select one bounding box entity from many overlapping boxes. We calculate the NMS of overlapping Fig.4B images to filter the best bounding box. Therefore, we utilize the NMS technique to refine the pneumonia detection model from X-ray images to produce a better and more accurate detection result.

The advantage of Faster R-CNN is that it is fast and precise enough to identify images, while CNN does not need to pay attention to the position of the object to be recognized in the image.

6. Conclusion

Detection of pneumonia symptoms is a fundamental challenge to distinguish between normal and pneumonia. To overcome this challenge, the current way of recommending the use of traditional machine learning. But it is expensive and time-consuming. Thus, this study proposes the Faster R-CNN algorithm to detect pneumonia symptoms to increase classification performance effectively. Based on the experimental result, Faster R-CNN can improve the accuracy with tiny losses.

Based on the experimental results, the proposed model can accurately detect pneumonia x-ray images marked with bounding boxes. In the training process, the research defined several hyperparameters with 10 epochs. The training process produces loss score = 0.1988, an area box loss = 0.1230, an objectivity loss = 0.0030, and an RPN box loss = 0.0039. To improve the model performance, we utilize the NMS method to detect the real bounding boxes by eliminating unprecise boxes to increase accuracy. In the testing process, our model can produce more bounding boxes than the conventional technique. Therefore, the proposed model can be a promising option to deal with pneumonia detection issues on a large dataset.

As future work in pneumonia detection study, further research can implement sophisticated algorithms to improve this paper, such as GAN algorithms. By using the GAN algorithm on 2D datasets, GAN has good Image Translation capabilities and provides an accurate solution for data shortages in medical image analysis. By developing dynamic models with large features, further research can produce higher quality accuracy.

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References

[1] Ibrahim Umar Abdullah, Mehmet Ozsoz, Sertan Serte Fadi Al-Turjman, Polycarp Shizawaliyi Yakoi. ”Pneumonia Classification Using Deep Learning from Chest X-ray Images During COVID-19. 2020.

[2] Stephen Okeke, Mangal Sain , Uchenna Joseph Maduh , and Do-Un Jeong “An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare”. Hindawi Journal of Healthcare Engineering. 2019

[3] Alsumairi Badr Sarah, Mohamed Maher Ben Ismail. “X-ray image based pneumonia classification using convolutional neural networks”. ACCENTS Transactions on Image Processing and Computer Vision, Vol 6. 2020.

[4] Yi Rong, Lanying Tang, Yuqiu Tian, Jie Liu, Zhihui Wu. “Identification and classification of

pneumonia disease using a deep learning-based intelligent computational framework." 2021.
[5] Correa Malena. “Automatic classification of pediatric pneumonia based on lung ultrasound pattern recognition”. 2018.
[6] Spesier L Jaime. “Predicting in-hospital mortality in pneumonia-associated septic shock patients using a classification and regression tree: a nested cohort study”. 2018.
[7] Torres Antoni et al.l. “Laboratory diagnosis of pneumonia in the molecular age”. 2016.
[8] Adnan Abidin , Hamzah , Marselina Endah H. “Efficient Fruits Classification Using Convolutional Neural Network”. International Journal of Informatics and Computation (IJICOM). 2021.
[9] Hamzah , Mohammad Diqi, Antomy David Ronaldo. “Effective Soil Type Classification Using Convolutional Neural Network”. International Journal of Informatics and Computation (IJICOM). 2021.
[10] Rajasenbagam.T, S. Jeyanthi, J. Arun Pandian “Detection of pneumonia infection in lungs from chest X-ray images using deep convolutional neural network and content-based image retrieval techniques". 2020.
[11] Asnaoui El Khalid “Design ensemble deep learning model for pneumonia disease classification”. International Journal of Multimedia Information Retrieval. 2021.
[12] Hou Jie and Tery Gao “Explainable DCNN based chest X-ray image analysis and classification for COVID-19 pneumonia detection”. 2021.
[13] Zhang Jianpeng. “Viral Pneumonia Screening on Chest X-Rays Using Confidence-Aware Anomaly Detection”. IEEE Transactions On Medical Imaging, VOL. 40, NO. 3. 2021.
[14] Nada M. Elshennawy and Dina M. Ibrahim. "Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images”. MDPI. 2020.
[15] Butt Charmaine et all “Deep learning system to screen coronavirus disease 2019 pneumonia”. 2121.
[16] Darice Buket Muazzez “Pneumonia Detection and Classification Using Deep Learning on Chest X-Ray Images”. IJISAE. 2020.
[17] Deepa Features N. Vamsha. “Feature Extraction and Classification of X-Ray Lung Images Using Haralick Texture”. 2018.
[18] Speiser Jaime L. “Predicting in-hospital mortality in pneumonia-associated septic shock patients using a classification and regression tree: a nested cohort study”. 2018.
[19] Irfan Abdullah, Akash L. Adivishnu, Antonio Sze-To3, Taher Dehkharghanian4, Shahryar Rahnamayan5 and H.R. Tizhoosh. “Classifying Pneumonia among Chest X-Rays Using Transfer Learning” 2020.
[20] Mihaela-Ruxandra Lascu “Deep Learning in Classifcation of Covid-19 Coronavirus, Pneumonia and Healthy Lungs on CXR and CT Images” 2021.
[21] Sabal Luca el all. “Sarificialial intelligence paradigms for tissue characteristic classification, ionionionnon-COVIDID-19 pneumonia against COVID-19 pneumonia in computed tomography lungs” 2021.
[22] P. Catur et al. "Implementation Of CNN For Plant Leaf Classification”. International Journal of Informatics and Computation (IJICOM) . 2020.
[23] Hanumant Magar et al. “Pneumonia Detection using X-Ray Images with Deep Learning”. International Journal of Computer Applications Technology and Research Volume 9–Issue 05, 183-185. 2020.
[24] Bandar Almaslukh. “A Lightweight Deep Learning-Based Pneumonia Detection Approach for Energy-Efficient Medical Systems”. Hindawi Wireless Communications and Mobile Computing Volume. 2021.
[25] Laishram Anuradha and Khelchandra Thongam. “Detection and Classification of Dental Pathologies using Faster-RCNN in Orthopantomogram Radiography Image”.International Conference Signal Processing and Integrated Networks (SPIN). 2020.
[26] Sheng Biaosheng et all. “A blood cell dataset for lymphoma classification using faster R-CNN”. Biotechnology & Biotechnological Equipment. 2020.
[27] Rahmat Taufik et all. “Classification of Chest X-Ray Images Using Faster R-CNN”. Malaysian Journal of Computing, 4 (1): 225-236. 2019.
[28] Yuntao Zhao et all. “A Malware Detection Method of Code Texture Visualization Based on an Improved Faster RCNN Combining Transfer Learning”. IEEE. 2020.
[29] Mulyan Sri Hasta et all. “DeepFruits: Efficient Citrus Type Classification Using the CNN Algorithm”.2020.
[30] G A Neela . “A Breast Cancer Detection Using Image Processing and Machine Learning

Techniques". 2019.
[31] Yao Haochen et al. "Severity Detection for the Coronavirus Diases 2019 (covd-19) Patiens Using a Meachine Learning Model Based On the blood and Urine Test". 2020.
[32] Irsyad Hafiz et al. "Classification of Pneumonia on Chest-Ray Lungs with Local Binary Pattern Feature Extraction Using Support Vector Maschine". 2021.