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The Deep Learning-Based Framework for Automated Predicting COVID-19 Severity Score

Yongchang Zheng\textsuperscript{a,}\textsuperscript{*}, Hongwei Dong\textsuperscript{b}

\textsuperscript{a}School of Artificial Intelligence and Computer Science, Jiangnan University, Jiangsu 214122, China
\textsuperscript{b}School of Artificial Intelligence and Computer Science, Jiangnan University, Jiangsu 214122, China

Abstract

With the COVID-19 pandemic sweeping the globe, an increasing number of people are working on pandemic research, but there is less effort on predicting its severity. Diagnostic chest imaging is thought to be a quick and reliable way to identify the severity of COVID-19. We describe a deep learning method to automatically predict the severity score of patients by analyzing chest X-rays, with the goal of collaborating with doctors to create corresponding treatment measures for patients and can also be used to track disease change. Our model consists of a feature extraction phase and an outcome prediction phase. The feature extraction phase uses a DenseNet backbone network to extract 18 features related to lung diseases from CXRs; the outcome prediction phase, which employs the MLP regression model, selects several important features for prediction from the features extracted in the previous phase and demonstrates the effectiveness of our model by comparing it with several commonly used regression models. On a dataset of 2373 CXRs, our model predicts the geographic extent score with 1.02 MAE and the lung opacity score with 0.85 MAE.

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Keywords: COVID-19; deep learning method; CXRs; feature extraction; estimate severity

1. Introduction

A novel coronavirus took the world by storm at the end of 2019, posing a major threat to people's lives and health all across the world while also having a massive influence on the global economy and politics. The World Health...
Organization (WHO) stated on January 30, 2020 that a new coronavirus pandemic would be classified as a public health emergency of international concern (PHEIC). The disease was dubbed COVID-19, which stands for coronavirus disease 2019, by the WHO in February. On March 11th, the new coronavirus pneumonia outbreak was proclaimed a global "Pandemic" [1].

COVID-19 patients are currently identified mostly through laboratory and imaging examinations, with epidemiological contact history also playing an important role. The most thorough inspection procedures are laboratory examinations, such as swab tests. Swab tests, on the one hand, take time, and the number of kits available in an emergency may be insufficient. Furthermore, the COVID-19 detection method of reverse transcription-polymerase chain reaction (RT-PCR) may result in false negatives [2]. According to American College of Radiology guidelines, CT should not be used to screen for or diagnose COVID-19 as a first-line diagnostic [3]. However, due to the deficiency of RT-PCR, the use of medical imaging as an adjunct to detection is becoming more and more popular. Fleischer Society has stated that lung medical images can be utilized to assess disease development [4]. In fact, minor patch shadows and interstitial changes were seen in the early stages of imaging examinations, which were visible in the extrapulmonary zone, and later progressed to multiple ground glass shadows and infiltration shadows in both lungs. Lung consolidation can occur in severe cases, but pleural effusion is uncommon [5,6]. As two significant evaluation indicators, geographic extent and lung opacity are important directions for doctors to interpret CXR. Nonetheless, as the thresholds are subjective, there is considerable heterogeneity in the prediction of severity when interpreting thoracic imaging, especially in the early stages of the disease when the area portrayed in the pictures is obscure. CXR and CT scans are the most common lung medical imaging. As a portable instrument, CXR has the advantages of low cost and easy operation compared to CT. Most of all, patients are exposed to less radiation, resulting in less radiation damage.

Artificial intelligence (AI) has now penetrated into all walks of life, creating great economic benefits for humans, especially in many scenarios in the medical field, such as digital pathology, medical testing, gene sequencing, medical robotics, radiological medicine, drug design, health management, assisted diagnosis, etc. One of the most important use of AI in the clinical field is to analyze the patient's medical images, which has the obvious advantage of high accuracy and better diagnosis and treatment efficiency [7]. Better performing AI models require large amounts of labeled data, however labeling data is a tedious and costly task, so migration learning is gaining attention. Since the outbreak of COVID-19, there have been many AI applications for predicting COVID-19, and the accuracy is as high as 98.9 percent [8]. However, the prognosis of illness severity has not been thoroughly reported.

Considering the above benefits, a chest radiograph will be utilized as a test sample to analyze the patient's disease development. The model consists of two phases, including a feature extraction phase and an outcome prediction phase. In this study, a method is proposed for filtering features. After the 18 features obtained in the feature extraction phase, several interrelated features were input to the next phase after the filtering step. What's more, in the outcome prediction phase, we test multiple regression models to demonstrate the superiority and effectiveness of our approach.

2. Related Work

In the early stages of the outbreak, research on COVID-19 was slow, and the main problem was the lack of public datasets. With the release of [9-11] datasets, research in this field accelerated.

Cohen [9] collects hundreds of front and side images of CXR and CT images from websites and publications, related to COVID-19 as well as MERS, SARA, and ARDS, so as to monitor the progress of the disease. It provides a large number of reliable datasets for tracking the evolution of the disease. In literature [10], a deep learning framework, COVNet, is proposed with ResNet50 as the backbone, which can extract visual features from CT slices, and then integrate the visual features of all slices to output probability scores to distinguish between COVID-19, community-acquired pneumonia (CAP) and other non-pneumonic. Literature [12] proposes a deep learning method that combines attention U-Net and adversarial critic model to perform semantic segmentation on the lungs of CXR, and then apply the trained model to other datasets and finally achieve DSC of 97.5% on the JSRT dataset. Literature [13] design an end-to-end framework in the paper. By comparing ResNet50, ResNet101, ResNet152, inceptionV3, and inceptionResNetV2 models based on convolutional neural networks, the author finally selects ResNet50 as the backbone network of the model, the model can automatically make effective judgments on normal, viral pneumonia, and bacterial pneumonia based on CXR. A patch-based convolutional neural network approach is devised in literature
First, the author uses semantic segmentation to separate the lungs from the CXR and then divides the isolated CXR into several smaller regions of the same size that could overlap each other for prediction. This method solves the shortage of experimental data in the early stage of the epidemic, and can use fewer trainable parameters to distinguish COVID-19 from other pneumonia.

So far, the majority of COVID-19 research has relied on medical imaging to diagnose the disease, and the results have been promising. On the basis of the COVID-19 diagnosis, we hope to anticipate the severity of the disease based on CXR characteristics. Because there are few datasets on this topic, and the most of them are private, there is less research in this area.

3. Model

To create an automated assessment of COVID-19 pulmonary disease severity on CXRs for long-term illness surveillance and prediction, a deep learning-based framework is present for predicting COVID-19 severity in this paper. As shown in Figure 1, the framework is divided into two phases, including feature extraction and outcome prediction. The framework is detailed in the following sections.

![Fig. 1. The flow chart of the framework.](image)

3.1. Feature Extraction Phase

In the field of computer vision, convolutional neural network (CNN) has become the most mainstream method. To improve the accuracy of prediction, continuously deepening the number of layers of CNN is a feasible method. However, when the number of CNN layers grows, the issue of gradient vanishing and model degradation arises, and the common use of Batch Normalization helps to mitigate this problem to some extent. And then, ResNet [15] was proposed to facilitate the backpropagation of gradients during training by creating "skip connections" between the front and back layers. Therefore, deeper networks can be trained to achieve higher accuracy. More and more people have proposed improved models based on "skip connections" to further alleviate these problems, while these methods are gradually applied to various fields.

DenseNet [16], which emerged in 2017, improves on ResNet by replacing "Skip Connection" with "Dense Connection" so that each layer accepts all previous layers as additional inputs. In the same "Dense Connection" block, the height of the feature layer does not change, but the number of channels does. Meanwhile, feature reuse via feature concatenation on channels is another fantastic feature. DenseNet can achieve superior performance with fewer parameters and computational expenses due to these qualities. As shown in Figure 2.
3.1 Feature Extraction Phase

The framework is divided into two phases. First, the author uses semantic segmentation to separate the lungs from the CXR and then divides the isolated CXR into several smaller regions of the same size that could overlap each other for prediction. This method solves the problem of small sample size and improves the accuracy of prediction. The framework is detailed in the following sections.

3.2 Outcome Prediction Phase

The multilayer perceptron (MLP) regression model is used in the outcome prediction phase. MLP is a neural network-based algorithm model. In this paper, a three-layer MLP is used for regression prediction of the extracted picture features of patients, which are input layer, hidden layer and output layer. The MLP model begins by normalizing the input data $x_1, x_2 \ldots x_N$. The goal of normalization is to transform features to be on a similar scale. This improves the performance and training stability of the model. Then input them as independent variables into the hidden layer. The hidden layer uses ReLU as the activation function. The calculation of ReLU is simple, which can improve the overall operation speed of the model. Because the normal neural network computation is linear and cannot capture the nonlinear characteristics of the data, using the activation function can introduce the MLP into the nonlinearity and strengthen the learning ability of the network. Finally, the output layer receives the activated vector from the hidden layer and outputs the predicted results of the model, as formulated in Equation 1.

$$
\begin{align*}
    f(x) &= \sum_{j}^{K} w_{ji}^{(2)} (ReLU(\sum_{i}^{N} (w_{ji}^{(1)}x_{i} + b_{0j})) + b_{1j})
\end{align*}
$$

Where $w_{ji}^{(1)}$, $w_{ij}^{(2)}$ is the connection coefficient of input layer and hidden layer, $K$ and $N$ represent the number of neurons in input layer and hidden layer respectively, $b_{0j}$ and $b_{1j}$ are bias terms of input layer and hidden layer. MLP needs to continuously adjust the weight coefficient to complete the learning process until the output is consistent with the training sample. MLP uses mean squared error (MSE) as the loss function, and uses Adam optimization algorithm to optimize the model. MSE function is shown in Formula 2, where $n$ is the total number of samples, $y$ is the real value of samples and $y$ is the predicted value of model regression.

$$
L(Y|f(x)) = \frac{1}{n} \|Y - f(x)\|^2 = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_i)^2
$$
4. Experimental Analysis

4.1. The datasets and labels

To compensate for the shortage of data volume to mitigate the risk of overfitting and squeeze all the information from the CXRs, a transfer learning technique is employed to teach the network powerful visual feature extraction abilities by pre-training it on massive datasets. Literature [18-24] gather 88079 CXRs of pulmonary illnesses, none of which contain COVID-19 cases.

Stonybrook Radiographic Assessment of Lung Opacity (RALO) is the dataset we used in our investigation. A total of 2373 anterior-posterior CXRs are collected by Stony Brook Medicine, and each CXR is scored by two thoracic radiologists on the left and right lungs based on the degree of involvement exhibited on chest radiographs. There are several CXRs for each patient and temporal information is included.

During the research on pulmonary edema, the authors indicate that the geographic extent and lung opacity may be utilized to assess the degree of lung injury. The GE score and the LO score [25] are two markers that can be used to quantify the severity of a disease. Each index is composed of two numbers that measure the degree of participation and involvement of the left and right lungs, respectively. Both measures are graded on a scale of 0 to 8. The scoring criteria of GE score depends on the extent of involvement by consolidation or ground glass opacity, 0 = no involvement; $1 \leq 25\%$; $2 = 25 - 50\%$; $3 = 50 - 75\%$; $4 \geq 75\%$ involvement. The LO score is decided by the size of the shaded area of the lung, 0 = no opacity; 1 = ground glass opacity; 2 = mix of consolidation and ground glass opacity (less than 50% consolidation); 3 = mix of consolidation and ground glass opacity (more than 50% consolidation); 4 = complete white-out [26]. Figure 3 depicts some CXRs of the two labels: GE score and LO score.

![Fig. 3. CXR images of the two labels: geographic extent (GE) score and lung opacity (LO) score.](image)

4.2. Feature Filter

After pre-training, the DenseNet model in the feature extraction phase, can extract 18 features from CXRs, which represent the severity of 18 different lung diseases. The details are listed in the Table 1 below. Our work is to determine the severity of COVID-19 from CXRs, therefore, features like "Cardiomegaly", "Fracture" and "Hernia" are not needed for us. In literature [25], the author simply extracts one of the features, "Lung Opacity", to predicting the severity of the disease. This strategy, however, is highly one-sided. We believe that some of these 18 features have a correlation, therefore we apply the feature selection filter to calculate the mutual information between them and create an $18 \times 18$ matrix, as shown in Figure 4. Several features ("Consolidation", "Infiltration", "Edema", "Pneumonia") that are strongly correlated with 'Lung Opacity' are chosen and entered as target features in the outcome prediction phase. In fact, as mentioned in Section 1, 'Consolidation' (MI = 0.85), 'Infiltration' (MI = 0.76), 'Pneumonia' (MI = 0.77), 'Edema' (MI = 0.71), are common symptoms on imaging examinations in patients with COVID-19, while 'Fracture'(MI = -0.28), 'Cardiomegaly' (MI = 0.0025), 'Atelectasis' (MI =0.13) are uncommon.
Atelectasis 0.42 0.09 0.32 0.22 0.19 0.06 0.44 0.38 0.44 0.31 0.16 0.13 0.27 0.35 0.33 0.44 0.13 0.33
Consolidation 0.42 0.69 0.62 0.66 0.38 0.34 0.47 0.72 0.61 0.11 0.12 0.34 0.46 0.57 0.28 0.071 0.85 0.64
Infiltration 0.69 0.69 0.53 0.39 0.19 0.36 0.48 0.67 0.13 0.17 0.49 0.36 0.63 0.21 0.35 0.67 0.43
Pneumothorax 0.32 0.02 0.1 0.05 0.1 0.04 0.41 0.12 0.03 0.04 0.41 0.14 0.47 0.11 0.18 0.36 0.51 0.40
Edema 0.1 0.86 0.54 0.43 1 0.81 0.14 0.5 0.77 0.27 0.15 0.15 0.11 0.24 0.22 0.71 0.65
Emphysema 0.23 0.26 0.13 0.22 0.23 1 0.86 0.5 0.61 0.15 0.74 0.24 0.24 0.87 0.43 0.62
Fibrosis 0.26 0.42 0.28 0.34 0.19 0.1 0.21 0.39 0.07 0.07 0.02 0.45 0.64 0.39 0.31 0.15 0.18 0.72
Effusion 0.64 0.67 0.49 0.44 0.5 0.72 0.23 0.1 0.86 0.5 0.15 0.15 0.34 0.24 0.24 0.87 0.43 0.62
Pneumonia 0.12 0.72 0.67 0.43 0.77 0.38 0.19 0.46 0.1 0.24 0.58 0.10 0.18 0.15 0.61 0.27 0.77 0.56
Chronic Thickening 0.44 0.51 0.33 0.52 0.27 0.42 0.67 0.5 0.24 0.1 0.12 0.40 0.49 0.12 0.22 0.37 0.31 0.38
Cardiomegaly 0.31 0.31 0.13 0.03 0.12 0.08 0.01 0.4 0.08 0.12 0.1 0.16 0.04 0.09 0.74 0.11 0.25 0.43
Nodule 0.018 0.52 0.44 0.41 0.35 0.49 0.62 0.30 0.40 0.16 0.1 0.62 0.22 0.11 0.37 0.58 0.25
Mass 0.27 0.4 0.34 0.47 0.25 0.39 0.80 0.34 0.28 0.49 0.94 0.62 0.1 0.62 0.12 0.31 0.65 0.43
Bleeding 0.29 0.087 0.031 0.11 0.12 0.19 0.63 0.21 0.25 0.42 0.55 0.22 0.02 1 0.073 0.2 0.26 0.032
Lung Lesion 0.13 0.29 0.22 0.19 0.24 0.14 0.19 0.24 0.1 0.22 0.074 0.13 0.12 0.073 1 0.12 0.18 0.20
Fracture 0.69 0.072 0.06 0.14 0.12 0.12 0.07 0.27 0.13 0.13 0.017 0.32 0.12 0.12 0.12 0.28 0.44 0.45
Lung Opacity 0.13 0.86 0.79 0.51 0.21 0.36 0.31 0.47 0.77 0.15 0.052 0.18 0.15 0.26 0.11 0.28 1 0.59
Cardiomegaly 0.33 0.63 0.43 0.48 0.65 0.64 0.21 0.41 0.56 0.18 0.43 0.015 0.36 0.032 0.28 0.46 0.59 1

Fig. 4. The "Dense Connection" block.

Table 1. 18 features extracted from CXRs

| Features       | Brief Description                                                                 |
|----------------|-----------------------------------------------------------------------------------|
| Atelectasis    | The collapse of part or all of a lung, is caused by a blockage of the air passages (bronchus or bronchioles) or by pressure on the lung. |
| Consolidation  | A region of normally compressible lung tissue that has filled with liquid instead of air. |
| Infiltration   | A substance denser than air, such as pus, blood, or protein, which lingers within the parenchyma of the lungs. |
| Pneumothorax   | A condition that air around or outside the lung.                                     |
| Edema          | A condition in which the lungs fill with fluid.                                     |
| Emphysema      | A lung condition that causes shortness of breath.                                   |
| Fibrosis       | A condition in which the lungs become scarred over time.                            |
| Effusion       | A condition that fluid builds up in the space between the lung and the chest wall.  |
| Pneumonia      | An infection that inflames the air sacs in one or both lungs.                       |
| Pleural Thickening | Pleural thickening occurs when scar tissue develops on the lining of the lungs, or the pleura. |
| Cardiomegaly   | An enlarged heart (cardiomegaly) refers to a heart that is bigger than typical.     |
| Nodule         | An abnormal growth that forms in a lung, spots smaller than 3 cm in diameter are considered lung nodules. |
Mass  A lung mass is defined as an abnormal spot or area in the lungs larger than 3 centimeters (cm), about 1.5 inches, in size.

Hernia  A lung hernia refers to part of a lung pushing through a tear, or bulging through a weak spot, in the chest wall, neck passageway or diaphragm.

Lung Lesion  Microscopically, lung lesions are evident 4 hours after experimental infection in which neutrophils fill the bronchial, bronchiolar, and alveolar spaces.

Fracture  A fractured rib occurs when one of the bones in your rib cage breaks or cracks.

Lung Opacity  Pulmonary opacification represents the result of a decrease in the ratio of gas to soft tissue (blood, lung parenchyma and stroma) in the lung.

Enlarged Cardiomediastinum  An enlarged heart may be the result of a short-term stress on the body or a medical condition.

### 4.3. Outcome Prediction

The MLP is a forward-structured artificial neural network for nonlinear separable problems. MLP’s nonlinear mapping capability and self-learning and adaptive capacity in the back-propagation process perform well in handling this type of task. Four commonly used regression models: linear regression, SVR, ridge, and Decision Tree, are chosen to compare with the MLP regression model. In order to show fairness and verify the robustness of the model, four indicators are used for evaluation: Pearson correlation coefficient, R Squared, MAE, and MSE.

The Pearson correlation coefficient (PCC) is a measure of the degree of correlation between the two variables. It is the ratio between the covariance of two variables and the product of their standard deviations. The R Squared(R2) is a statistical measure that represents the proportion of variance of the dependent variable explained by one or more independent variables in a regression model. Mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon, an arithmetic average of the absolute errors. For regression problems, MSE is the most commonly used error evaluation index to measure the square error (the average of all data points) between the predicted value and the real target value of each data point in the train set.

The RALO dataset contains 2373 CXRs, which are divided into a train set and a test set in an 8:2 ratio. After CXRs are extracted by the feature extraction phase, the results are imported into a regression model.

Table 2 lists all of the diffident regression indicators. It can be seen from the table that the multilayer perceptron (MLP) technique outperforms the other methods on all metrics (PCC = 0.82, R2 = 0.67), demonstrating that MLP’s nonlinear mapping capability and self-learning and adaptive capacity in the back-propagation process are well suited to the task.

| Task   | Regressions | PCC | R2 | MAE | MSE  |
|--------|-------------|-----|----|-----|------|
| GE score | Linear Regression | 0.80 | 0.65 | 1.05 | 1.81 |
|        | SVR         | 0.79 | 0.60 | 1.06 | 1.83 |
|        | Ridge       | 0.79 | 0.62 | 1.05 | 1.81 |
|        | Decision Tree | 0.74 | 0.59 | 1.17 | 2.34 |
|        | MLP         | **0.82** | **0.67** | **1.02** | **1.75** |
| LO score | Linear Regression | 0.75 | 0.54 | 0.87 | 1.20 |
|        | SVR         | 0.73 | 0.55 | 0.95 | 1.17 |
|        | Ridge       | 0.73 | 0.54 | 0.90 | 1.17 |
|        | Decision Tree | 0.70 | 0.50 | 1.03 | 1.31 |
|        | MLP         | **0.78** | **0.56** | **0.85** | **1.16** |
5. Conclusion

The COVID-19’s high infectivity and concealment, two important characteristics, have considerably enhanced the challenge of epidemic prevention and control, as well as explaining the virus's rapid spread over the world. Patients with fever, exhaustion, and a dry cough as the primary symptoms, as well as nasal congestion, runny nose, and other upper respiratory symptoms, are uncommon in the early stages of the disease. After one week, around half of the patients developed dyspnea, and the severe cases quickly progressed to acute respiratory distress syndrome, septic shock, metabolic acidosis that was difficult to cure, and coagulation dysfunction [27]. It's worth noting that severe and critically ill patients may have a low or no fever at all during the course of their illness. Effective prevention, early detection, and treatment are critical in the current epidemic condition to halt the pandemic spread. As a result, the purpose of this work is to investigate the severity of COVID-19 lung infection based on CXR, to aid doctors and students in determining the severity of COVID-19 pulmonary infection, and to provide patients with appropriate treatment options. It not only relieves some of the load on doctors, but it also has the potential to help with clinical triage and process optimization.

The author of [28] discussed the limitations of transfer learning, claiming that pre-training with diverse datasets yields vastly disparate results, even when they all complete the same task. As a result of the short number of datasets, we are unable to execute the pre-training stage, which is a limitation of this study. Meanwhile, CXR alone is insufficient for the diagnosis and process research of lung diseases, and laboratory exams such as pulmonary function tests (PFT) and fractional exhaled nitric oxide (FeNO) are needed. If we could collect more precise clinical information matching CXR, our model would be greatly enhanced.

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