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PAPER

Classification Model Using Transfer Learning for the Detection of Pneumonia in Chest X-Ray Images

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ABSTRACT

In the current global context, there has been a significant increase in respiratory system diseases, particularly pneumonia. This disease has a higher incidence of mortality in children under five years old and adults over 60 years old because it leads to complications if not treated in time. This research leverages convolutional neural networks (CNNs) to classify images, specifically to detect the presence of pneumonia. The data processing methodology utilized in this study is CRISP-DM. The dataset consists of 5,856 images of anteroposterior chest X-rays downloaded from the open repository "Kaggle," divided into 5,216 images for training, 16 for validation, and 624 for testing. Preprocessing involved image augmentation through modifications to the original images, scaling, and batch division in tensor format. A comparative analysis was conducted among the transfer models: DenseNet, VGG19, and ResNet50 version 2. Each transfer model was the header of a CNN with four subsequent layers. The models underwent training, validation, and testing phases. The test's results showed that DenseNet achieved an accuracy of 0.87, VGG19 achieved 0.86, and ResNet50 achieved 0.91. These results affirm the effectiveness of ResNet50 in image classification, considering that the model's output is binary, where 0 represents that the patient does not have pneumonia and 1 indicates that the patient has pneumonia.

KEYWORDS

classification models, transfer learning, convolutional neural networks (CNNs), pneumonia, data augmentation, image data generator

1 INTRODUCTION

Pneumonia is characterized by an inflammatory lung response to the invasion of microorganisms into the distal airways and lung parenchyma. This condition typically progresses through distinct anatomopathological phases, including the congestion or inflammatory edema phase, the red hepatization phase, the gray hepatization

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phase, and resolution. The treatment approach for pneumonia varies depending on its type and may involve antibiotics, antiviral agents, and antimitotic drugs.

Globally, pneumonia is the leading cause of infant mortality, claiming the lives of over 700,000 children under the age of five annually, with more than 153,000 newborns [1]. In Peru, during the colder seasons, 9,334 cases of pneumonia have been recorded in children under the age of five, of which 68 died and 29.3% required hospitalization. In addition, 10,157 cases of pneumonia were reported among elderly adults over 60, of which 1,074 died and 40.5% required hospitalization [2]. Notably, the prevalence of pneumonia in the pediatric population has become intertwined with the ongoing COVID-19 crisis, emphasizing the importance of its accurate detection.

In Peru, pneumonia is the leading cause of infant mortality, prompting initiatives such as vaccination campaigns and increased investments in healthcare [3]. A potential solution for pneumonia detection lies in deep learning, a form of machine learning that employs computer models to predict the presence of the disease.

Artificial intelligence through machine learning enables solving classification problems that require models to be trained and subsequently evaluated [4–7]. Machine learning models facilitate data classification by effectively processing data and images [8–12], thereby detecting patterns and behavioral trends.

To create a robust model, convolutional neural networks (CNNs) are employed. These models may incorporate multiple convolutional layers, which, in turn, necessitate considerable computational resources, including processing speed and storage capacity [13]. The adoption of residual layers has been explored by using transfer models as the headers of CNNs. Prior studies demonstrating enhanced model accuracy using transfer learning inform this strategy.

The primary objective of this research is to develop a machine learning model based on CNNs, incorporating transfer models, for the detection of pneumonia. This will be accomplished using chest X-ray images as input data. Specifically, this study will compare three transfer models: DenseNet, VGG19, and ResNet50, to determine which yields the best results. Ultimately, this research aims to contribute to early and timely diagnosis, reducing the number of pneumonia-related fatalities.

2 RELATED WORK

This section provides an overview of relevant scientific articles and research supporting the models proposed in this study.

Flores-Rodriguez and Cabanillas-Carbonell [3] proposed a mobile application based on CNN for pneumonia diagnosis. Their study involved both a control group and a study group of 33 medical staff members who utilized the application. Results indicated that the application enabled the early detection of pneumonia and reduced the need for extensive medical assistance.

Pinto Gaitán's research [14] aimed to develop a decision support system for pneumonia classification using deep learning models with support vector machines (SVM). The study used SVM to classify the regular class, while a specialized CNN was employed to differentiate viral and bacterial pneumonia cases. This approach achieved a classification accuracy greater than 91% for the normal class and a percentage greater than 93% for viral and bacterial pneumonia cases.

Iparraguirre-Villanueva et al. [15] investigated four CNN models for image detection: VGG16, VGG19, ResNet50, and Inceptionv3. Their research reported that the Inceptionv3 model achieved an accuracy of 72.9%.

Cabrejos Yalan's study [16] primarily aimed to implement CNNs to expedite the diagnosis of pneumonia in radiology. They developed a web system to visualize the probability percentages of pneumonia based on X-ray images, resulting in more accurate diagnoses. Using the AlexNet algorithm with ReLU layers, the research successfully reduced incorrect diagnoses by 80.7% and attained an accuracy greater than 95%.

In their research, Aira Céspedes et al. [17] focused on the applications and use cases of artificial intelligence techniques, particularly in the context of COVID-19. They highlighted the significance of AI in the detection and diagnosis of lung diseases such as pneumonia, emphasizing its value as an innovative tool for early identification of coronavirus infections and patient monitoring.

Luren Smith's research [18] aims to create a computerized social distancing monitoring system that includes hardware such as cameras, sensors, and a Raspberry Pi microcontroller board, along with software such as the Arduino language and deep learning algorithms. These components enable real-time tracking of the distance between individuals. The study concludes that for the monitoring system, deep learning algorithms like centroid tracking were employed to calculate the separation between people and classify whether established norms are being met.

As reviewed in previous studies, transfer models optimize image classification accuracy, and by working in the present investigation with chest X-rays, which are two-channel images, good results are expected.

Transfer learning is a deep learning methodology that takes pre-trained models for a specific task and reuses them for other similar tasks. These pre-trained models have been prepared with a large dataset, which allows them to be reused in models with smaller amounts of data. Another great advantage of using transfer learning is the reduction of training time and the reduced use of computing resources. Finally, it allows for the use of model architectures developed by the deep learning research community, which can be freely accessible from the Internet.

All these advantages would allow us to fulfill the research question, which is to find a model that optimizes the accuracy of the classification of pneumonia from chest X-rays.

3 METHODOLOGY

In this research, we followed the CRISP-DM (cross-industry standard process for data mining) methodology to guide our machine learning work. This methodology encompasses several key stages, including business understanding, data understanding, data preparation, modeling, and evaluation.

3.1 Business understanding

The primary goal of this study is to develop a machine learning model utilizing CNNs to enhance the classification of chest X-ray images for the diagnosis of pneumonia. We executed this using the Python programming language and various tools, including Jupyter Notebook from Anaconda [19]. So, it is intended to create a system that can assist healthcare specialists in diagnosing pneumonia with a high degree of confidence in the results. The research process involved the following stages:

Stage 1: Collection of chest X-ray images to form the dataset.
Stage 2: Understanding and preparing the dataset through image processing techniques.
Stage 3: Development of three CNN models incorporating transfer learning.
Stage 4: Evaluation of the results produced by the models.

3.2 Data understanding

For this study, we selected images from the Kaggle database repository [20]. These images consist of anterior-posterior chest X-rays taken from pediatric patients aged one to five years at the Guangzhou Women and Children Medical Center, a public facility in the Guangzhou province, China.

The dataset comprises images in JPEG format with dimensions of 150 × 150 pixels, organized into three main folders: training, testing, and validation. Within these folders, there are two subfolders—one containing images with pneumonia and the other containing images without pneumonia, denoted as "normal."

A total of 5840 chest radiographic images were used. Among these, 5,216 were allocated for training, 16 for validation, and 624 for testing. In the training folder, 1,341 images belong to the "normal" category and 3,875 to the "pneumonia" category. In the test folder, 234 images were classified as "normal" and 390 as "pneumonia."

Figure 1 illustrates two radiographs labeled "Pneumonia" and "Normal," representing, respectively, individuals affected by the disease and individuals without pneumonia. These labeled images were used to train the model.

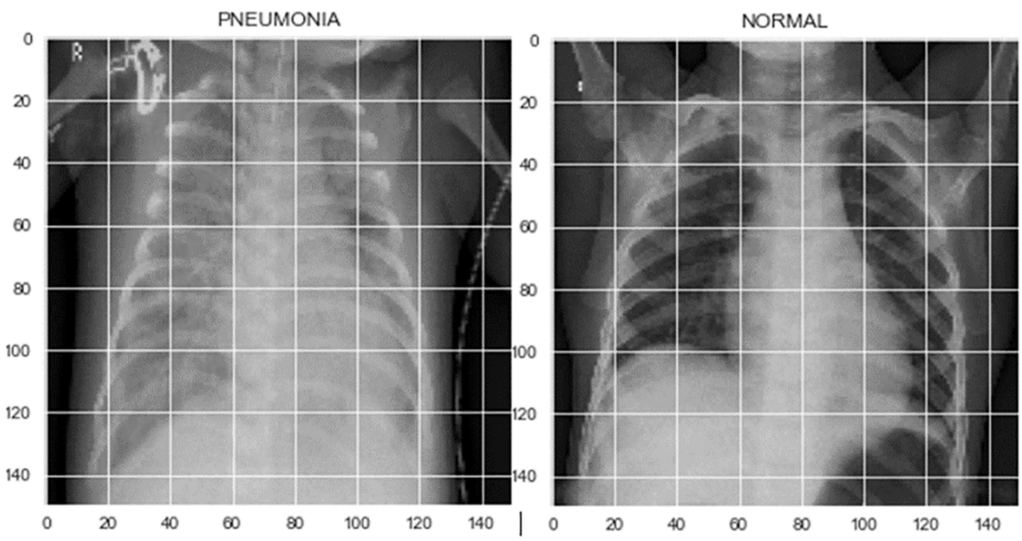


Fig. 1. Chest X-ray with pneumonia and without pneumonia

3.3 Data preparation

A label count graph was created to assess class distribution, revealing an imbalance that predominantly favors the "pneumonia" class, which contains a significantly larger number of images. In order to mitigate the risk of the model leaning towards the "pneumonia" class, we employed data augmentation techniques using the ImageDataGenerator function provided by the TensorFlow library. This process generated new images by applying various transformations to the existing ones, including changes in rotation, scale, zoom, and brightness. Consequently, we augmented the "normal" class dataset by creating an additional 1200 images through this function.

Figure 2 showcases ten randomly transformed images as examples, with the parameters configured according to the function's settings.

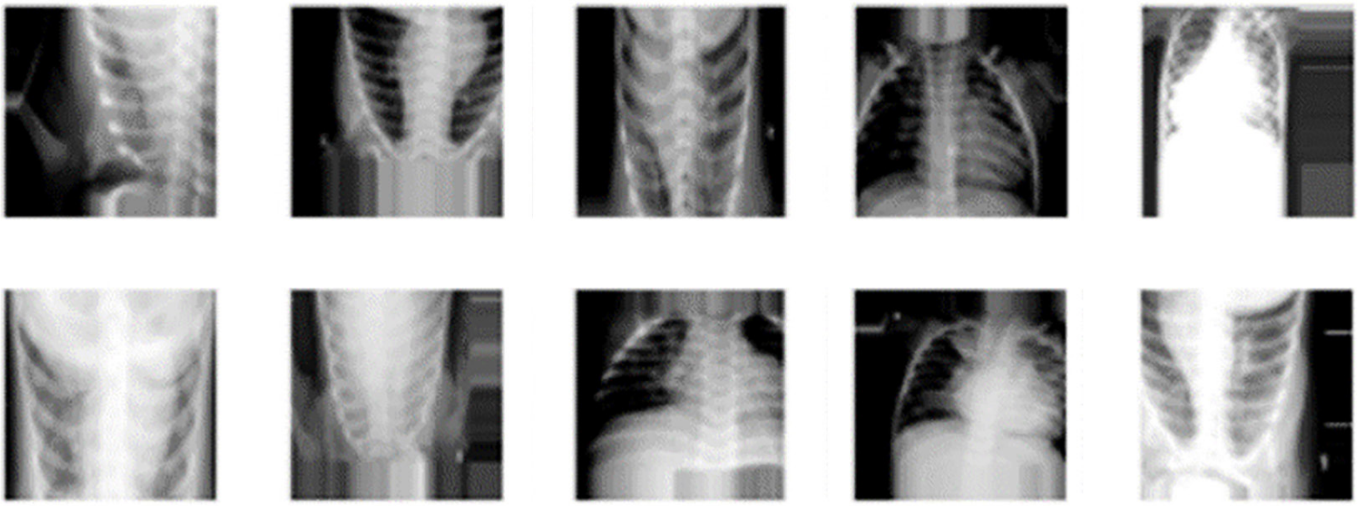


Fig. 2. Radiographs adulterated by the ImageDataGenerator function

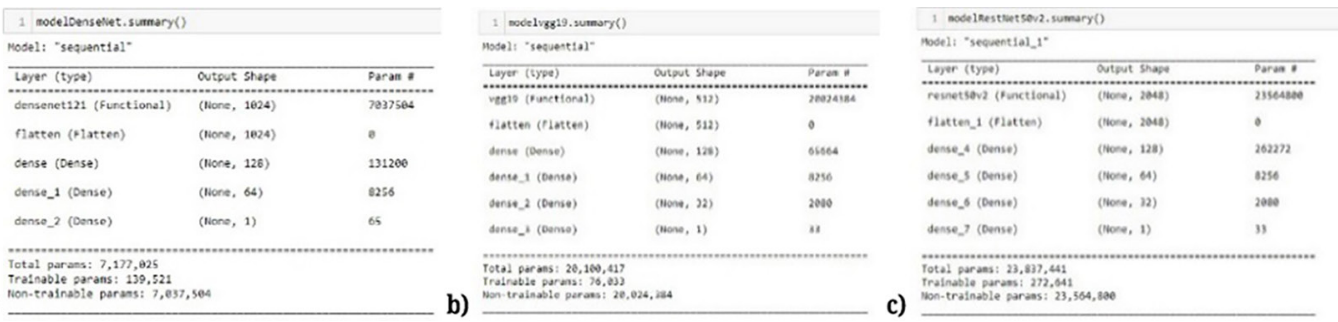
The radiographic images were resized from 150 × 150 to 224 × 224, as they are in grayscale. Furthermore, we applied image normalization with a scaling factor of 1/255 and segmented them into batches of 32 images. This not only ensures uniform image dimensions but also facilitates dataset management, as it obviates the necessity to load all images into memory.

3.4 Modeling

A thorough review of related literature revealed a consensus among experts that the development of a CNN model is the most appropriate approach for image-based classification and prediction.

Considering this, our research involved the creation of three distinct CNN models, specifically designed to efficiently classify pneumonia from chest radiographic images. Each of these models was constructed using a pre-trained model with transfer learning. The chosen pre-trained models included Res-Net50 version 2, DenseNet, and VGG19. The CNN had these as its headers, followed by a series of four dense layers with 128, 64, 32, and 1 neuron, respectively. The activation functions applied were ReLU for the first three layers and Sigmoid for the last layer.

Figure 3 provides a visual representation of three CNNs, with the transfer model as CNN's first layer, followed by four dense layers. In Figure 4a, the summary of the CNN architecture with DenseNet as the first layer is plotted; in Figure 4b, the architecture of the CNN with VGG19 as the first layer; and in Figure 4c, the architecture of the CNN with ResNet50 as the first layer is depicted.



a)

```
1 modelDenseNet.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
densenet121 (Functional)	(None, 1024)	7037504
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 128)	131200
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 1)	65

Total params: 7,177,025
Trainable params: 139,521
Non-trainable params: 7,037,504

b)

```
1 modelvgg19.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None, 512)	20024384
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 128)	65664
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 32)	2080
dense_3 (Dense)	(None, 1)	33

Total params: 20,100,417
Trainable params: 76,033
Non-trainable params: 20,024,384

c)

```
1 modelRestNet50v2.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
resnet50v2 (Functional)	(None, 2048)	23564800
flatten_1 (Flatten)	(None, 2048)	0
dense_4 (Dense)	(None, 128)	262272
dense_5 (Dense)	(None, 64)	8256
dense_6 (Dense)	(None, 32)	2080
dense_7 (Dense)	(None, 1)	33

Total params: 23,837,441
Trainable params: 272,641
Non-trainable params: 23,564,800

Fig. 3. Applying CNN models: a) DenseNet b) VGG19 c) ResNet50

The models underwent three phases: training, validation, and testing.

During the training and validation phase, the models were configured to run for 30 epochs, resulting in training accuracies of 0.918 for DenseNet, 0.912 for VGG19, and 0.955 for ResNet50.

Figure 4 shows how well DenseNet, VGG19, and ResNet50 CNN models detect pneumonia. In Figures 4a, 4b, and 4c, on the right-hand side, you can see the training accuracy in green and the validation accuracy in red, and on the left-hand side, the training loss value in green and the validation loss value in red.

In Figure 4a, the accuracy of the CNN with the DenseNet transfer model is displayed, starting at 0.85 in the first epoch, reaching its highest value in epoch 24 with an accuracy of 0.93, and concluding at epoch 30 with an accuracy of 0.918. In Figure 4b, the accuracy of the CNN with the VGG19 transfer model is depicted, starting at 0.81 in the first epoch, reaching its peak in epoch 25 with an accuracy of 0.92, and finishing at epoch 30 with an accuracy of 0.912. In Figure 4c, the accuracy of the CNN with the ResNet50 transfer model is shown, beginning at 0.89 in the first epoch, reaching its highest value in epoch 17 with an accuracy of 0.95, and concluding at epoch 30 with an accuracy of 0.955.

In the graphs, it can be observed that the most consistent line corresponds to the CNN with VGG19, as it has discrete minimum and maximum values within certain time periods; however, it is the model that achieved the lowest accuracy. On the other hand, the graph with the most variable line corresponds to the CNN with ResNet50, as it exhibits very high or very low peaks within its graphical line, nevertheless achieving the highest accuracy values.

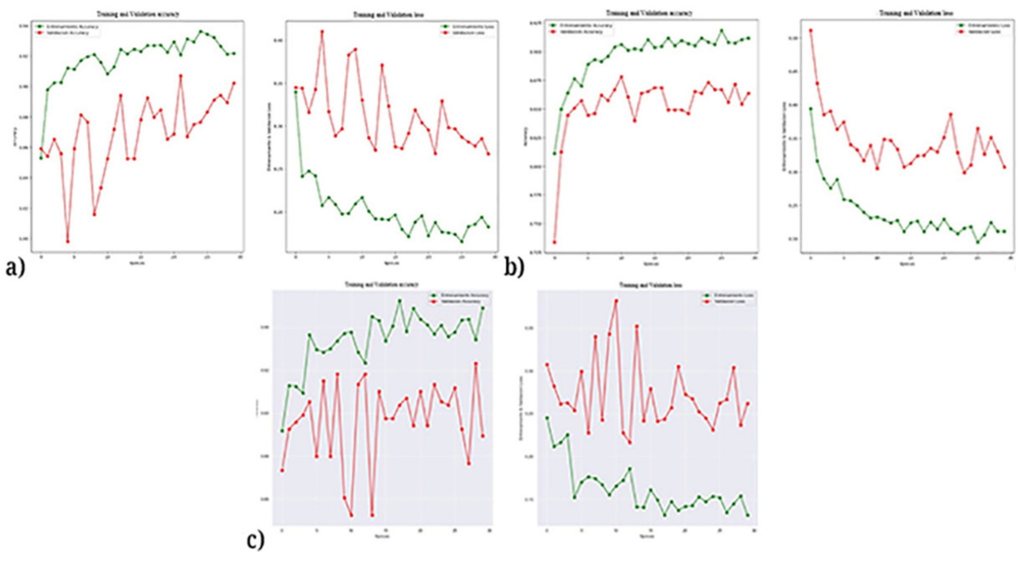


Fig. 4. Performance training graph of the CNN models applying: a) DenseNet, b) VGG19, and c) ResNet50

3.5 Evaluation

After concluding the training and validation phases, the testing phase was carried out to assess which of the three models achieved higher accuracy using a new dataset of images containing 624 radiographic images. The confusion matrix for each model was plotted to verify their successes and errors, as seen in Figure 5.

In Figure 5a, the confusion matrix of the CNN model contains DenseNet. It is visualized that it correctly classifies 548 images (the sum of the values on the matrix's main diagonal) and misclassifies 76 images. Out of these, the system predicted that in

38 images it was not pneumonia when it really was (false negatives), and the system predicted that in 38 images it was pneumonia when it really wasn't (false positives).

In Figure 5b, the confusion matrix of the CNN model contains VGG19. It is visualized that it correctly classifies 542 images and misclassifies 82 images; out of these, the system predicted 38 images as false negatives and 44 images as false positives.

In Figure 5c, the confusion matrix of the CNN model contains ResNet50. It is visualized that it correctly classifies 570 images and misclassifies 54 images; out of these, the system predicted 17 images as false negatives and 37 images as false positives.

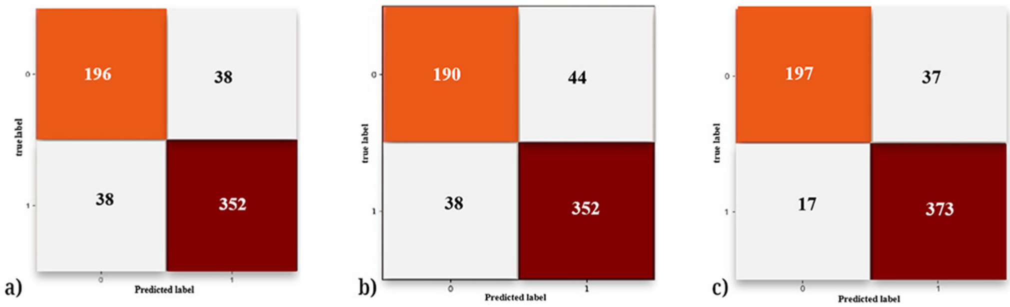


Fig. 5. Confusion matrix of the CNN models applying: a) DenseNet, b) VGG19, and c) ResNet50

Based on what was previously mentioned, it can be inferred that the CNN model applying ResNet50 yielded the best results. The observed outcome can likely be attributed to the ResNet50 architecture, which is composed of 50 deep layers that facilitate transfer learning. This architecture uses residual blocks, each with two convolution layers and ReLU activation. The output of one block is combined with the input of another.

4 RESULTS AND DISCUSSION

4.1 Results

During the evaluation stage, involving 624 radiographic images, the models achieved the following accuracies: 0.878 for DenseNet, 0.868 for VGG19, and 0.913 for ResNet50.

The test results strongly support the superiority of the CNN model with ResNet50 over the DenseNet and VGG19 models, as presented in Table 1.

Table 1. Results of the evaluation of the three models

Metric	DenseNet	VGG19	ResNet50
Accuracy	0.8782	0.8686	0.9135
Precision	0.9026	0.8889	0.9098
Recall	0.9026	0.9026	0.9564
F1-Score	0.9026	0.8957	0.9325

With respect to sensitivity, the recall value shows equal values in DenseNet and VGG19 of 0.9026; on the other hand, the ResNet50 model had a slight advantage in improving the sensitivity to 0.9564, indicating that this model has fewer cases of false negatives. With respect to accuracy, the VGG19 model scored the lowest with 0.8889, followed by the DenseNet model with 0.9026, and the ResNet50 model gained a slight advantage with 0.9098, indicating that the ResNet50 model had more true positives versus false positives.

The test results strongly support the superiority of the CNN model with ResNet50 over the DenseNet and VGG19 models.

Other metrics were applied for the model that obtained the best performance: the CNN model with ResNet50, applying metrics to measure the error, finding a mean absolute error (MAE) of 0.087 and a mean squared error of 0.087, which indicates a low percentage of error. Also, the computed area under the curve (AUC) was obtained at 0.899, which means that the model can separate the two classes "normal" and "pneumonia" by approaching the curve in the upper left corner of the graph. From this value, the ROC curve is plotted, as shown in Figure 6.

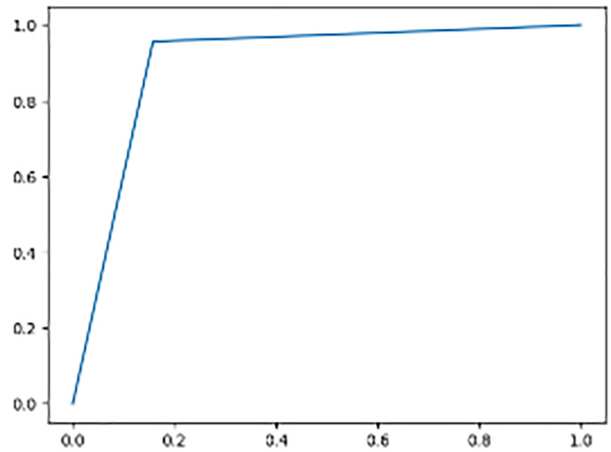


Fig. 6. ROC of the CNN model applying ResNet50 in the evaluation stage

4.2 Discussion

The development of multiple pneumonia detection models based on X-ray image analysis underscores the significant interest in the application of machine learning within the field of medicine. To embark on this journey, it is imperative to equip ourselves with essential tools, including a comprehensive dataset, prediction models, and image analysis algorithms.

In Pinto's research [14], CNNs were employed in conjunction with pre-trained models like AlexNet, VGG16, VGG19, ResNet50, and Inceptionv3. Some of these models reported accuracy levels ranging from 73% to 91%. Notably, our research achieved an accuracy rate of 91%, signifying a commendable degree of precision. In Table 2, the results obtained by Pinto's research are compared with the proposed model using ResNet50 in the current investigation.

Table 2. Comparison of metrics with the models proposed by Pinto Gaitán

Metric	Pinto(2021)			Proposed
	ResNet18	ResNet50	InceptionResNetV2	ResNet50v2*
Accuracy	88.20%	88.60%	91.11%	91.35%
Precision	94.24%	95.75%	98.33%	90.98%
Recall	98.33%	97.66%	98.33%	95.64%
F1-Score	96.24%	96.70%	98.33%	93.25%

Notes: *In the proposed neural network model, ResNet50v2 has been taken as the first layer, and other layers have been added to improve accuracy.

Table 3 presents a comparison between the results obtained by Iparraguirre et al. [15] and the model proposed in the current investigation.

Table 3. Comparison of metrics with the models proposed by Iparraguirre et al.

Metric	Iparraguirre et al. (2022)			Proposed
	VGG16	VGG19	InceptionV3	ResNet50v2*
Accuracy	62.50%	63.10%	72.90%	91.35%
Precision	70.00%	72.00%	83.00%	90.98%
Recall	88.90%	88.70%	93.70%	95.64%
F1-Score	73.40%	73.80%	82.00%	93.25%

Notes: *In the proposed neural network model, ResNet50v2 has been taken as the first layer, and other layers have been added to improve accuracy.

The proposed model demonstrates a highly promising level of accuracy in comparison to the other models.

4.3 Validation in a new dataset

In order to validate the performance of the model objectively, an external dataset found in the open database Kaggle [21], different from the one initially used. This new dataset contains in its "test" folder 234 images for the "normal" category and 390 for the "pneumonia" category. Regarding the number of images, both datasets have the same quantity in the "test" folder; the difference lies in the fact that the images in the new dataset used for model validation include rotated and flipped images.

By applying the performance metrics, it can be seen that the values obtained are:

Accuracy: 0.8841807909604520
Precision: 0.7581699346405228
Recall: 0.9666666666666667
F1-Score: 0.8498168498168498
AUC: 0.9042735042735043

This indicates that the level of accuracy has decreased from 0.91 to 0.88, with a minimum decrease of 0.03. The same can be seen in the precision and f1-score metrics; however, the recall metric has increased, which means that the sensitivity of the model has improved and. therefore, the number of false negatives has decreased.

5 CONCLUSION

In conclusion, after comparing three convolutional neural network models—ResNet50, DenseNet, and VGG19—we found that ResNet50 consistently outperforms the others, which is consistent with previous research. The ResNet50 model achieved an accuracy rate of 91.35% during the evaluation phase, especially after adding four subsequent layers with the appropriate number of neurons. In order to validate the model objectively, a new dataset was used to realize a new evaluation phase, obtaining a minimal decrease in accuracy value from 91% to 88%, which may be due to the fact that this dataset uses other image processing techniques, performing twists and turns on original images. Furthermore, our research underscored the critical role of image preprocessing in improving overall performance. The use of preprocessing techniques such as scaling, data augmentation, conversion to numerical format, normalization, and tensor batching played a crucial role in optimizing computational resources and assisting the model in image recognition. In general, transfer learning models offer several advantages, such as faster training processes and reduced computer resource consumption. However, they have limitations in that many of the parameters configured in the pre-trained model are invisible to the end user, such as the learning rate of the neural network.

6 DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest regarding the research, authorship, and/or publication of this article.

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8 CONTRIBUTION

Gisella L. E. Maquen-Niño, Jhojan G. Nuñez-Fernandez, and Fany Y. Taquila-Calderon are the prime contributors. Gisella L. E. Maquen-Niño performed the selection and processing of images from the first dataset, as well as the development of the methodology. Jhojan G. Nuñez-Fernandez developed the three original models and trained them, while Fany Y. Taquila-Calderon evaluated the three models. Ivan Adrianzen Olano validated the ResNet50 model on a new dataset and drafted its evaluation. Percy De-La-Cruz-VdV optimized the model using ResNet50 and discussed the results, and Gilberto Carrión-Barco validated the methodology compliance and drafted the previous works and conclusions. All authors reviewed the draft, addressed peer observations, and validated the article's final version.

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