Classification of pediatric pneumonia using ensemble transfer learning convolutional neural network

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ABSTRACT

Pneumonia is a condition characterised by the sudden inflammation of lung tissue, which is triggered by microorganisms such as fungi, viruses, and bacteria. Chest X-ray imaging (CXR) can detect pneumonia, but it requires considerable time and medical expertise. Consequently, the objective of this study is to diagnose pneumonia using CXR imaging in order to effectively detect early cases of pneumonitis in children. The study employs the ensemble transfer learning convolutional neural network (ETL-CNN) transfer learning ensemble, which combines multiple CNN transfer learning models. Resnet50-VGG19 and VGG19-Xception are the ETL-CNN models used in this investigation. Comparing ETL-CNN models to CNN transfer learning models such as Resnet50, VGG19, and Xception. Pediatric CXR pneumonia, which consists of a normal and pneumonia image, is the source of these study results. The results of this analysis indicate that Resnet50-VGG19 achieved the highest level of accuracy, 99.14%. Additionally, the Resnet50-VGG19 obtained the highest levels of precision and recall when comparing to other models. Consequently, the conclusion of this study is that the Resnet50-VGG19 model can generate acceptable classification performance for pediatric pneumonia based on CXR. This study improves classification results for performance when compared to earlier studies.

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1. INTRODUCTION

Pneumonia is a condition characterised by the sudden inflammation of lung tissue, which is triggered by microorganisms such as fungi, viruses, and bacteria [1]. The World Health Organisation reports that pneumonia causes inflammation in one or both lung parenchyma and can be fatal, particularly in children under the age of five, adults over the age of 65, and those with preexisting health conditions [2]. Consequently, it is critical to identify pneumonia at an early stage, especially in infants, in order to provide the most suitable treatment. Rapid diagnostic tests with a high degree of sensitivity can assist medical personnel in the treatment of pneumonia in children [3].

Chest X-ray (CXR) images can be used to detect pneumonia, but this requires time and medical expertise [4]. Significant progress has been made in the utilization of medical data by means of deep learning technology [5]. This technology permits the use of deep learning models previously taught on large and complex datasets, thereby accelerating the training of new models with high accuracy [6]. Convolutional neural networks (CNNs) are a widely used deep learning model for disease identification in the field of medicine [7]-[9].

Previous research has developed CNN employs advanced deep learning models such as Resnet50 [10], VGG19 [11], AlexNet [12], InceptionV3 [13], and Xception [14] for detecting pneumonia in CXR images. CNN transfer learning is the model utilized in these investigations. Only one CNN transfer learning model is utilized in these studies to detect pneumonia, which is a limitation. The transfer learning models can be combined to incorporate the benefits of each model; this ensemble is known as the CNN transfer learning ensemble (ETL-CNN) [15]-[17]. Earlier studies [18]-[20] have been conducted on the detection of pneumonia using a CNN transfer learning ensemble. In the meantime, prior research [21]-[23] focused on the identification of pneumonia in adults only through the analysis of CXR images. The physiological structures of adults and children differ [24]. This had an effect on the deep learning model used to distinguish between adult and pediatric pneumonia. To classify pediatric pneumonia using CXR images, this study integrates Resnet50 and VGG19 transfer learning models using ETL-CNN.

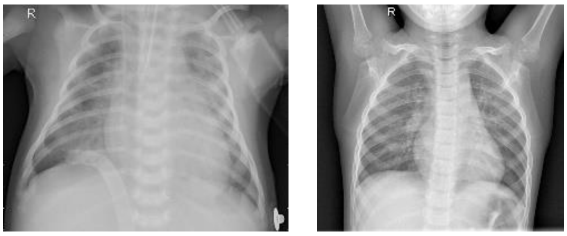
This research contributes to the application of CNN transfer learning ensemble, specifically the combination of Resnet50 and VGG19, for the classification of pediatric pneumonia. This study aims to develop an image classification model for the early detection of childhood pneumonia based on CXR images using a novel combination of the Resnet50-VGG19 method. Furthermore, this investigation enhances the investigation of the suggested model with VGG19-Xception, Resnet50, VGG19, and Xception in order to identify the model with the highest performance in detecting pediatric pneumonia.

2. MATERIAL AND METHODS

The classification of pediatric pneumonia based on CXR images employs deep learning with the widely used ensemble transfer learning CNN model. The study method includes four main steps: data preparation, modeling data, hyperparameter tuning, and model evaluation. The evaluation approach employs a confusion matrix to compute metrics like as accuracy, precision, recall, and F1-measure.

2.1. Dataset

The study utilized the pediatric CXR pneumonia dataset, which consists of CXR images of children between the ages of 1 and 5 years who had pneumonia which consisted of an overall total of 5856 CXR images. The dataset is depicted in Figure 1 which consists of Figure 1(a) pneumonia CXR and Figure 1(b) normal CXR [25]. Table 1 illustrates the distribution of the training and testing data in the dataset. The data is partitioned in an 8:2 ratio, with 80% of the data allocated for training and the remaining 20% for testing.



(a) (b)

Figure 1. Illustration of pneumonia and normal CXR images; (a) pneumonia CXR and (b) normal CXR

Table 1. The distribution of dataset

Dataset/class	Pneumonia	Normal	Total
Train	3883	1349	5232
Test	390	234	624
Total	4273	1583	5856

2.2. Data pre-processing

After data collection, data preparation is the next stage. In deep learning modelling, data preparation is used to prepare data for processing. Data enhancement, image rescaling, and image resizing are included in data preprocessing. Within the dataset, the image size can be expanded to 224 by 224 pixels. The pixel values are typically divided by 255 when rescaling an image. Data preparation using the ImageDataGenerator class from the Keras library requires data enhancement. By employing a validation split ratio of 0.20, the dataset is partitioned into distinct validation and training sets.

2.3. Data modeling

This investigation employs ETL-CNN, which implements Resnet50-VGG19, VGG19-Xception, Resnet50, VGG19, and Xception. The process of building the model is executed through the utilization of Jupyter Notebook, Python 3.10, an Intel Core i7 processor, 16 gigabytes of RAM running at a frequency of 3600 MHz, and an Nvidia Cuda GPU. Moreover, within this research, the selection of the model was performed by opting for ensemble transfer learning models, specifically Resnet50-VGG19 and VGG19-Xception. These models were juxtaposed with the transfer learning models Resnet50, VGG19, and Xception. This comparative analysis of models was conducted to ascertain the optimal performance outcomes. Figure 2 depicts the image of the network architecture utilized in this investigation.

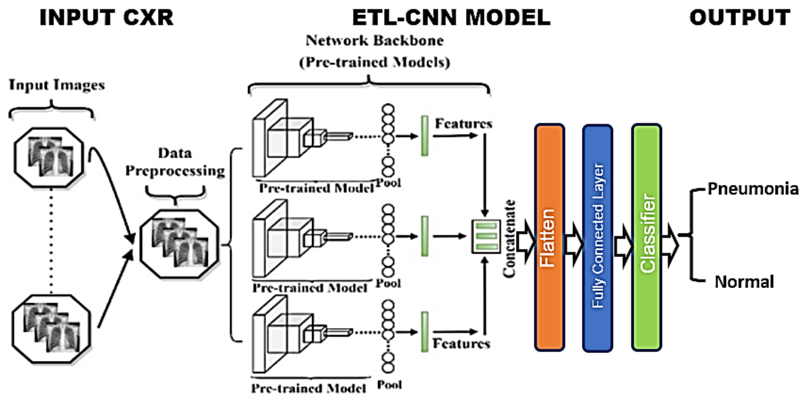


Figure 2. Network architecture applied in this study

The CNN transfer learning models utilized in this study have been pre-trained using the ImageNet dataset. The pre-trained models, obtained from the Keras library, consist of convolutional layers specifically designed to extract features from images. The network's input dimensions are defined as (224, 224, 3). To convert the 2D feature matrix into a single vector, a flatten layer is added after the convolutional layer. In addition, the model includes a fully connected layer (FCL) that utilizes a hyperbolic tangent (tanh) activation function and consists of 128 neurons. Finally, in order to provide image classification results, a softmax activation layer is appended.

The Resnet50-VGG19 architecture leverages the collective output derived from two distinct models, specifically Resnet50 and VGG19. The Resnet50-VGG19 model applies a transfer learning ensemble technique referred to as "Stacking." In this stacking approach, the algorithm takes the outcomes from the sub-models as input and endeavors to comprehend the optimal amalgamation of these input predictions to enhance the overall predictive output. Stacking integrates a parallel transfer learning model in a manner that enhances its capacity to generate more accurate forecasts in subsequent instances.

2.4. Hyperparameter tuning

Hyperparameter tuning is employed to ascertain the most advantageous configuration for the experimental conditions. The parameters employed within this investigation encompass the number of epochs, the loss function, the optimizer, the batch size, and the model activation. The categorical cross-entropy serves as the chosen loss function in this study. Concurrently, the selected optimizer is stochastic gradient descent (SGD). The batch size applied is set at 16, and the training process occurs over 10 epochs. Furthermore, the hyperbolic tangent (tanh) is utilized as the model activation function.

3. RESULTS AND DISCUSSION

This study employs four distinct classification models are employed: Resnet50-VGG19, VGG19-Xception, Resnet50, VGG19, and Xception. Figure 3 presents a visual position of the accuracy outcomes derived from the models utilized within this investigation. The hybrid Resnet50-VGG19 model exhibits the most elevated accuracy performance, achieving a noteworthy accuracy rate of 99.15%. Subsequently, the Resnet50 model secures the second-highest accuracy score at 98.21%. The VGG19 and VGG19-Xception models follow suit, presenting accuracy values of 97.86% and 97.44% respectively. Lastly, the Xception model garners an accuracy rate of 97.01% in each data scenario.

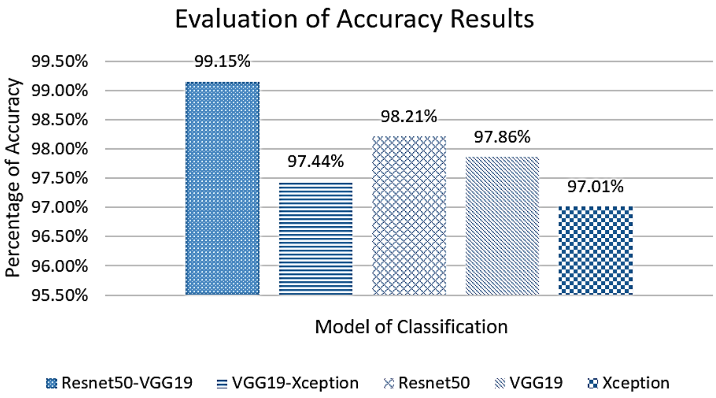


Figure 3. Comparison of accuracy results

Precision and recall are also incorporated into the evaluation process within this research. The assessment aims to gauge the effectiveness of with regard to the classification approach of Pediatric pneumonia images. Table 2 presents a comparative analysis of precision and recall values. The Resnet50-VGG19 model displays comparatively elevated precision and recall metrics when contrasted with the other models. Specifically, the precision and recall values for Resnet50-VGG19 stand at 99.18% and 99.65%, respectively. Following this, the subsequent model with the most favorable precision and recall values is VGG19-Xception, recording precision and recall rates of 98.93% and 97.55%. The subsequent models showcasing superior precision and recall values, in sequence, are Resnet50, VGG19, and Xception.

Table 2. The comparison of precision and recall values

	Precision (%)	Recall (%)
Resnet50-VGG19	99.18	99.65
VGG19-Xception	98.93	97.55
Resnet50	97.68	97.77
VGG19	97.34	97.24
Xception	95.85	96.65

The Resnet50-VGG19 model emerged as the top-performing model when compared to its counterparts. This superiority can be attributed to the architectural fusion of the Resnet50 and VGG19 models. The Resnet50 component employs residual blocks, which enable the network to achieve greater depth without encountering training challenges. This results in the extraction of more intricate features, ultimately leading to enhanced performance. On the other hand, the VGG19 model boasts convolutional blocks that effectively capture features as they traverse through the layers. This attribute proves valuable for analysis and interpretation, as VGG19 provides clear insights into the development of features with increasing network depth. By combining the attributes of both the VGG19 and Resnet50 models, the Resnet50-VGG19 model capitalizes on the strengths of each, consequently delivering superior performance in comparison to other models.

The Resnet50-VGG19 model has better performance compared to the VGG19-Xception hybrid in pediatric pneumonia. The VGG19 uses repetitive convolutions block with a small filter (3×3) and does not have a skip connection, while the Xception has a deeper convolution block with separable convolution that allows for more powerful feature learning. Resnet50-VGG19 has special features in the form of skip connections or shortcut connections that help solve the problem of vanishing gradients, which can help in model training for classification tasks. So, the Resnet50-VGG19 model is superior to the VGG19-Xception model because it can solve the problem of vanishing gradients and enable more efficient learning.

The Xception model has the lowest performance compared to other models in CXR imaging classification in pediatric pneumonia. Xception has a higher level of complexity than ResNet50 and VGG19 due to the use of deep separable convolution. This can make models more difficult to train with relatively small or less diverse datasets. In some cases, excessive complexity can lead to overfitting, especially if the amount of training data is limited. Additionally, Xception may have a larger number of parameters than ResNet50 or VGG19, depending on the configuration used. A larger amount of parameter can result in models being more prone to overfitting, especially if there is not enough training data. Xception has specific hyperparameters that need to be adjusted well, such as kernel size, network depth, and drop-out rate. Failure to adjust these hyperparameters correctly can affect the model performance.

The performance outcomes are enhanced by the examination of model performance in this study as opposed to those of prior research [26]. Prior research produced an ensemble transfer learning CNN model with the following accuracy, precision, and recall percentages: 98.3%, 99.29%, and 98.36%, respectively. After conducting this investigation, it has been determined that the Resnet50-VGG19 model exhibits the highest level of performance. Recall, precision, and accuracy are generated by the Resnet50-VGG19 model at 99.15%, 99.18%, and 99.65%, respectively. Consequently, this investigation presents an enhanced performance of paediatric pneumonia detection utilising CXR Images.

4. CONCLUSION

This research achieved successful classification of pediatric pneumonia based on CXR images through the application of ensemble transfer learning CNN, specifically the Resnet50-VGG19 model. These models were systematically contrasted with the performance of VGG19-Xception, Resnet50, VGG19, and Xception to identify the most proficient model. The study's objective was to classify CXR images into two categories: pneumonia and normal. Notably, the Resnet50-VGG19 model exhibited the highest accuracy, recording an accuracy rate of 99.15%. Following closely, the Resnet50 model secured the second-best accuracy. Subsequently, the accuracy values for VGG19, VGG19-Xception, and Xception models were documented. In addition to its accuracy prowess, the Resnet50-VGG19 model also demonstrated comparatively elevated precision and recall metrics in comparison to the other models.

Future research has the opportunity to explore alternative transfer learning models for constructing ensemble transfer learning, such as InceptionV3 or AlexNet, in order to put in row their performance against the ensemble transfer learning models examined in this study. Moreover, future research can entail the integration of different models with distinct deep learning architectures, such as vision transformer, bidirectional long short-term memory (BiLSTM), or LSTM. This strategic combination aims to further enhance the system's capability to classify pediatric pneumonia based on CXR images, potentially leading to improved performance outcomes.

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