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Pneumonia Classification Based on Lung CT Scans Using Vgg-19

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Abstract: This research harnesses technology for critical health applications, specifically, pneumonia detection through medical imaging. X-ray photography allows radiologists to visualize the patient's health state, including the detection of lung infections signifying pneumonia. The study's centerpiece is the application of the VGG-19 model in classifying lung CT scan images, helping discern normal from pneumonia-indicative conditions. A comprehensive preprocessing procedure is employed, entailing pixel rescaling and data augmentation techniques. To address data imbalance, a critical issue in machine learning, we incorporate the Synthetic Minority Over-sampling Technique (SMOTE). The developed VGG-19 model demonstrates impressive performance, achieving a 94.6% accuracy rate in classifying lung CT scans. This finding underscores the potential of the VGG-19 model as a reliable tool for pneumonia detection based on lung CT scans. Such a tool could revolutionize the field, providing an efficient and accurate method for early pneumonia diagnosis, thereby allowing for timely treatment.

Keywords: Pneumonia Detection; CT Scan Classification; VGG-19 Model; Deep SMOTE; Data Augmentation.

INTRODUCTION

The crucial role of medical imaging lies in its ability to classify or identify diseases. One prevalent method is through X-ray imaging, a technique employed by radiologists to observe the patient's body condition. Additionally, the advantages of X-ray photography include its ease of use and high economic value. Lung area infections caused by viruses, bacteria, fungi, or other parasites are characterized by a grayish-white area. This area can alert doctors to identify potential diseases a patient may be suffering from, such as pneumonia (Tej Bahadur Chandra, 2020). Pneumonia is an infection that inflames the air sacs in one or both lungs, caused by fungi, bacteria, and viruses. In addition, the lung alveoli, small balloon-like sacs at the bottom of the bronchioles, are greatly affected by this lung infection. (Muhammad et al., 2021a). With the help of technology, artificial intelligence (AI) and machine learning classifiers (MLCs) are capable to diagnose pneumonia from lung CT scans, drawing from large-scale electronic health record data and demonstrating comparable accuracy to experienced pediatricians (Liang et al., 2019).

According to a study conducted (Maysanjaya, 2020) the CNN method can be used to classify pneumonia in lung X-ray images, with an accuracy of 89.58%. This result is higher compared to similar studies using deep learning, contributing to the advancement of science, particularly for classifying pneumonia in lung X-ray images. Conversely, the research (Mahin et al., 2021) has classified COVID-19 and pneumonia using deep transfer learning. Different trained artificial neural network (CNN) models were used to extract deeper features. Based on these findings, deep transfer learning can detect COVID-19 and pneumonia from CXR images with models like MobileNetV2 achieving 98% accuracy,

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InceptionV3 achieving 96.92% accuracy, EffNetthreshold with 94.95% accuracy, and VGG19 achieving 92.82% accuracy. MobileNetV2 has the best accuracy among all these models.

VGG is a widely used CNN model proposed by Karen Simonyan and Andrew Zisserman. This model is a stack of convolutional layers, followed by three fully connected (FC) layers. Specifically, the first two layers each have 4096 neurons, and the third layer performs CIFAR-10 and MNIST classification. The last layer is the softmax layer (Zhou et al., 2021). (Illahi et al., 2022) introduced a scheme where four different pre-trained models were used. The dataset contained 115 Covid-19 samples, 322 pneumonia cases, and 60,361 healthy case samples. Among the models, VGG16 and VGG19 performed best. VGG19 achieved 81% accuracy for classifying Covid-19 versus pneumonia. The VGG-19 architecture has 19 deep layers. VGG-19 can be utilized to extract features from an image to classify whether an individual has pneumonia or not.

LITERATURE REVIEW

Pneumonia Classification, as the term suggests, aims to classify the presence of pneumonia in patients. The process of prediction using the VGG-19 (Visual Geometry Group) algorithm can be elucidated as follows, based on the flowchart provided by Muhammad et al., 2021b: (1). Inputting training data in the form of lung CT scan data which includes patients with pneumonia and those without it. (2). The VGG-19 algorithm will perform feature extraction and produce a trained VGG-19 model for pneumonia prediction. (3). Inputting testing image data into the already trained Softmax classification model. (4). The VGG-19 model will generate an output prediction whether the CT scan is normal or indicative of pneumonia (Muhammad et al., 2021b).

VGG-19 (Visual Geometry Group)

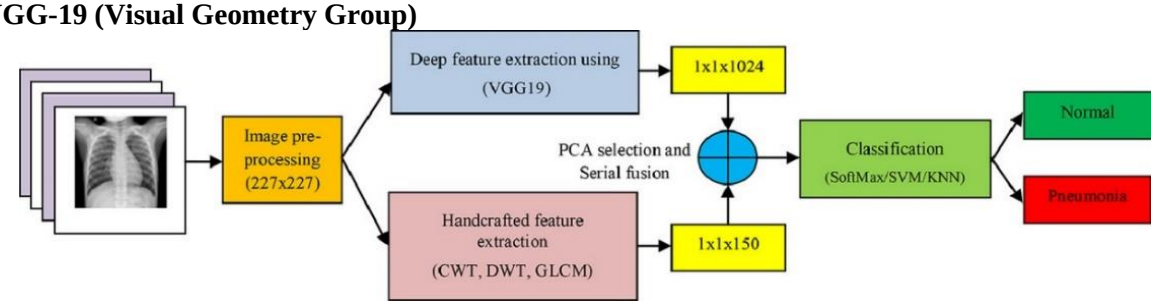

Fig 1. Illustration of Pneumonia Binary Classification with VGG-19

VGG-19 has 16 convolutional layers grouped into 5 blocks. After each block, there is a Maxpool layer that reduces the size of the input image by 2 and also doubles the number of convolutional layer filters (Lee et al., 2020). The dimensions of the last three dense layers in block 6 are each 4096, 4096, and 1000. VGG classifies the input image into 1000 different categories (Khattar & Quadri, 2022).

Contribution

This research paper presents a unique approach in the field of pneumonia detection by leveraging CT scan datasets. It integrates and expands upon methods and models from various prior studies. For example, Ali's work (Ali, 2023) utilized VGG-19 on X-ray datasets, achieving an impressive accuracy of 94.88%. Setiawan's research (Setiawan, 2020) also utilized the VGG architecture but compared it to other Convolutional Neural Networks (CNN) for image classification. Chandra (Zhou et al., 2021) proposed an adaptation of VGG19 that employed an Ensemble Feature Scheme (EFS) combining both handcrafted features and Deep-Features (DF) obtained through Transfer-Learning (TL) practices. Perdananto's study (Perdananto, 2019) used CNNs for pneumonia prediction based on X-ray images, though its primary focus was web application deployment. Finally, the research of Saputro and Santoso (Saputro & Santoso, 2023) applied CNNs to predict pneumonia using X-ray images, but did not detail the architecture of each layer. By synthesizing these varied methodologies and approaches, this paper introduces an advanced method for pneumonia classification using VGG-19 based on lung CT scans, aiming to provide an accurate prediction model while also explaining the details of the preprocessing and hyperparameter that was not described by the previous studies.

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METHOD

The methodology section of this study outlines the procedures and techniques employed to achieve our research objectives. Our principal goal is to develop a machine learning model, specifically using the VGG-19 architecture, to accurately predict pneumonia from chest X-ray images. The methodologies detailed in this section involve several stages, including data collection, data preprocessing, model training and validation, and finally, model testing and evaluation. Each stage is crucial in ensuring that the model is effective and reliable in its predictions.

The pipeline of this research is as follows:

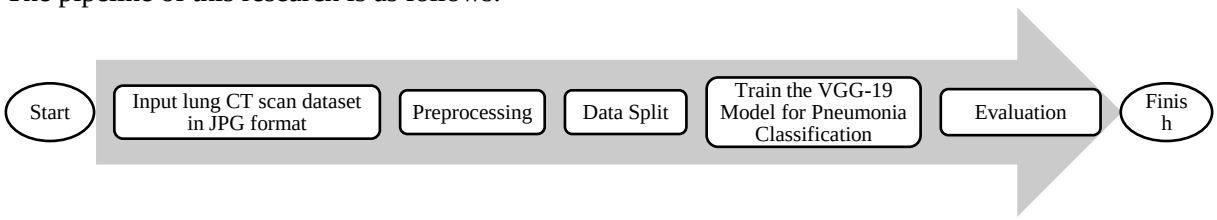

Fig 2. Research Pipeline

The stages as displayed in Fig. 3, are as follows:

1. Input lung CT scan dataset in JPG format.
   The dataset consists of 5216 images which have been separated into Normal and Pneumonia data(https://data.mendeley.com/datasets/rscbjbr9sj/2). The Dataset to be used in this research are the pneumonia dataset from Kermany et al. The sample of the images can be seen in the following figure (Agrawal et al., 2022).

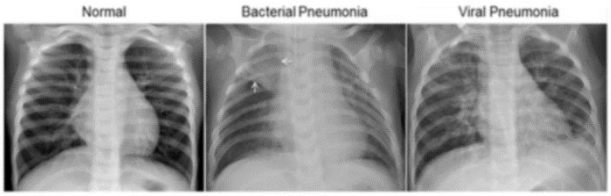

Fig 3. Example Illustration of Normal Lung X-ray Photo and those with Pneumonia

2. Preprocessing
   The preprocessing step is performed to enhance the performance of the pneumonia classification model based on lung CT scans using the VGG-19 architecture. Initially, the image size is adjusted to 224x224 px. Then, the Data Augmentation method provides variation and augmentation to the image data to train the model with better variations, improve model generalization, and reduce the risk of overfitting. Below is the summary of the preprocessing process (Oyelade & Ezugwu, 2021).

Table 1. Preprocessing Steps

Preprocessing	Value	Explanation
Target Size	(224,224,3)	Target size of the image to be changed. The image will be changed to have a width of 224 pixels, a height of 224 pixels, and 3 color channels.
Rescale	1./255	The rescale process is done to change the range of pixel values of the image to a range between 0 and 1. This process helps in reducing dimensions and accelerating the model training process.
Shear Range	10	Shear range refers to the maximum angle at which the image can be tilted. Using a value of 10 means the image can be tilted at a maximum angle of 10 degrees.

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Zoom Range	0.3	Zoom range controls how far the image can be enlarged or reduced. In this case, the image can be enlarged or reduced by up to 30% of its original size.
Horizontal Flip	True	Horizontal flip refers to the decision to flip the image horizontally. In this case, the image can be flipped horizontally to train the model with better variations.
Vertical Flip	True	Vertical flip refers to the decision to flip the image vertically. In this case, the image can be flipped vertically to train the model with better variations.
Brightness Range	[0.5, 2.0]	Brightness range controls how far the pixel values can be changed to adjust the brightness of the image. In this case, the brightness range is between 0.5 and 2.0.
Width Shift Range	0.2	Width shift range controls the random horizontal shift from the original image. Using a value of 0.2 means the image can be shifted horizontally by up to 20% of its original width.
Rotation Range	20	Rotation range controls the maximum angle at which the image can be randomly rotated. Using a value of 20 means the image can be rotated randomly by up to 20 degrees.
Fill Mode	nearest	Fill mode refers to how empty pixels will be filled after the image transformation is performed. "Nearest" means empty pixels will be filled with the nearest pixel from the original image.
Validation Split	0.2	Validation split refers to the division of data into training and validation parts. In this case, 20% of the data is used for model validation during the training process.
Labeling	Normal/Pneumonia	Images in the folder containing normal images will be labeled "normal", while images in the folder containing pneumonia images will be labeled "pneumonia".
Smote	random_state = 11	Preprocessing using the SMOTE (Synthetic Minority Over-sampling Technique) method is carried out in this study to overcome the imbalance in the number of samples between normal and pneumonia classes.

3. Data Split
   The split ratio of the data in this study is 80% for training, 10% for validation, and 10% for testing.
4. Train the VGG-19 Model for Pneumonia Classification
   Two training scenarios are used, namely model training with a minimum learning rate and a maximum learning rate using the slice (scale) method (Bayu, 2022). The model architecture tested in both these scenarios is VGG-19. To train the pneumonia classification model based on lung CT scans using the VGG-19 architecture in this study, the following parameters are applied to the model (Abu et al., 2022):

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Parameter	Value	Explanation
Pre-trained Weights	'imagenet'	Using pre-trained weights from the ImageNet dataset to initialize the VGG-19 model.
Include Top	False	Ignoring the fully-connected (top) layers in the original VGG-19 model.
Input Shape	(224, 224, 3)	Expected input image shape by the model.
Trainable Layers	False	Setting all layers in the VGG-19 model to be untrainable so they can be used to classify Pneumonia.
Dense Layer 1	Units: 128, Activation: 'relu'	The first Dense layer with 128 neuron units and ReLU activation function.
Output Layer	Units: 1, Activation: 'sigmoid'	The output layer with 1 neuron unit and sigmoid activation function, which produces binary predictions.
Loss Function	Binary Crossentropy	Using the Binary Crossentropy loss function for binary classification problems.
Optimizer	Adam	Using the Adam optimizer to train the model.
Metrics	Accuracy	Using the accuracy metric to evaluate model performance.
Batch Size	32	The number of image samples processed in each training iteration.
Epochs	10	The number of training iterations to be performed.
Steps per Epoch	100	The number of steps (batches) to be run at each epoch or training iteration.

5. Evaluation of the VGG-19 Model
   The final process is to evaluate the model's performance by calculating the model's accuracy by knowing the results of True Negative (TN), True Positive (TP), False Negative (FN), and False Positive (FP) predictions. Then the calculation of accuracy (Nugroho, 2019) can be done as follows (Xiao et al., 2020):

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (1)$$

Dataset

The Dataset to be used in this research are the pneumonia dataset from Kermany et al. The sample of the images can be seen in the following figure (Agrawal et al., 2022).

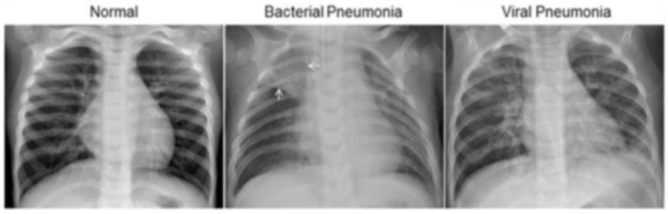

Fig 4. Example Illustration of Normal Lung X-ray Photo and those with Pneumonia

All chest X-ray imaging was conducted as part of the patient's routine clinical care with the following specifications:

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Table 2. Dataset Description

Description	Value
Number of data (N)	5216 data
Independent Variables (x)	Personal and medical data of patients (2 variables)
Dependent Variables (y)	Normal or Pneumonia
Number of negative data (ny=0)	1341 (Normal)

RESULT

In this research, the result section provides a detailed account of the performance of a VGG-19 machine learning model trained to classify pneumonia over 10 training epochs, highlighting its progression in learning from the training data and its ability to generalize this learning to unseen validation data, as evidenced by the rising accuracy values. The imbalanced (before preprocessing) and balanced (after preprocessing) data can be observed from the Figure below.

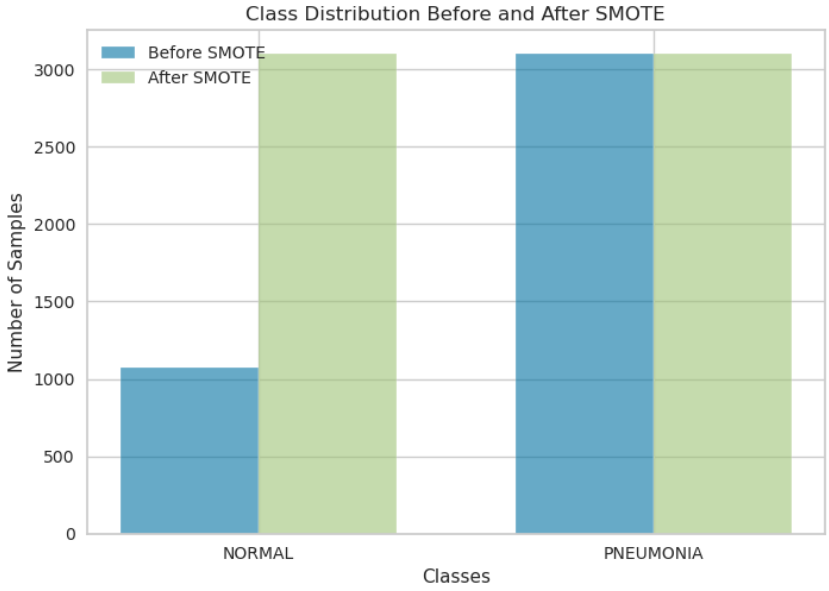

Fig 5. Before and After SMOTE

After preprocessing the input data and training the model, the evaluation stage is a critical step as it provides an opportunity to assess the model's effectiveness. This evaluation involves checking the model's accuracy during both the training and testing processes. In this case, we used the VGG-19 model to classify datasets, and the performance comparison between the training and validation datasets offers valuable insights. The model underwent training in 10 trials and demonstrated progressive improvement, suggesting it has effectively learned to better classify pneumonia.

The training results provide a detailed view of the machine learning model's performance across these 10 "epochs" or full passes through the dataset. The model's success is measured not only by its ability to absorb knowledge from the training data but also its ability to generalize that knowledge to new, unseen data—namely the validation data. As the epochs advanced, the model's accuracy on the training data saw a consistent upward trend, ultimately reaching a high accuracy above 85% by the final epoch. This consistent improvement underscores the model's success in learning from the training data.

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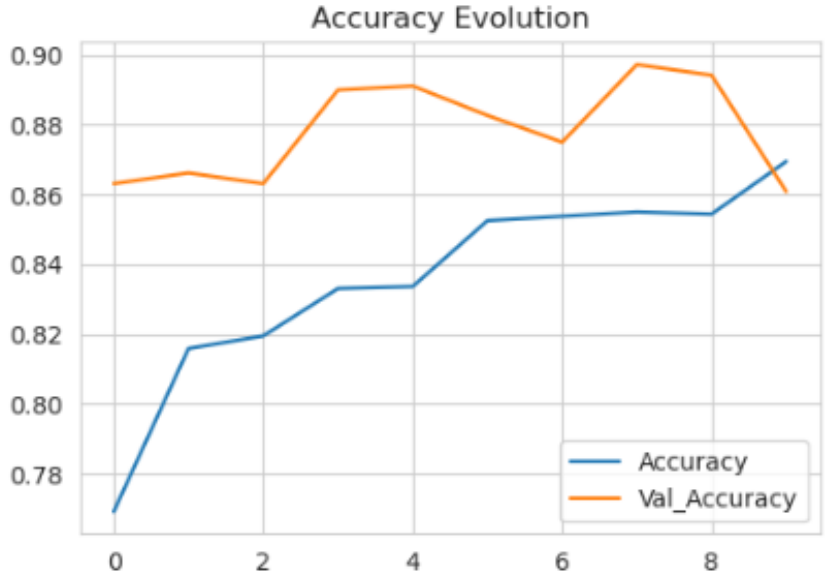

Fig 6. Accuracy Evolution of The Training Process

Finally, the Confusion Matrix table can be used to see how much accuracy the pneumonia classification performed by the VGG-19 model on the Test Dataset used to test the model.

Table 3. Confusion Matrix of Test Result

	Predicted Normal	**Predicted Pneumonia**
Actual Normal	119	15
Actual Pneumonia	13	375

Using the confusion matrix, we can calculate various evaluation metrics, including accuracy. Accuracy illustrates the extent to which the model can correctly predict the existing classes. Accuracy is calculated by dividing the number of correct predictions (Predicted Normal and Predicted Pneumonia that match Actual Normal and Actual Pneumonia) by the total number of samples.

Finally, accuracy can be calculated as follows:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} = \frac{(119+375)}{(119+15+13+375)} = 94.6\% \quad (2)$$

DISCUSSIONS

In this study, the accuracy of classifying pneumonia based on lung CT scans using the VGG-19 model was evaluated using the confusion matrix outlined in Table 3.3, which was used to illustrate the model's prediction results in distinguishing between normal images and images indicating the presence of pneumonia. The testing result table contains four categories to observe: Predicted Normal, Predicted Pneumonia, Actual Normal, and Actual Pneumonia. In this context, "Predicted Normal" refers to the number of samples predicted as normal by the model, while "Predicted Pneumonia" refers to the number of samples predicted as having pneumonia. On the other hand, "Actual Normal" refers to the actual number of normal samples based on the true labels, while "Actual Pneumonia" refers to the actual number of samples indicating the presence of pneumonia.

Based on the table, the results are as follows: (1). The number of samples predicted as normal and truly are normal (True Negatives): 119. (2). The number of samples predicted as having pneumonia while actually normal (False Positives): 15. (3). The number of samples predicted as normal while actually having pneumonia (False Negatives): 13. (4). The number of samples predicted as having pneumonia and truly have pneumonia (True Positives): 375

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CONCLUSION

In this study, pneumonia was classified based on lung CT scans using the VGG-19 model, with the application of preprocessing and the SMOTE method. Evaluation was carried out based on the accuracy calculated from the confusion matrix of the testing results. Based on the evaluation results, an accuracy of 94.6% was obtained for the pneumonia classification model after applying preprocessing with SMOTE. This result indicates that the model has good capabilities in classifying lung CT scan images as normal or indicating the presence of pneumonia. The preprocessing performed includes pixel rescaling, data augmentation, and the separation of data into train, validation, and test sets. The SMOTE method was also applied to address the imbalance in the number of samples between the normal and pneumonia classes. This helped enhance the model's performance by strengthening the representation and diversity of data in the minority class. In the context of using this model, the high evaluation results demonstrate the model's potential application in supporting the diagnosis of pneumonia based on lung CT scans.

Although this study has successfully designed a VGG-19 model that can classify pneumonia, there are a few suggestions that can be made for further improvements in this research: (1). The development of the study by investigating other models besides VGG-19 to further investigate reliable models for performing Pneumonia classification. (2). The development of a larger and more diverse dataset is necessary to obtain a more comprehensive picture of the performance of the VGG-19 model in classifying Pneumonia with lung CT scans.

ACKNOWLEDGMENT

This study would not have been possible without the remarkable work of Kermany et al. Their diligent efforts in documenting and organizing a significant dataset of lung CT scans, labeled as normal and pneumonia, provided the essential basis for this research. Their substantial contribution to the field of medical imaging and machine learning is deeply acknowledged and appreciated.

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