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INTEGRATED HYBRID MODEL FOR LUNG DISEASE DETECTION THROUGH DEEP LEARNING

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Abstract. *The burden of lung diseases on world health is substantial, underscoring the vital necessity of timely detection. The VGG16 architecture with additional convolutional layers is used in this study to provide a hybrid method to lung disease classification. It incorporates the Synthetic Minority Over-sampling Technique (SMOTE) to improve model performance in response to the problem of imbalanced class instances. The subset of the NIH Chest X-ray dataset is used to train and assess the model. The designed model classifies the images into 8 different classes of lung diseases. They are Emphysema, Cardiomegaly, Atelectasis, Edema, Consolidation, Mass, Effusion, Pneumothorax. The proposed model delivered accuracy of 96.42% which demonstrates the efficacy in precise classification of lung diseases. The Graphical User Interface (GUI) is integrated for better interaction between the patient and the model. Through improved diagnostic capabilities, this suggested method not only promotes technological innovation but also shows promise for enhancing patient care and health care outcomes.*

Keywords: lung disease, deep learning, VGG16, GUI

ZINTEGROWANY MODEL HYBRYDOWY DO WYKRYWANIA CHORÓB PŁUC Z WYKORZYSTANIEM GŁĘBOKIEGO UCZENIA SIĘ

Streszczenie. *Obciążenie chorobami płuc dla światowego stanu zdrowia jest znaczne, co podkreśla istotną konieczność ich szybkiego wykrywania. W pracy wykorzystano architekturę VGG16 z dodatkowymi warstwami konwolucyjnymi, aby stworzyć hybrydową metodę klasyfikacji chorób płuc. Obejmuje ona technikę generowanie próbek syntetycznych z klasy mniejszościoweji (SMOTE) w celu poprawy wydajności modelu w odpowiedzi na problem niezrównoważonych instancji klasowych. Podzbiór danych NIH Chest X-ray jest używany do trenowania i oceny modelu. Zaprojektowany model klasyfikuje obrazy do 8 różnych klas chorób płuc: rozedma płuc, kardiomegalia, niedodma, obrzęk, konsolidacja, masa, wysięk, odma opłucnowa. Zaproponowany model zapewnił dokładność na poziomie 96,42%, co świadczy o dużej skuteczności w precyzyjnej klasyfikacji chorób płuc. Dla lepszej interakcji między pacjentem a modelem zintegrowano graficzny interfejs użytkownika (GUI). Dzięki ulepszonym możliwościom diagnostycznym proponowana metoda nie tylko wspomaga innowacje technologiczne, ale także dobrze rokuje dla poprawy opieki nad pacjentem i efektów opieki zdrowotnej.*

Słowa kluczowe: choroby płuc, uczenie głębokie, VGG16, GUI

Introduction

Lung diseases are a major worldwide health concern that require prompt and precise diagnosis in order to enable successful therapies and enhance patient outcomes [2]. The unique hybrid approach for lung disease diagnosis described in this paper makes use of deep learning methods, specifically Convolutional Neural Networks (CNNs). Our methodology is based on the use of two different CNN architectures: VGG16 and a specially-made CNN with convolutional layers [7]. Our goal is to improve the robustness and correctness of lung disease categorization from medical pictures, especially chest X-rays, by leveraging the characteristics of these architectures.

The uneven distribution of class instances within the dataset is one of the main obstacles to creating efficient classification models for lung illnesses. We incorporate the Synthetic Minority Over-sampling Technique (SMOTE), a popular technique for balancing class distributions, to overcome this problem and enhance the overall performance of our models. We study a variety of lung illnesses, such as Emphysema, Cardiomegaly, Atelectasis, Edema, Consolidation, Mass, Effusion, and Pneumothorax, using a limited portion of the NIH Chest X-ray dataset [5]. These illnesses are considered clinically serious problems that need to be accurately and promptly diagnosed in order to receive the proper medical care.

We aim to revolutionize automated lung disease diagnosis and medical image classification through the advancement of robust deep learning frameworks. By effectively addressing the challenges of imbalanced class instances and leveraging state-of-the-art CNN and VGG architectures, we strive to provide medical practitioners with a powerful diagnostic tool that can significantly enhance patient outcomes and healthcare delivery worldwide. Through our innovative approach, we are dedicated to combating the global burden of lung diseases and advancing the field of deep learning-based medical picture analysis for the betterment of patient lives.

1. Literature review

Ahmed et al. [1] have recently developed a multiclass convolutional neural network to detect tuberculosis and pneumonia. By utilizing transfer learning methods from pre-trained architectures such as ResNet or VGG16, the model improves its ability to extract features. Furthermore, techniques for augmenting the dataset, including translation, scaling, and rotation, are investigated in order to enhance model generalization. The dataset that is used as input is Chest X-ray Dataset. The methodology generated an average accuracy of 96.48%, which was far superior to previous state-of-the-art methods. The model demonstrates high recall scores for individual diseases, while minimizing false negatives. Applying the model to photos from various datasets may limit the model's applicability.

In a recent study, Ibrokhimov et al. [6] introduced a model combining VGG19 and ResNet150 architectures for lung disease classification using the Covid-QU EX dataset. By integrating these architectures, the model aims to successfully depict intricate patterns within the dataset. The Covid-QU EX dataset, tailored for lung disease classification, provides a robust foundation for model training and evaluation. Leveraging deep learning techniques, the model strives to achieve high accuracy in classifying various lung diseases. The deep layers can automatically learn and represent complex patterns that helps to excel at feature extraction. The model is effective in handling diverse and previously unseen radiography images. Deploying such models in resource-constrained environments, such as on edge devices, may pose challenges.

Shamrat et al. [9] proposed a multiclass classification network utilizing MobileNetV2 architecture for analyzing Chest X-ray images. Leveraging the Chest X-ray dataset, the model aims to accurately classify various lung diseases. MobileNetV2's efficiency in feature extraction facilitates precise classification of multiple disease classes. The model's efficiency in handling complex image data contributes to accurate disease classification. This model doesn't need large annotated datasets as it can quickly adapt to recognize features by fine-tuning. Inconsistencies or biases in the dataset may impact the model's generalization to new cases.

A methodology was put forth by Farhan et al. [4] to detect various lung diseases using a novel hybrid model comprising 2D Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Random Forest algorithms. By integrating these diverse techniques, the model aims to leverage the strengths of each approach to improve disease detection accuracy. The Chest X-ray dataset serves as the foundation for training and evaluating the hybrid model, providing a comprehensive range of lung pathology images. High accuracy is obtained as multiple algorithms are combined in a hybrid model. Severity analysis of the disease is not addressed in the given study.

Sharma et al. [8] have proposed an architecture utilizing eight pre-trained models, including SVM, VGG, ResNet, among others, for analysis using the Cohen Covid19 dataset. Leveraging these pre-trained models enables the architecture to benefit from their learned representations and capabilities in feature extraction and classification tasks. The Cohen Covid19 dataset, tailored for COVID-19 detection, provides a comprehensive collection of chest X-ray images necessary for model training and evaluation. By incorporating multiple pre-trained models, the architecture aims to enhance its ability to accurately classify COVID-19 cases and differentiate them from other respiratory conditions.

A comprehensive study was undertaken by Bhandari et al. [3] in an effort to develop a convolutional neural network (CNN) employing deep learning techniques and explainable AI (XAI) to classify various lung diseases. Utilizing a publicly available dataset consisting of 7132 images, the CNN is trained to effectively identify patterns and features indicative of different lung pathologies. By integrating XAI methods, such as saliency maps or attention mechanisms, the model's decision-making process becomes interpretable, providing insights into which regions of the images contribute most to the classification. The XAI techniques provide insights into how the deep learning model draws its predictions, making the classification process more transparent. Overfitting is a problem with the suggested model, which causes it to perform extremely well on training data but poorly on fresh, untested data.

2. Proposed methodology

The methodology consisted of four sections: Dataset collection, Data Visualization, Data pre-processing, and Model Training. Figure 1 represents the proposed methodology for the lung disease detection through chest x-rays.

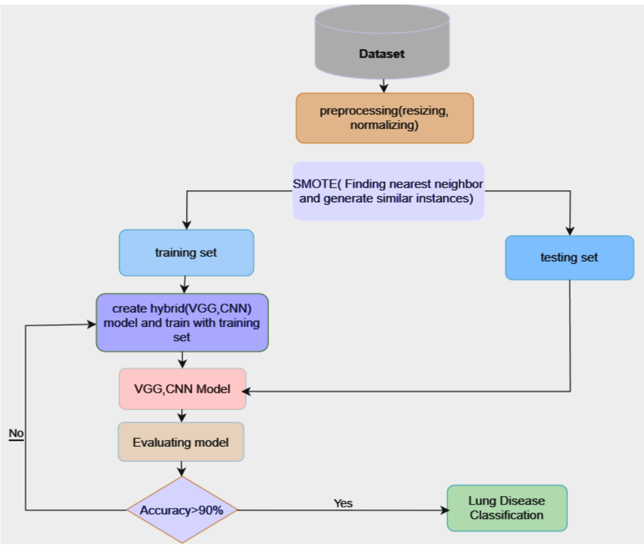

Fig. 1. Methodology for detecting lung disease in chest x-rays

2.1. Dataset collection

The dataset used for this proposed system was subset of NIH chest x-ray dataset that is obtained from Kaggle and consists of 15000 chest x-ray images [10]. Each image has a resolution of 1024 by 1024 pixels, providing a detailed view. To evaluate the system's performance, a subset of 5000 images was reserved for testing purposes, while 10,000 images were allocated for training the model. Using this dataset, machine learning models will be created with the intention of accurately categorizing x-rays into eight groups. In addition to supporting medical professionals in their decision-making process, this classification assignment is essential for improving the efficiency of early detection of lung diseases.

Fig. 2. Sample image of the chest x-ray dataset

2.2. Data visualization

The dataset that is used in this project is "Subset of NIH Chest x-ray Dataset". The dataset is first imported or loaded. The dataset consist of classification of chest x-rays into eight classes of lung diseases. In this module, different visualization techniques used to represent some relationship between attributes.

A pie chart is used to represent distribution of disease over gender. It is observed that the male are more effected with lung diseases compared to the female. It is represented using Fig. 3.

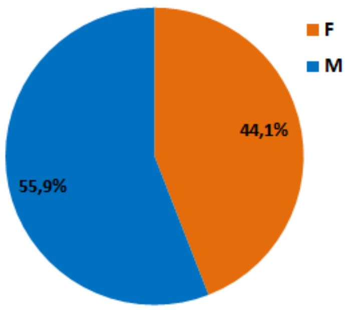

Fig. 3. Distribution of patients by Gender

A histogram is used to represent age group of patient who are mostly affected by lung diseases. From Fig. 4, it is observed that the patients of age group 40-60 are most affected.

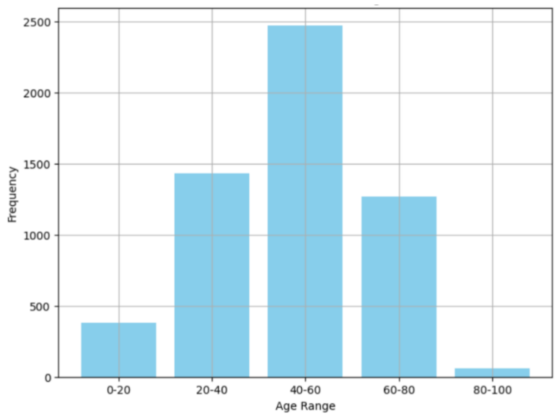

Fig. 4. Distribution of patient ages

2.3. Data preprocessing

For deep learning models, it is crucial to resize the photos to a uniform size since this makes sure that all of the images have the same dimensions and can be input into the model for both inference and training. In this instance, the original photos' 1024x1024 pixels dimensions are changed to a uniform 244x244 pixels size. Reducing the size of the photographs also lessens the memory and computational demands.

One method used to lessen the class imbalance is the SMOTE. For the minority class, SMOTE produces artificial samples. To accomplish this, it picks an instance of a minority class and finds in the feature space its closest neighbours. Figure 5 shows the distribution of classes both before and after the SMOTE method was applied.

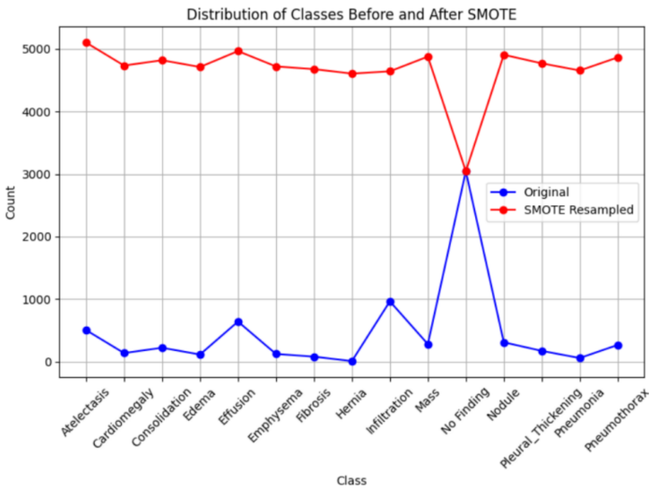

Fig. 5. Distribution of classes before and after applying SMOTE

2.4. Model training

After the preprocessing of the chest x-ray images, high level features are extracted to train the developed model. In this project, VGG16 is used which is variant of VGG model. The trained model is used to classify the skin lesion images into one of eight classes of disease. They are Emphysema, Cardiomegaly, Atelectasis, Edema, Consolidation, Mass, Effusion, Pneumothorax.

Figure 6 represent the architecture of the VGG16. With three fully connected layers and thirteen convolutional layers, the VGG16 is a 16-layer convolutional neural network (CNN). For detailed feature extraction, the convolutional layers use small receptive fields (3x3 filters) with a stride of 1, whereas the max-pooling layers use a 2x2 window with a stride of 2 for down sampling and computational complexity reduction. After every convolutional layer, rectified linear unit (ReLU) activation functions add non-linearity, and batch normalization is used to speed up and stabilize the training process. The final fully linked layers function as the prediction classifier. Because of its ease of use and efficiency, VGG16 is frequently employed for picture classification tasks. It has also found widespread use in computer vision research and real-world applications.

The model summary, as shown in Fig. 7, provides in-depth insights into the network's architecture, detailing the structure of each layer and the number of trainable parameters used. After constructing the model, the compilation phase involved specifying the optimizer, loss function, and evaluation metric. The Adam optimizer and binary cross-entropy loss are chosen to optimize and assess the model's performance.

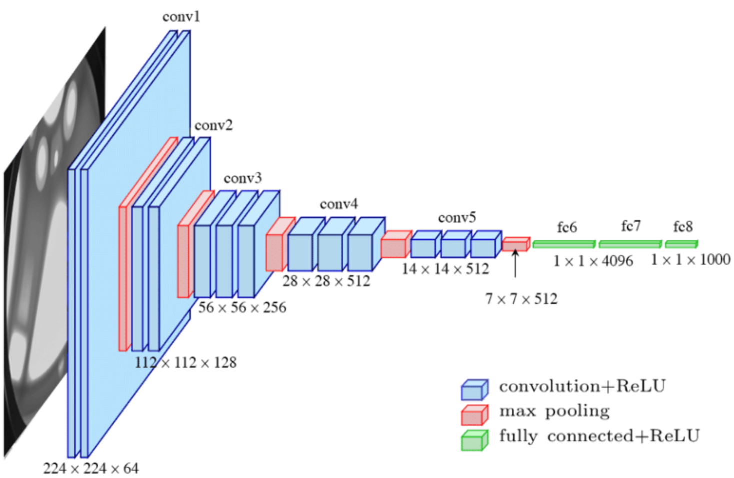

Fig. 6. Proposed VGG16 architecture

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten_2 (Flatten)         (None, 25088)             0

 dense_3 (Dense)             (None, 512)               12845568

 activation_2 (Activation)   (None, 512)               0

 batch_normalization_1 (Bat  (None, 512)               2048
 chNormalization)

 dropout_1 (Dropout)         (None, 512)               0

 dense_4 (Dense)             (None, 16)                8208

 activation_3 (Activation)   (None, 16)                0

=================================================================
Total params: 27570512 (105.17 MB)
Trainable params: 27569488 (105.17 MB)
Non-trainable params: 1024 (4.00 KB)
```

Fig. 7. Proposed model's summary

3. Results and analysis

A line plot that depicts the evolution of loss values over training epochs is used to visualize the training history, as seen in Fig. 8. The training loss and validation loss were plotted against the number of epochs on the x-axis in this plot. The training loss curve demonstrated how the model iteratively reduced its loss over the course of subsequent epochs as it optimized its parameters. At the same time, the validation loss curve showed how well the model performed on unknown validation data, providing information on its generalization skills. The training and validation loss curves did not significantly diverge, indicating that the model may be trained practically without experiencing major over fitting. This visualization made it easier to track the convergence and generalization of the model during training, which directed subsequent efforts to optimize and modify the model.

The process of creating the training history diagram for accuracy is shown in Fig. 9. Its goal, similar to the loss visualization, was to track the model's performance over the training and validation epochs. On the graph, the number of epochs was represented by the x-axis, while the training and validation accuracy was represented by the y-axis. Over the duration of training, the training accuracy curve showed a progressive climb, indicating the model's increasing ability to correctly classify samples from the training dataset. Similarly, by demonstrating the model's performance on unobserved validation data, the validation accuracy curve demonstrated the model's ability to generalize across subsequent epochs. It was simpler to discern how model convergence and generalization were evolving over time with this visualization.

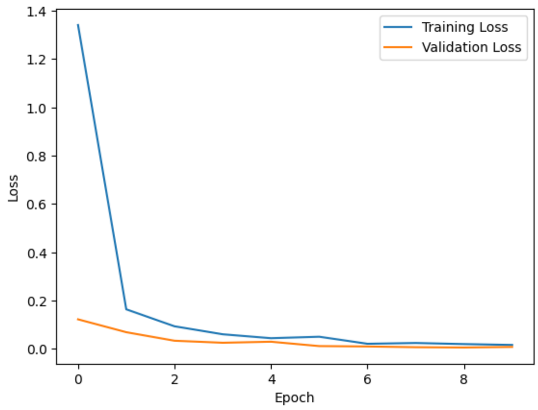

Fig. 8. Training and Validation loss plot of the model

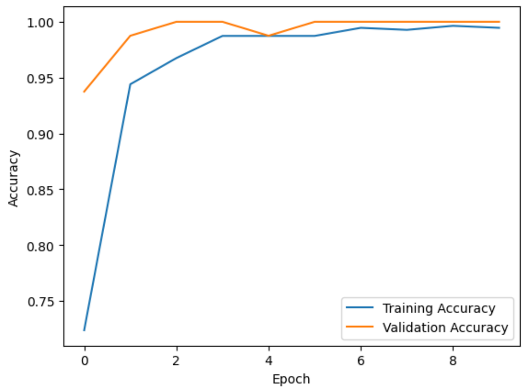

Fig. 9. Training and Validation accuracy plot of the model

Table 1 describes the model's accuracy, precision, recall, and F1-score values.

Table 1. Performance metrics of the modified VGG16 model

Model	Accuracy (%)	Precision	Recall	F1-score
VGG16 with additional CNN layers	96.42	1.00	0.98	0.99

We have created a GUI for interaction between the user and the model. In the GUI, the welcome page consist of the header as Lung Disease Classifier and there is button to select an image from the device. When the user click on the button, a tab is opened to select image from the device or system. Finally, when the image is selected, the model will predict the class label of the image. This output is represented by the Fig. 10 and 11.

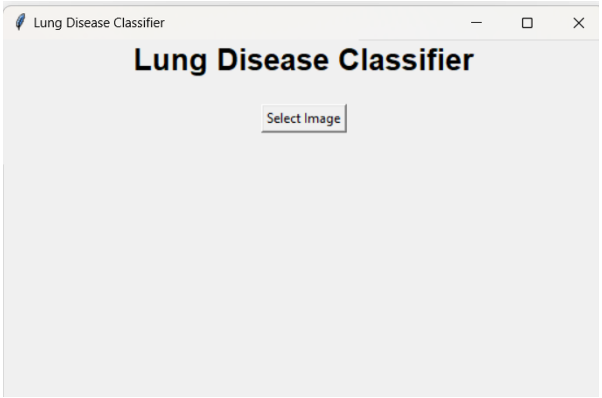

Fig. 10. Welcome page of the GUI

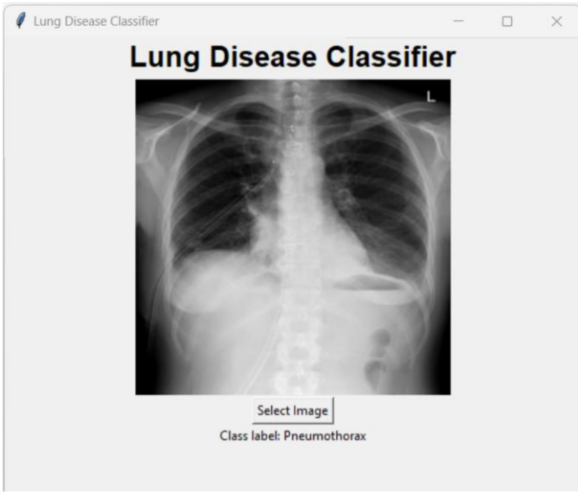

Fig. 11. Output of the GUI

4. Conclusion

In conclusion, this project presents a robust and effective hybrid approach to lung disease classification using Convolutional Neural Networks(CNNs). This developed CNN with five convolutional layers and VGG architecture have allowed us to make substantial progress towards automated diagnosis of lung diseases. By addressing imbalanced class instances, the Synthetic Minority Over-sampling Technique (SMOTE) has improved the accuracy and performance of the model. Furthermore, by focusing on crucial areas in X-ray pictures, the integration of Class Activation Mapping (CAM) enhances interpretability and boosts confidence in classification choices. The models showed consistent and positive results after being thoroughly trained and assessed on a variety of NIH Chest X-ray datasets.

The Graphical User Interface (GUI) is a prominent tool that enhances accessibility and usability by facilitating user interaction and enabling the seamless input of X-ray pictures for real-time classification. All things considered, the suggested architectures have enormous potential to transform automated lung disease diagnosis and medical picture classification, greatly advancing global health initiatives.

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