IMPROVING BRONCHITIS DIAGNOSIS IN PEDIATRICS: A STUDY OF DEEP LEARNING MODELS ON CHEST X-RAY IMAGES

[1]AYDA RANA OZLEM ERDAS, [2]CAGATAY BERKE ERDAS

[1]Department of Pediatrics, Ankara Education and Research Hospital, Ankara, Turkey
[2]Department of Computer Engineering, Başkent University, Ankara, Turkey,
E-mail: berdas@baskent.edu.tr

Abstract - Acute bronchitis is a prevalent respiratory condition in pediatrics, frequently resulting in hospitalizations and resource-intensive diagnostic procedures. The objective of this study is to develop a computer-aided diagnosis system that can automatically classify bronchitis in pediatric patients based on chest X-ray images, utilizing deep learning techniques. The dataset employed comprises pediatric chest X-ray images from the VinDr-CXR collection, encompassing 1016 cases of bronchitis and 1016 healthy controls. The performance of five deep learning architectures such as Xception, DenseNet-121, InceptionV4, EfficientNetV2B7, and ResNet-101, was evaluated in distinguishing bronchitis from control cases. Following rigorous training and testing procedures, including K-fold cross-validation, the classification performance of each model was evaluated based on accuracy, precision, F1 score, and Matthew's correlation coefficient. The InceptionV4 model demonstrated the highest accuracy (0.943) and overall performance among the tested models, closely followed by EfficientNetV2B7. The findings demonstrate that deep learning models, particularly InceptionV4, have the potential to enhance the diagnostic process for bronchitis by reducing the workload of physicians and minimizing the possibility of diagnostic errors. This computer-aided diagnosis approach has the capacity to improve pediatric healthcare by facilitating rapid and precise bronchitis diagnosis. Future work will concentrate on integrating interpretability features and validating the efficacy of the model across diverse datasets.

Keywords - Pediatric Bronchitis, Deep Learning, X-Ray Imaging, Computer-Aided Diagnosis

I. INTRODUCTION

Acute bronchitis is one of the most common diseases in pediatrics and is one of the most common reasons for hospitalization. This disease is among the most expensive pediatric diseases in Western countries [1]. Acute bronchitis is one of the frequently reported infection types in children. In 2001, in the routine consultation data analysis conducted by the Weekly Returns Service (WRS) in England and Wales, one or more cases of acute bronchitis were reported in 6.2% of children aged 0-14 years [2]. In addition, 15.5% were reported as acute respiratory tract infections. It is possible to categorize lower respiratory tract infections simply as bronchitis and pneumonia. Acute bronchitis is one of the most common infections in children under 5 years of age and one of the leading causes of hospitalization [3]. Acute bronchitis disease occurs with an inflammation developing in the tracheobronchial tree. With this inflammation, oedema develops in the airway mucosa, and bronchial secretion increases. Acute bronchitis cases have been reported in WRS for 35 years. Bronchi and bronchioles, which form the respiratory tracts in the lungs, are structures covered with protective mucosa. Bronchitis occurs due to inflammation in the mucosa covering the bronchi and bronchioles [4].

When these airways carrying air to our lungs become infected, they swell, and mucus forms in them. This mucus layer causes narrowing in the airways and makes breathing difficult. The patient who comes to the doctor with the symptom of bronchitis is first listened to the complaints and then a physical examination is performed. Preliminary diagnosis can be made by listening to the lungs during breathing. However, physicians may request sputum samples, chest X-rays, and pulmonary function tests to select better the definitive diagnosis and treatment method [5].

For physicians, the diagnostic process for common childhood illnesses such as acute bronchitis can be very tedious and error-prone due to frequent repeat patient presentations. In such cases, doctors need to perform a variety of tests for each patient, including physical examination, respiratory listening, sputum sampling, and imaging, which can be time-consuming. Chest X-rays, especially to detect narrowing and mucus accumulation in the lungs, constitute an important part of this process.

The rapid development of computer science and the combination of artificial intelligence algorithms with medical imaging have the potential to alleviate this tedious process. AI-enabled systems that can automatically analyse X-ray images can quickly and accurately detect signs of bronchitis, such as inflammation in the lungs and bronchial narrowing. Such technologies can alleviate the workload of doctors, while also contributing to the reduction of human errors in the diagnostic process.

These developments can improve the quality of healthcare by enabling frequent infections such as bronchitis, which require treatment, to be quickly assessed by automated analyses under the supervision of a physician. This study aims to design an artificial

intelligence based bronchial disease diagnosis system based on deep learning algorithms fed with X-ray images.

II. MATERIALS AND METHODS

2.1. General Framework

Analysing chest X-rays of a symptomatic child to determine whether the child has bronchitis or not can be considered a classification problem in the field of medical imaging. In this process, two-dimensional greyscale X-ray images obtained from children provide input data to a deep learning model that can detect the presence or absence of diseases such as bronchitis. Deep learning models are developed using training data; in this stage, the features of the model are learned with X-ray images of bronchitis and healthy individuals, and these features are optimized so that the model can make accurate predictions. In the training phase, the images are divided into training and test datasets. The model learns the patterns by repeatedly working on the training data set. After training, the accuracy and generalization ability of the model is measured by exposing it to test data that it has never seen before. The goal of the model is to accurately predict the labels (e.g. 'bronchitis' or 'healthy') of the images in the test dataset. In this process, parameter updates between layers, optimization processes to discriminate the features of the images and techniques to minimize the error rate of the model are applied. As a result, AI-based bronchitis diagnosis has the potential to reduce the workload of doctors and minimize human errors in the diagnosis process, while providing a significant improvement in the medical field. The diagram describing the overall process is shown in Figure 1 and presents the training, testing, and prediction phases of the model step by step.

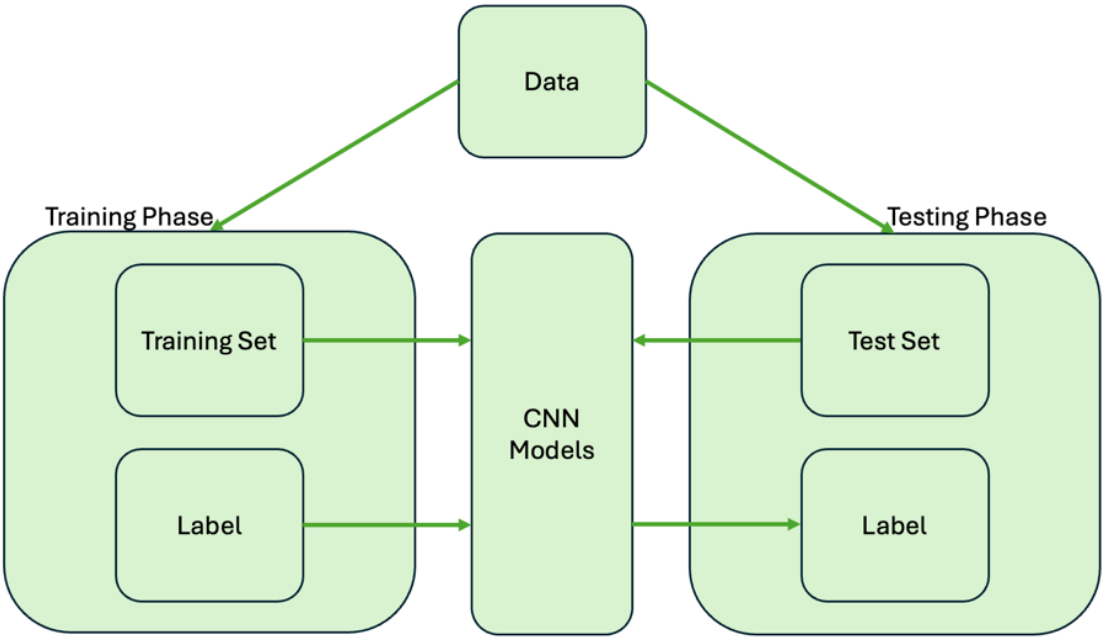


Figure 1. The general overview

2.2. Dataset

The dataset used in this study was a new pediatric VinDr-CXR dataset consisting of 9125 studies collected retrospectively at the Vietnam Phu Tho Obstetric & Pediatric Hospital between 2020 and 2021. Each scan was manually labelled by an experienced radiologist for the presence of 36 critical findings and 15 diseases. The dataset was introduced to the literature by Pham et al [6]. The VinDr-CXR dataset was labelled for a total of 36 findings and 15 diagnoses. The labels were divided into two categories: local labels (1-36) and global labels (37-51). The selection of these labels was based on two criteria: firstly, that they were common, and secondly, that they could be distinguished on CXRs. To facilitate the labelling process, a web-based framework called VinDr-Lab was designed and built, enabling a team of three experienced radiologists to annotate the data remotely.

Although the images belong to different disease types and control groups, in this study, only bronchitis images were used as subjects; in this context, a total of 2032 images were used, 1016 bronchitis and 1016 control. Examples of bronchitis are given in Figure 2, while examples of control groups are presented in Figure 3.



Figure x2. The examples of bronchitis



Figure 3. The examples of control groups

2.3. Models

The Xception algorithm is a network structure based on Inception networks. The 36 convolutional layers serve as the network's framework for feature extraction. Except for the first and last modules, the 36 convolutional layers are organized into 14 modules with residual connections [7].

Huang et al. [8] presented the DenseNet model in 2016. In this sort of convolutional neural network, all of the layers are directly connected to one another through dense blocks. In this study, DenseNet-121, which has 121 blocks, was utilized.

The fourth iteration of the Deep Learning Convolutional Architectures series is designated as Inception-V4 [9]. Inception-V4 is one of the most sophisticated models currently in use for the categorization of images. The design of this model involves the creation of a new filter through the combination of several convolutional filters of varying sizes. This approach results in a reduction in the computational complexity of the model, as it necessitates the teaching of a reduced number of parameters. The model is composed of both symmetric and asymmetric building blocks, including fully linked layers, average pooling, max pooling, and convolution.

In 2021, the EfficientNetV2 model was introduced. By uniformly scaling the neural network's depth, width, and resolution, the objective is to increase accuracy while consuming the fewest possible processing resources[10]. EfficientNet, which has many different models and versions, is specifically used in this study, EfficientNetV2 B7.

Residual blocks are combined layer by layer to construct the ResNet architecture. The basic ResNet block avoids vanishing gradients by learning the difference between the input and output dimensions and deepening the network. One key characteristic that sets ResNet models apart from other deep networks is their architecture [11]. In this study, the ResNet-101 design, which has 101 blocks, was utilized.

2.4. Experimental Setup and Performance Evaluation

The learning rate and epoch metrics were identified as 0.01 and 50, respectively, while the batch size was selected as 32 within the parameters of all experiments conducted during the experiments of this study.

In this study, the k-fold cross-validation procedure was applied to each experiment. The dataset was split into k randomly chosen sections using this method. Each component was set aside for testing, while the remaining components were utilized throughout the training stage. This process was repeated k times. Evaluation criteria, including accuracy, sensitivity, precision, F1 score, and Matthew's correlation coefficient, were employed in conjunction with the sequence of measurement to assess the models' classification performance [12].

The degree of accuracy achieved by the model in categorizing the data is defined as the accuracy rate. This is calculated using the formula presented in Equation (1).

$$\text{Accuracy} = (TP+TN)/(P+N) \quad (1)$$

Sensitivity assesses the capacity of the classifier to identify each positive example, whereas precision

gauges the extent to which the classifier can classify negative examples as positive. Equations (2) and (3) are employed to calculate sensitivity and precision, respectively.

$$\text{Sensitivity} = (TP)/(TP+FN) \quad (2)$$

$$\text{Precision} = (TP)/(TP+FP) \quad (3)$$

The F1 score is a harmonic of precision and sensitivity, representing a single metric that balances both. This metric measures the overall performance of the model in a balanced way, considering both false positives (FP) and false negatives (FN). The formula for the F1 score is shown in Equation (4).

$$\text{F1 Score} = TP/(TP+ (1/2 * (FP+FN))) \quad (4)$$

The Matthew's Correlation Coefficient (MCC) is a balanced evaluation metric that is employed to assess the performance of a classification model. It offers more dependable outcomes, particularly in the context of imbalanced datasets, due to its consideration of the equilibrium between positive and negative classes. The MCC formula is presented in Equation (5).

$$MCC = (TP*TN - FP*FN)/ \sqrt{((TP+FP) * (TP+FN)*(TN+FP)*(TN+FN))} \quad (5)$$

In this context, TP, TN, P and N represent the true positives, true negatives, total positives and total negatives, respectively, in that order.

III. RESULTS

Xception, DenseNet-121, InceptionV4, EfficientNetV2B7, ResNet-101 deep learning models were tested in related hypothesis classification experiments. In this context, when analysing the results in Table I, the best classification performance is obtained by the InceptionV4 model, which achieves values of 0.943, 0.935, 0.950, 0.942, 0.886 for the Accuracy, Sensitivity, Precision, F1 Score, MCC metrics, respectively. For the same metrics, the EfficientNetV2B7 model, with values of 0.940, 0.932, 0.951, 0.941, 0.882, obtained results close to the best performance, but remained in second place. While the Xception and ResNet-101 models showed a moderate performance, DenseNet-121 showed a below average performance with values of 0.851, 0.875, 0.824, 0.849, 0.703 and could not reach the desired level.

	Accuracy	Sensitivity	Precision	F1 Score	MCC
Xception	0.891	0.928	0.857	0.891	0.782
DenseNet-121	0.851	0.875	0.824	0.849	0.703
InceptionV4	0.943	0.935	0.950	0.942	0.886
EfficientNetV2B7	0.940	0.932	0.951	0.941	0.882
ResNet-101	0.919	0.925	0.911	0.918	0.837

Table 1. The classification results of models

IV. DISCUSSION AND CONCLUSION

In this study, five advanced deep learning were evaluated for their capacity to classify pediatric bronchitis using chest X-ray images. The findings indicate that the InceptionV4 model exhibits superior performance compared to the other architectures, attaining the highest accuracy, precision, F1 score, and Matthew's correlation coefficient (MCC). Additionally, the EfficientNetV2B7 model exhibits high performance, yielding results that are comparable to those of the InceptionV4 model. This illustrates the potential utility of the EfficientNetV2B7 model for the accurate classification of bronchitis.The accuracy of the proposed model is of particular significance, as it offers a reliable methodology for pediatricians to diagnose bronchitis through automated X-ray analysis. The superior performance of these models indicates that systems based on deep learning have the potential to reduce the time and resources required for diagnosis, which could facilitate more expedient treatment decisions. Furthermore, the use of AI-based diagnostic tools can help minimize the incidence of diagnostic errors and contribute to improved clinical outcomes for pediatric patients by reducing the reliance on subjective assessments. Nevertheless, several limitations warrant consideration. Firstly, although the dataset is comprehensive, it is region and hospital-specific, which may limit the generalizability of the findings. To address this, future studies could improve this by including datasets with diverse geographical and clinical backgrounds. Secondly, there is a lack of interpretability specific to deep learning models, which may hinder clinical acceptance. To address this, further work could focus on incorporating explainable AI (XAI) methods to make the model's decision-making process more transparent for healthcare providers.

In conclusion, the findings of this study demonstrate that deep learning models, particularly InceptionV4 and EfficientNetV2B7, offer an effective approach for diagnosing pediatric bronchitis using X-ray images. With further refinement and validation, such models can serve as valuable tools in computer-aided diagnosis and improve the efficiency and accuracy of bronchitis diagnosis in clinical practice. Future work should continue to optimize model performance,

explore interpretability solutions, and validate these models in larger, more diverse data sets to confirm their usefulness in a variety of clinical settings.

REFERENCES

[1] Wopker, P.M., Schwermer, M., Sommer, S., Längler, A., Fetz, K., Ostermann, T. andZuzak, T.J. (2020). Complementaryandalternativemedicine in thetreatment of acutebronchitis in children: A systematicreview. *ComplementaryTherapies in Medicine*, 49, p.102217. doi:https://doi.org/10.1016/j.ctim.2019.102217.

[2] Fleming, D., Verlander, N.Q., Elliot, A.J., Zhao, H., Gelb, D., D. JehringandNguyen-Van-Tam, J.S. (2010). An assessment of theeffect of statinuse on theincidence of acuterespiratoryinfections in Englandduringwinters 1998–1999 to 2005–2006. EpidemiologyandInfection, 138(9), pp.1281–1288. doi:https://doi.org/10.1017/s0950268810000105.

[3] Woodhead, M. (2011). New guidelinesforthemanagement of adultlowerrespiratorytractinfections. EuropeanRespiratoryJournal, 38(6), pp.1250–1251. doi:https://doi.org/10.1183/09031936.00105211.

[4] RadaMarkova (2024). AcuteandChronicBronchitis in Childhood: CysticFibrosis. IntechOpeneBooks. doi:https://doi.org/10.5772/intechopen.113138.

[5] Paul, J. (2024). RespiratoryTractInfections. SpringereBooks, pp.99–148. doi:https://doi.org/10.1007/978-3-031-28567-7_3.

[6] Pham, H. H., Tran, T. T., & Nguyen, H. Q. (2022). VinDr-PCXR: An open, large-scale pediatric chest X-ray dataset for interpretation of common thoracic diseases (version 1.0.0). *PhysioNet*. https://doi.org/10.13026/k8qc-na36.

[7] N. An, "Xception Network for Weather Image Recognition Based on Transfer Learning," *2022 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE)*, Guangzhou, China, 2022, pp. 330-333, doi: 10.1109/MLISE57402.2022.00072.

[8] Z. Huang, X. Zhu, M. Ding and X. Zhang, "Medical Image Classification Using a Light-Weighted Hybrid Neural Network Based on PCANet and DenseNet," in *IEEE Access*, vol. 8, pp. 24697-24712, 2020, doi: 10.1109/ACCESS.2020.2971225

[9] R. Athilakshmi, R. Jansi and R. Upadhyay, "Enhancing Diabetic Retinopathy Diagnosis with Inception v4: A Deep Learning Approach," *2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2023, pp. 905-910, doi: 10.1109/ICIRCA57980.2023.10220890.

[10] T. S. Chi *et al*., "Enhancing EfficientNet-YOLOv4 for Integrated Circuit Detection on Printed Circuit Board (PCB)," in *IEEE Access*, vol. 12, pp. 25066-25078, 2024, doi: 10.1109/ACCESS.2024.3359639

[11] Y. Jusman, "Comparison of Prostate Cell Image Classification Using CNN: ResNet-101 and VGG-19," *2023 IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE)*, Penang, Malaysia, 2023, pp. 74-78, doi: 10.1109/ICCSCE58721.2023.10237088

[12] Çağatay Berke Erdaş and Emre Sümer (2023). A fully automated approach involving neuro imaging and deep learning for Parkinson's disease detection and severity prediction. PubMed Central, 9, pp.e1485–e1485. doi:https://doi.org/10.7717/peerj-cs.1485.

★★★