

**CLASSIFICATION OF CHEST X-RAY IMAGES OF LUNG  
DISEASES USING DEEP CONVOLUTIONAL NEURAL NETWORK**

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**DECEMBER, 2022**

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**BY**

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**A DISSERTATION SUBMITTED TO THE SCHOOL OF  
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ENGINEERING, COLLEGE OF ENGINEERING, COVENANT  
UNIVERSITY, OTA, OGUN STATE**

**DECEMBER, 2022**

## **ACCEPTANCE**

This is to attest that this dissertation has been accepted in partial fulfilment of the requirements for the award of the degree of Masters of Engineering in Computer Engineering in the Department of Electrical and Information Engineering, College of Engineering, Covenant University, Ota, Nigeria.

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## **DECLARATION**

**I, OLAYIWOLA, JOY OLUWABUKOLA (20PCJ02085)** declare that this dissertation is a representation of my work and is written and implemented by me under the supervision of Dr. Joke A. Badejo of the Department of Electrical and Information Engineering, Covenant University, Ota, Nigeria. I attest that this dissertation has in no way been submitted either wholly or partially to any other university or institution of higher learning for the award of a masters' degree. All information cited from published and unpublished literature has been duly referenced.

**OLAYIWOLA, JOY OLUWABUKOLA**

**Signature and Date**

## **CERTIFICATION**

This is to certify that the research work “**CLASSIFICATION OF CHEST X-RAY IMAGES OF LUNG DISEASES USING DEEP CONVOLUTIONAL NEURAL NETWORK**” is an original research work carried out by **OLAYIWOLA, JOY OLUWABUKOLA (20PCJ02085)**, meets the requirements and regulations governing the award of Masters of Engineering (M.Eng.) degree in Computer Engineering from the Department of Electrical and Information Engineering, College of Engineering, Covenant University, Ota, and is approved for its contributions to knowledge and literary presentation.

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## **DEDICATION**

This research work is dedicated first and foremost to God Almighty, the custodian of all wisdom, knowledge, and understanding, for His grace and favour throughout the duration of carrying out this research. Then to my family for their endless support and love.

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## ABSTRACT

The accurate diagnosis of lung disease in infected patients is a crucial step in coping with and combating such diseases. Lung opacity, tuberculosis, COVID-19, bacterial pneumonia, and viral pneumonia are examples of infectious diseases that similarly affect the lungs. Classifying accurately which of these diseases (lung opacity, tuberculosis, COVID-19, bacterial pneumonia, and viral pneumonia or normal) an image of chest X-ray is being infected with despite the similarities in the images is crucial. Therefore, this research aimed at developing a convolutional neural network, CNN-based model to classify the lung diseases. In this research work, four convolutional neural network models, MobileNetV2, Resnet-50, ResNet-101, and AlexNet were empirically analysed in order to classify lung diseases from images of chest X-rays. The models were utilised in three classification modes: 6-subclass (lung opacity, tuberculosis, COVID-19, bacterial pneumonia, viral pneumonia, and normal), 5-subclass (lung opacity, viral pneumonia, COVID-19, tuberculosis, and normal), and 4-subclass (lung opacity, viral pneumonia, COVID-19, and normal); to investigate the effect of high interclass similarity. The retrained ResNet-50 architecture provided the best classification accuracy with 97.22%, 92.14%, and 96.08% for 6-subclass, 5-subclass, and 4-subclass respectively. Nevertheless, ResNet-101 has the lowest classification accuracy with 78.12% and 79.49% for 6-subclass and 5-subclass respectively while MobileNetV2 has the lowest classification accuracy of 88.89% for 4-subclass. The findings suggest that the ResNet-50 model can be applied to accurately diagnose lung diseases from chest images of X-rays even with high interclass similarity. Also, this corroborates the success of adopting computer-aided detection (CAD) systems designed for decision support in the classification of lung diseases.

**Keywords:** *Lung disease, Deep Learning, Diagnosis, ResNet-50, MobileNetV2, Transfer Learning.*