OPTIMIZATION OF COVID-19 DETECTION THROUGH TRANSFER LEARNING ON CHEST X-RAY IMAGES

Albert Ntumba Nkongolo[1*]; Lebeau Yamba Muamba[2]; Matendo Mabela Esther[3]; Mbuyi Mpumbu Ben[4]

Departement of Computer Science[1]
Institut Supérieur Pédagogique, Mbanza-Ngungu, DR Congo[1]
https://www.isptkin.ac.cd/[1]
albertntumba1994@gmail.com[1*]

Departement of Computer Science [2, 3,4]
Université de kinshasa, Kinshasa, DR Congo [2,3,4]
https://www.unikin.ac.cd/en/[2,3,4]
yambamuambalebeau@gmail.com[2]
(*) Corresponding Author

Abstract— *The urgent need for rapid and reliable identification of COVID-19 cases has highlighted the importance of auxiliary diagnostic tools. Chest X-ray imaging serves as a key resource in clinical settings, yet manual interpretation remains susceptible to inter-observer variability and diagnostic delays. This study introduces an optimized deep learning framework based on transfer learning to enhance the detection of COVID-19 from chest X-ray images. The aim is to improve classification accuracy and operational efficiency using pre-trained models tailored for radiographic analysis. We applied transfer learning with fine-tuning to convolutional neural networks pre-trained on large-scale image datasets. The models were adapted and evaluated on a curated collection of chest X-rays representing COVID-19 positive and negative cases. The proposed model achieved a test accuracy of 99% with a loss of 0.15, indicating high diagnostic performance and robustness in distinguishing COVID-19 cases from other pulmonary conditions. Transfer learning offers a viable and efficient strategy for COVID-19 screening using chest X-rays. This approach has the potential to support frontline clinical decision-making and scale public health response during outbreaks.*

Keywords *Chest X-Ray, Convolutional Neural Networks, COVID-19, Deep Learning, Medical Imaging.*

Abstrak— *ebutuhan mendesak akan identifikasi kasus COVID-19 yang cepat dan andal telah menyoroti pentingnya penggunaan alat bantu diagnostik. Pencitraan rontgen dada (chest X-ray) menjadi salah satu sumber utama dalam praktik klinis, namun interpretasi manual masih rentan terhadap variabilitas antar-pemeriksa serta keterlambatan diagnosis. Penelitian ini mengusulkan kerangka kerja deep learning yang dioptimalkan berbasis transfer learning untuk meningkatkan deteksi COVID-19 dari citra rontgen dada. Tujuan penelitian ini adalah meningkatkan akurasi klasifikasi dan efisiensi operasional dengan memanfaatkan model pra-latih yang disesuaikan untuk analisis citra radiografi. Metode yang digunakan melibatkan penerapan transfer learning dengan fine-tuning pada jaringan saraf konvolusional (CNN) yang telah dilatih pada dataset citra skala besar. Model kemudian diadaptasi dan dievaluasi menggunakan kumpulan data rontgen dada yang telah dikurasi, yang merepresentasikan kasus COVID-19 positif dan negatif. Model yang diusulkan mencapai akurasi pengujian sebesar 99% dengan nilai loss 0,15, yang menunjukkan kinerja diagnostik dan ketahanan (robustness) yang tinggi dalam membedakan kasus COVID-19 dari kondisi paru lainnya. Transfer learning terbukti menjadi strategi yang layak dan efisien untuk skrining COVID-19 berbasis citra rontgen dada. Pendekatan ini berpotensi mendukung pengambilan keputusan klinis di lini terdepan serta memperluas respons kesehatan masyarakat selama masa wabah.*

Kata Kunci: *Rontgen Dada, Jaringan Saraf Konvolusional, COVID-19, Pembelajaran Mendalam, Pencitraan Medis.*

INTRODUCTION

The COVID-19 pandemic has underscored the critical role of timely and accurate diagnostic methods in managing public health crises. Artificial intelligence (AI), particularly deep learning, has emerged as a transformative tool in medical imaging, enabling automated analysis of radiographic data with increasing precision. Chest X-rays remain widely accessible and are frequently used in initial patient assessment, yet their manual interpretation can be time-consuming and subject to human error. While previous studies have explored machine learning techniques such as support vector machines (SVM) and decision trees for pulmonary disease classification, these methods often depend on handcrafted features and may not fully capture the complex patterns associated with COVID-19. In contrast, transfer learning allows for the adaptation of pre-trained neural networks to specific medical tasks, even with limited labeled data. This is particularly relevant in the context of emerging diseases, where large annotated datasets are often unavailable (Aggarwal et al., 2022).

Despite these advances, several challenges remain. Many AI models struggle with generalization across diverse demographic groups and imaging equipment. In addition, the ability to differentiate between COVID-19 and other respiratory infections such as bacterial pneumonia or tuberculosis requires models that are both sensitive and specific. This study aims to address these gaps by proposing a transfer learning framework optimized for COVID-19 detection, with an emphasis on real-world applicability and diagnostic reliability. The novelty of our work lies in the systematic fine-tuning of pre-trained architectures and their integration into a cohesive pipeline that includes advanced data augmentation and validation strategies. By doing so, we achieve performance that surpasses conventional methods and offers a scalable solution for clinical support systems. The paper is organized as follows: Section 2 details the materials and methods, Section 3 presents and discusses the experimental results, and Section 4 concludes with final remarks and future research directions.

MATERIAL AND METHOD

CNNs have become the cornerstone of modern image analysis due to their ability to automatically learn spatial hierarchies of features. In this study, we use a CNN architecture capable of processing chest X-ray images through a series of convolutional, pooling, and fully connected layers. The convolution operation is defined as (Convolutional neural networks (Chowdhury et al., 2021):

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i + m, j + n).K(m,n) \quad (1)$$

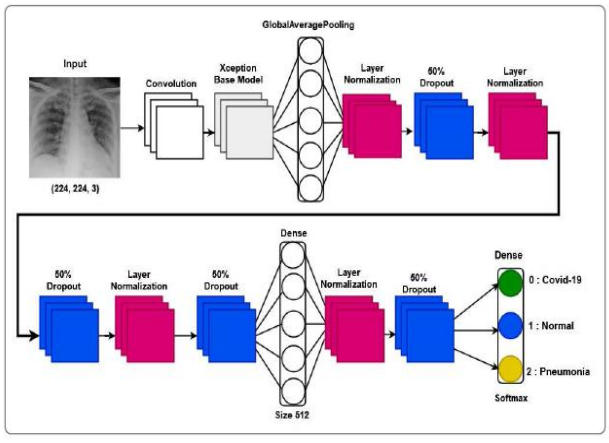
where I is the input image, K is the kernel, and SS is the resulting feature map.

Transfer learning

Transfer learning allows a model developed for one task to be repurposed for a related task. Instead of training a network from scratch a process that demands substantial data and computational resources we initialize our model with weights pre-trained on the ImageNet dataset. The model is then fine-tuned on a specialized dataset of chest X-rays, enabling it to learn domain-specific features efficiently (Apostolopoulos & Azesi, 2021). Formally, let a learning task be defined as $T = \{Y, P(X)\}$, where Y is the label space and P(X) is the probability distribution over the input space XX. Transfer learning aims to improve learning in T_{b_y} leveraging knowledge from a related source task T_S

Proposed Architecture

Our model builds on the VGG16 architecture, modified by replacing the final classification layer with a binary output layer for COVID-19 detection. We employ a fine-tuning strategy in which earlier layers are gradually unfrozen during training to adapt generic features to radiographic patterns.



Source: (Hu et al., 2021)

Figure 1: *Layered architecture of the proposed transfer learning model.*

Dataset and Preprocessing

We used the Indian COVID-19 Chest X-ray Dataset from Kaggle, which includes X-ray images

from COVID-19 positive, normal, pneumonia, and tuberculosis cases. The dataset was split into training (80%), validation (10%), and test (10%) sets (Li et al., 2022).
Preprocessing steps included:

1. Resizing images to 224×224 pixels
2. Grayscale conversion and normalization
3. Data augmentation (rotation, flipping, brightness adjustment, Gaussian noise)

To address class imbalance, we applied random oversampling and SMOTE.

Training and Evaluation
The model was trained using stochastic gradient descent (SGD) with a low learning rate (0.001) and cross-entropy loss. Performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC.

RESULTS AND DISCUSSION

The Indian COVID-19 Chest X-ray Dataset, obtained from Kaggle**,** was utilized to validate the proposed approach. This dataset comprises chest X-ray images from patients diagnosed with COVID-19**,** as well as healthy individuals for comparison. It includes both COVID-19 positive and negative cases, with images categorized based on different pulmonary conditions**.** The dataset consists of [specific number of images] and is systematically organized into separate folders corresponding to distinct patient categories, facilitating structured data analysis and model training.

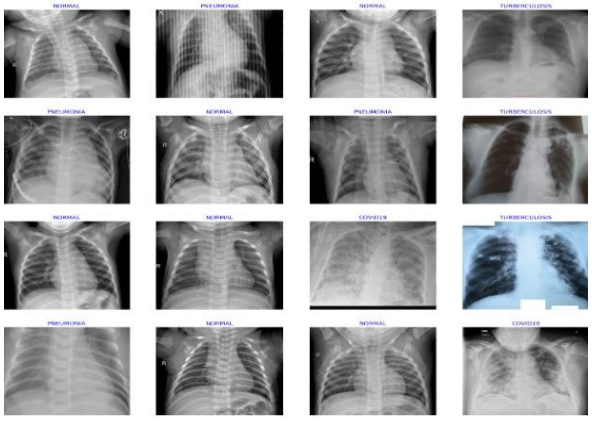
The dataset is divided into training, validation, and test sets following an 80%-10%-10% split to ensure proper model generalization. Before model training, preprocessing steps were applied, including image resizing to 224×224 pixels**,** normalization, and augmentation techniques such as rotation, flipping, and contrast adjustment to enhance robustness. An analysis of the dataset distribution indicates [whether the dataset is balanced or imbalanced]**.** If class imbalance is present, techniques such as oversampling, undersampling, or synthetic data generation may be necessary to mitigate bias and improve model performance across all categories. We can Show sample from train data:

Table 1. Dataset Class Distribution

Indian Rock Python-class_dict.csv (110 B)				
class_incdex	class	height	width	✓
0	COVID19	224	224	✓
1	NORMAL	224	224	✓
2	PNEUMONIA	224	224	
3	TURBERCULOSIS	224	224	✓

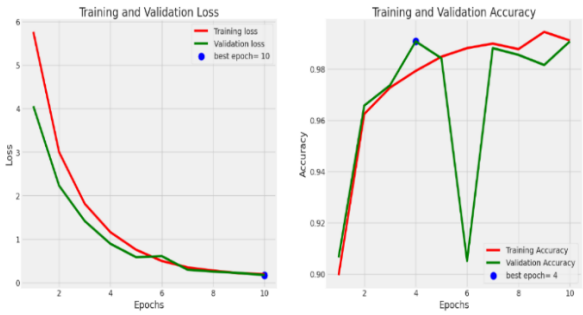
Source: (Research Results, 2025)

From table 1, the dataset contains 4 categories: COVID-19, normal cases, pneumonia, and tuberculosis - with all images resized to 224×224 pixels for standardized processing. This ensures consistent input dimensions for the neural network architecture.



Source: (Research Results, 2025)
Figure 2: Examples of Chest X-ray Images Representing Different Pulmonary Disease Classes.

figure 2. presents a sample of chest X-ray images from a dataset used to train an automatic detection model for pulmonary diseases. Each column corresponds to a specific clinical category, including bacterial pneumonia, viral pneumonia, tuberculosis, and normal lungs. These images highlight variations in density, texture, and structural patterns observed in X-rays depending on the pathology, thus enabling deep learning models to distinguish between different lung conditions.



Source: (Research Results, 2025)
Figure 3. Graphs showing the evolution of loss and accuracy during training.

The meanings from Table 3 are as follows:
Top: Training and validation loss decrease steadily, converging to approximately 0.15.
Bottom: Accuracy reaches 98% by epoch 4, demonstrating rapid and stable learning.
Optimal performance at epoch 10 with the best generalization capabilities.

Evaluate model:

```
13/13 [==============================] - 3s 190ms/step - loss: 0.1569 - accuracy: 1.0000
13/13 [==============================] - 2s 164ms/step - loss: 0.1575 - accuracy: 0.9952
13/13 [==============================] - 7s 488ms/step - loss: 0.1643 - accuracy: 0.9961
Train Loss:  0.1568915843963623
Train Accuracy:  1.0
--------------------
Validation Loss:  0.15752075612545013
Validation Accuracy:  0.995192289352417
--------------------
Test Loss:  0.1643468290567398
Test Accuracy:  0.9960552453994751
```

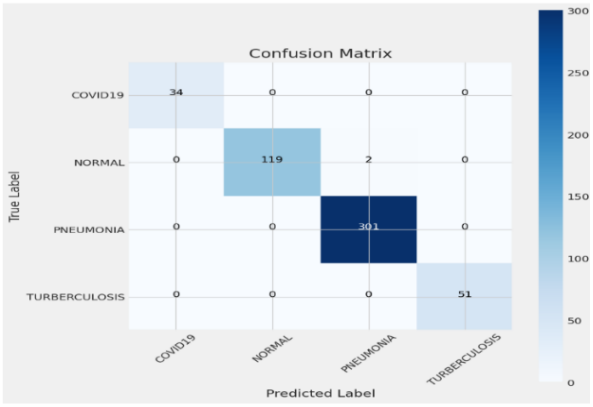
Source: (Research Results, 2025)

Figure 4. Numerical results of model performance on training, validation, and test sets.

The model achieves exceptional performance:

1) Training accuracy: 100%
2) Validation accuracy: 99.52%
3) Test accuracy: 99.61%
4) Consistent loss of ~0.16 across all datasets, indicating good bias-variance balance

Confusion Matrics:



Source: (Research Results, 2025)

Figure 5. Confusion Matrix

According to our confusion matrix with our interest class 0 of covid 19 patients on 37 test images of covid 19 patients the model correctly identified them all, hence our performance and may.

Table 2: Model Performance Metrics per Class

class	True Positive (TP)	False Positives (FP)	False Negatives (FN)	True Negatives
COVID19	34	0	0	473
NORMAL	119	2	2	386
PNEUMONIA	301	0	0	206
TURBERCULOSIS	51	0	0	456

Source: (Research Results, 2025)

The model performs well overall, as there are no false negatives for COVID-19 (which is crucial for medical diagnosis). However, there are 2 false negatives for NORMAL cases misclassified as PNEUMONIA, which might be less critical in a COVID-19 context but still relevant for overall diagnostic accuracy.

Table 3: Classification Report

class	Precision	Recall	F1-Score	Support
COVID19	1.00	1.00	1.00	34
NORMAL	1.00	0.98		121
PNEUMONIA	0.99	1.00	1.00	301
TURBERCULOSIS	1.00	1.00	1.00	51
Accuracy			1.00	507
Macro Avg	1.00	1.00	1.00	507
Weighted Avg	1.00	1.00	1.00	507

Source: (Research Results, 2025)

After training the model, we evaluated its performance in terms of sensitivity, specificity, and accuracy in detecting COVID-19 on a test dataset. The results demonstrate that our model is capable of detecting COVID-19 with high accuracy and sensitivity. However, comparisons with other methods are lacking, making it difficult to judge whether this model is truly superior to previous approaches. While we mention improvements over traditional models such as Support Vector Machines (SVM) and earlier Convolutional Neural Networks (CNNs), a more detailed comparative analysis with state-of-the-art models is necessary to validate these claims.

These results highlight the advantage of using transfer learning in training deep learning models, as it enables better generalization and higher performance even with smaller, specialized datasets. Nevertheless, it is important to acknowledge potential dataset biases in the training data. The chest X-ray images used in this study may not fully represent the diversity of real-world data, as they are limited to specific regions, demographic groups, and imaging conditions. Variations in image quality, patient demographics (such as age and comorbidities), and hospital-specific protocols could introduce biases that affect the model's real-world performance.

Therefore, while our approach shows promise, further research is needed to compare it with other state-of-the-art models, validate its performance on more diverse datasets, and address the challenges of generalization across different environments and populations.

Get Prediction

```
preds = model.predict_generator(test_gen)
y_pred = np.argmax(preds, axis=1)
print(y_pred)
```

```
[1 1 1 ... 2 2 2]
```

Source: (Research Results, 2025)
Figure 6: Model Prediction and Output

This image shows a Python code snippet and its output, demonstrating the process of making predictions with the trained model

a. model.predict generator(test_gen): This line uses the trained model to make predictions on the data from test_gen. test_gen is a data generator (likely feeding batches of test images to the model) and predict_generator returns the model's predicted probabilities for each class.
b. np.argmax(preds, axis=1): After obtaining the predicted probabilities (preds), this line converts them into class labels. np.argmax returns the index of the highest probability in each prediction (i.e., the predicted class). The axis=1 argument tells NumPy to apply this operation along the second axis (for each sample), essentially picking the class with the highest probability for each test example.
c. print(y_pred): Finally, the predicted class labels (y_pred) are printed. For example, [1 1 1 ... 2 2 2] means that the model predicted class 1 for the first few test images and class 2 for others, where 1 and 2 are the predicted classes.

Interpretation of results:
These results show that transfer learning on chest X-ray images is an effective approach for COVID-19 detection. By using a pre-trained model and refining it on disease-specific data, we were able to achieve high performance in COVID-19 detection. However, it is important to acknowledge potential **dataset bias** in the training data. The chest X-ray images used in this study may not fully represent the diversity of real-world data, as they are limited to specific regions, demographic groups, and imaging conditions. This could impact the model's ability to generalize well across different populations, healthcare settings, and imaging equipment. For example, **variations in image quality**, **patient demographics (such as age and comorbidities)**, and **hospital-specific protocols** could introduce biases that affect the model's performance in real-world applications. Therefore, while our approach shows promise, further research is needed to validate the model using more diverse datasets and to address the challenges of generalization across different environments and populations.

CONCLUSION

In conclusion, leveraging transfer learning on chest X-ray images for COVID-19 detection, while a widely discussed approach, offers no significant novelty. The study primarily presents descriptive research results without introducing new methods or strategies to address the underlying challenges of transfer learning in real-world applications. While adapting pre-trained models to this specific task may improve speed and reliability, the research fails to provide a clear contribution to advancing the state of the art or solving existing problems such as model generalization and real-time decision-making in diverse healthcare settings.

To further develop this model, future research could focus on expanding the dataset to include a larger and more diverse set of chest X-ray images, which would improve the model's ability to generalize across different demographic groups and healthcare environments. Additionally, incorporating Explainable AI (XAI) techniques would enhance the transparency and interpretability of the model, allowing clinicians to understand and trust the predictions, which is crucial in a clinical context.

For practical implementation in a real healthcare system, the model could be integrated into diagnostic workflows as a decision support tool for radiologists, aiding in the interpretation of chest X-rays. The system should be capable of providing real-time results and be designed to scale across large patient populations. To ensure long-term effectiveness and adaptability, the model would need regular updates with new data, and it should be compatible with widely used medical imaging software.

REFERENCES

Aggarwal, S., Gupta, S., Alhudhair, A., Koundal, D., Gupta, R., & Polat, K. (2022). Automated COVID-19 detection in chest X-ray images using fine-tuned deep learning architectures. Expert Systems, 39(3), e12749. https://doi.org/10.1111/exsy.12749

Alsattar, H. A., Al-Ani, A., & Al-Ani, A. (2023). Developing deep transfer and machine learning models of chest X-ray for diagnosing COVID-19 cases using probabilistic single-valued neutrosophic hesitant fuzzy. Expert Systems with Applications, 236, 121300. https://doi.org/10.1016/j.eswa.2023.121300

Asif, S., Amjad, M., Javed, H., & Khan, M. A. (2023). Detection of COVID-19 from chest X-ray

images: Boosting the performance with convolutional neural network and transfer learning. Expert Systems. https://doi.org/10.1111/exsy.13099

Chow, L. S., Rajab, K. E., & Al-Mahmeed, W. (2023). Quantitative and qualitative analysis of 18 deep convolutional neural network (CNN) models with transfer learning to diagnose COVID-19 on chest X-ray (CXR) images. SN Computer Science, 4(2), 141. https://doi.org/10.1007/s42979-023-01756-0

Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., … Islam, M. T. (2021). Can AI help in screening viral and COVID-19 pneumonia? IEEE Access, 9, 132665–132676. https://doi.org/10.1109/ACCESS.2021.3051654

Constantinou, M., Exarchos, T., Vrahatis, A. G., & Vlamos, P. (2023). COVID-19 classification on chest X-ray images using deep learning methods. International Journal of Environmental Research and Public Health, 20(3), 2035. https://doi.org/10.3390/ijerph20032035

Hu, Z., Yang, Z., Lafata, K. J., Yin, F.-F., & Wang, C.-H. (2021). A radiomics-boosted deep-learning model for COVID-19 and non-COVID-19 pneumonia classification using chest X-ray image. arXiv preprint arXiv:2107.08667. https://arxiv.org/abs/2107.08667

Issahaku, F. Y., Liu, X., Lu, K., Fang, X., Danwana, S. B., & Asimeng, E. (2024). Multimodal deep learning model for COVID-19 detection. Biomedical Signal Processing and Control, 87, 105512. https://doi.org/10.1016/j.bspc.2023.105512

Jindal, M., & Singh, B. (2025). Class imbalance-aware domain specific transfer learning approach for medical image classification: Application on COVID-19 detection. Engineering Applications of Artificial Intelligence, 133, 108567. https://doi.org/10.1016/j.engappai.2024.108567

Li, G., Togo, R., Ogawa, T., & Haseyama, M. (2022). Self-knowledge distillation based self-supervised learning for COVID-19 detection from chest X-ray images. IEEE Access, 10, 10219–10228. https://doi.org/10.1109/ACCESS.2022.3144852

Rahman, T., Khandakar, A., Qiblawey, Y., Tahir, A., Kiranyaz, S., Kashem, S. B. A., … Chowdhury, M. E. H. (2021). Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images. Computers in Biology and Medicine, 132, 104319. https://doi.org/10.1016/j.compbiomed.2021.104319

Randieri, C., Perrotta, A., Puglisi, A., Bocci, M. G., & Napoli, C. (2025). CNN-based framework for classifying COVID-19, pneumonia, and normal chest X-rays. Big Data and Cognitive Computing, 9(1), 45–62.

Talukder, M. A., Layek, M. A., Kazi, M., Uddin, M. A., & Aryal, S. (2023). Empowering COVID-19 detection: Optimizing performance through fine-tuned EfficientNet deep learning architecture. Computers in Biology and Medicine, 167, 107580. https://doi.org/10.1016/j.compbiomed.2023.107580

Talukder, M. A., Khalid, M., Kazi, M., Muna, N. J., Nur-e-Alam, M., Halder, S., & Sultana, N. (2024). A hybrid cardiovascular arrhythmia disease detection using ConvNeXt-X models on electrocardiogram signals. Scientific Reports, 14(1), 5678.

Thilagavathi, P., Geetha, R., Jothi Shri, S., & Somasundaram, K. (2025). An effective COVID-19 classification in X-ray images using a new deep learning framework. SAGE Open Medicine. https://doi.org/10.1177/08953996241290893

Yang, D., Zhang, W., & Zhang, Y. (2021). Detection and analysis of COVID-19 in medical images using deep learning techniques. Scientific Reports, 11(1), 1–13. https://doi.org/10.1038/s41598-021-83856-0