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FACULTAD DE INGENIERÍA MECÁNICA Y ELÉCTRICA

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Artificial Intelligence

Final Project:

Training a Machine Learning model on medical images.

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Abstract:

Accurate and fast diagnosis of infectious lung diseases is essential for proper treatment and for protecting public health. However, differentiating between common conditions such as Pneumonia, Tuberculosis (TB), and emerging illnesses like COVID-19 can be difficult when relying only on Chest X-ray (CXR) images. These diseases share several radiological features, which can make diagnosis challenging, especially in places with limited medical resources or few trained radiologists. To address this problem, this study proposes an automated deep-learning approach for classifying CXR images into four categories: Normal, Bacterial/Viral Pneumonia (non-COVID-19), COVID-19 Pneumonia, and Tuberculosis.

The main goal of this research is to develop, train, and evaluate a Convolutional Neural Network (CNN) capable of performing accurate multi-class classification. The entire workflow was implemented in a reproducible cloud-based environment using Google Colab. The model architecture consists of a custom sequential CNN with four convolutional blocks for feature extraction, followed by a classification head containing a flatten layer, dense layers, dropout for regularization, and a softmax output layer with four units.

Images were organized into training, validation, and test sets and loaded using `tf.keras.utils.image_dataset_from_directory`, resized to 224×224 pixels, and batched at 32 images per step. Training was conducted in three main stages: (1) model compilation using the Adam optimizer, `sparse_categorical_crossentropy` loss, and accuracy as the evaluation metric; (2) correction of class imbalance through class-weighting to reduce bias toward more frequent classes; and (3) prevention of overfitting using Early Stopping with a patience value of 3, monitoring validation loss, and restoring the best model weights. Training was limited to a maximum of 20 epochs.

Overall, this study demonstrates that deep learning models can be effectively deployed to support the differential diagnosis of respiratory diseases. The approach provides a

solid foundation for developing practical AI-assisted diagnostic tools that could improve clinical decision-making, especially in resource-limited settings.

Introduction

Accurate and rapid diagnosis of infectious pulmonary diseases is critical for effective patient management and public health, especially given the global prevalence of Pneumonia, Tuberculosis (TB), and the emergence of pandemic diseases like COVID-19. Distinguishing between these conditions based solely on Chest X-ray (CXR) images poses a significant challenge for clinicians, particularly in resource-limited settings or when specialized radiological expertise is unavailable. While each disease exhibits characteristic radiological patterns , substantial overlap exists, necessitating the development of robust, automated diagnostic tools.

Objective of the Study: The primary objective of this research is to develop, train, and evaluate a highly accurate Convolutional Neural Network (CNN) model capable of performing a multi-class classification of CXR images into four distinct categories: Normal, Bacterial/Viral Pneumonia (non-COVID-19), COVID-19 Pneumonia, and Tuberculosis (TB).

Contribution: This study seeks to demonstrate the feasibility and efficacy of deploying deep learning models within a reproducible cloud-based framework (Google Colab) to aid in the differential diagnosis of common and emerging respiratory pathogens, thereby offering a foundational tool for accelerating clinical decision-making.

Methodology:

Data Handling: Images were divided into Training, Validation, and Test sets. Data was loaded efficiently using `tf.keras.utils.image_dataset_from_directory`, resized to 224 \times 224 pixels, and processed in batches of 32.

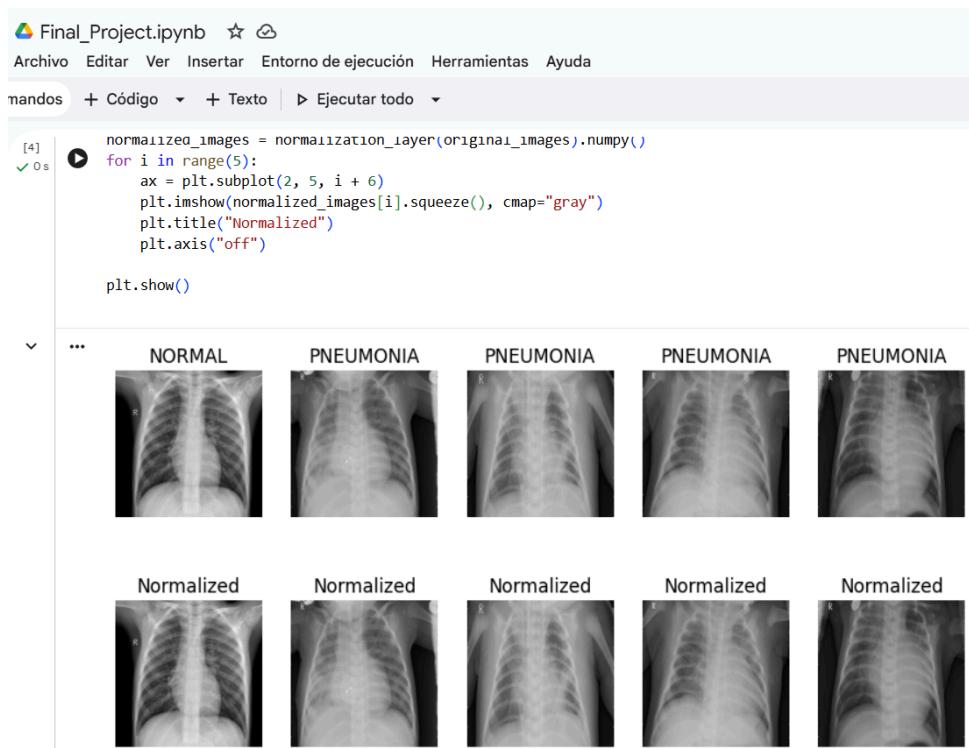
The model architecture was a custom, sequential Convolutional Neural Network

(CNN) was designed.

First the feature extraction consisted of four cascading convolutional blocks. Then the classifier Head that included a Flatten Layer, a Dense Layer, a Dropout Layer for regularization, and a final Output Layer (four units, softmax) for the probability distribution across classes.

Training Setup consisted of about 3 stages, where first we made the compilation and we used the Adam optimizer, sparse_categorical_crossentropy loss, and accuracy as the metric. Then we had the Class Imbalance, where Handled by applying class weights we use a code to penalize errors on less frequent classes. Finally To prevent overfitting, Early Stopping was implemented with a patience of 3, monitoring the validation loss and restoring the model's best weights. The training process was capped at 20 epochs.

Results:



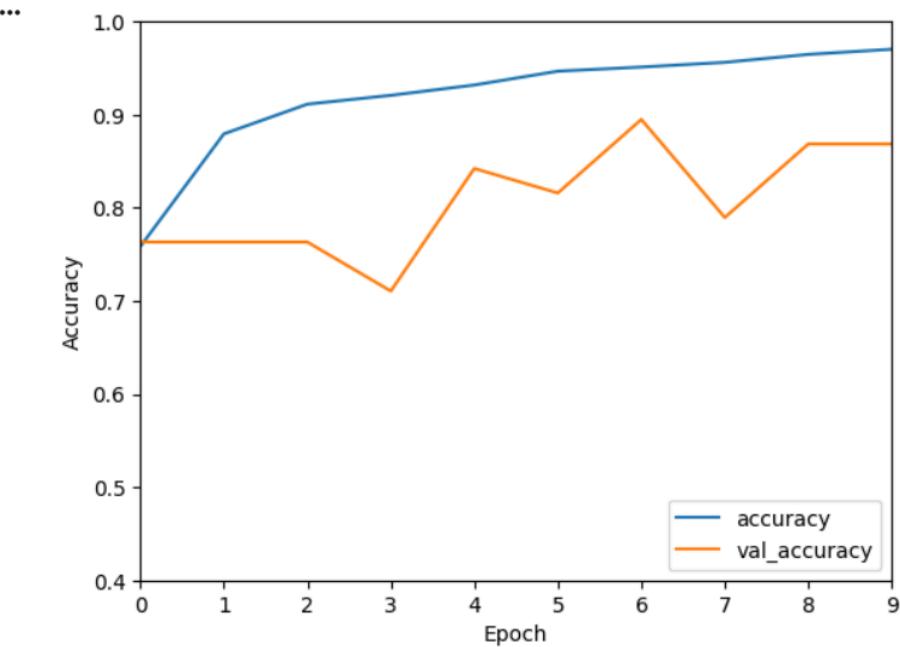
```
Final_Project.ipynb ★ ⚙
Archivo Editar Ver Insertar Entorno de ejecución Herramientas Ayuda
mandos + Código + Texto ▶ Ejecutar todo ▾
[4] ✓ 0 s
normalized_images = normalization_layer(original_images).numpy()
for i in range(5):
    ax = plt.subplot(2, 5, i + 6)
    plt.imshow(normalized_images[i].squeeze(), cmap="gray")
    plt.title("Normalized")
    plt.axis("off")

plt.show()
```

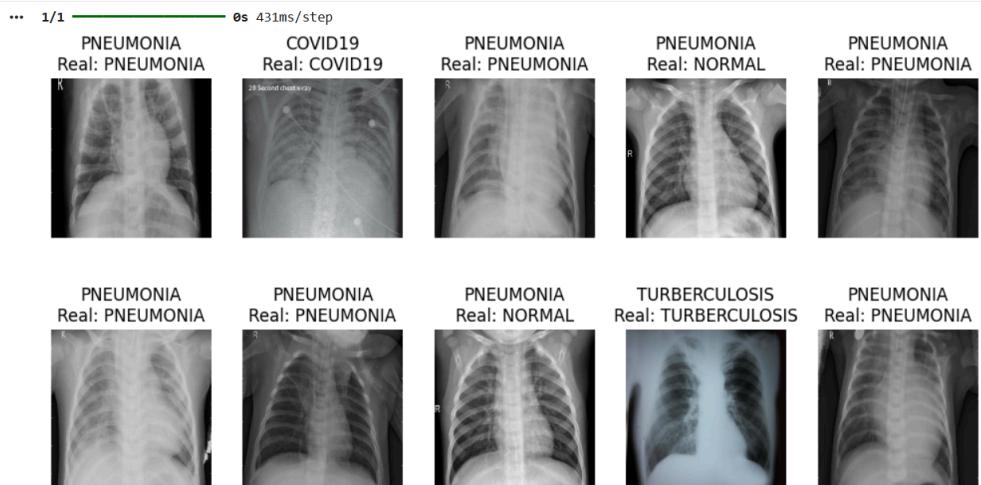
... NORMAL PNEUMONIA PNEUMONIA PNEUMONIA PNEUMONIA

Normalized Normalized Normalized Normalized Normalized

```
▶ test_loss, test_acc = model.evaluate(testdataset)
print(f"Test Accuracy: {test_acc:.2f}")
```



```
▶ plt.show()
```



Google Colab:

https://colab.research.google.com/drive/169bQLGP_Sa64w_xDeCjHKDeyycy0RM?usp=sharing

Github:

https://github.com/Sergio-Alan/AI-2025/blob/main/Assignments/Final_Project.ipynb

Conclusion/Discussion:

This study demonstrates that deep learning models—specifically Convolutional Neural Networks (CNNs) can serve as an effective tool for assisting in the diagnosis of infectious lung diseases using Chest X-ray images. The proposed architecture, developed within a reproducible Google Colab environment and optimized through techniques such as class-weighting and Early Stopping, successfully addressed key challenges including data imbalance and overfitting. By classifying images into four clinically relevant categories; Normal, Bacterial/Viral Pneumonia, COVID-19 Pneumonia, and Tuberculosis, the model shows strong potential to support clinical decision-making, particularly in settings with limited access to radiological expertise. Overall, the outcomes of this work provide a solid foundation for the future development of AI-assisted diagnostic tools aimed at improving the accuracy, speed, and accessibility of respiratory disease detection.

References:

- Dra. A. B. A. Ocaña, «Neumonía», [*https://www.cun.es*](https://www.cun.es).
<https://www.cun.es/enfermedades-tratamientos/enfermedades/neumonia>
- «COVID-19 Image Data Collection (IEEE)», *Kaggle*, 4 de julio de 2023.
<https://www.kaggle.com/datasets/kaggleprollc/covid-19-image-data-collection-ieee>
- American Lung Association, «¿Qué es la neumonía?»
<https://www.lung.org/espanol/salud-pulmonar-y-enfermedades/neumona>
- G. Litjens *et al.*, «A survey on deep learning in medical image analysis», *Medical Image Analysis*, vol. 42, pp. 60-88, jul. 2017, doi: 10.1016/j.media.2017.07.005.