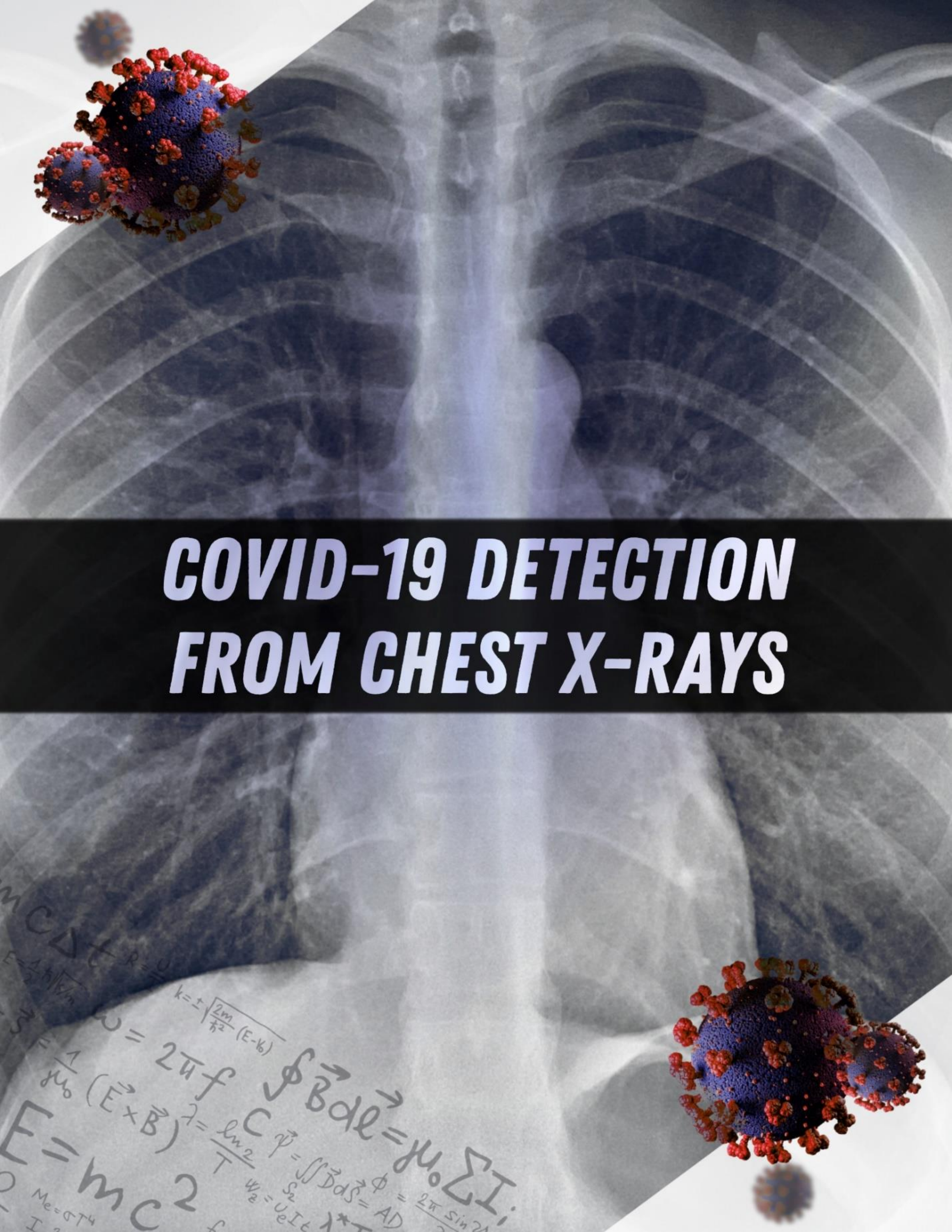

COVID-19 DETECTION FROM CHEST X-RAYS

Jordan University of Science and Technology

Course: Deep Learning

Project: COVID-19 Detection from Chest X-Rays

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Problem Definition

This project focuses on identifying **COVID-19** infections using chest **X-ray** images. Chest **X-rays** are **quick**, **non-invasive**, and widely **available**, which makes them a very **effective** tool for identifying **respiratory diseases**. Using a system that can detect **COVID-19** through **X-ray** images can help doctors in many areas where **limited** resources are an issue, it can help in diagnosing patients faster which ensures early isolation and care.

For example, being able to promptly distinguish between **Normal**, **COVID-19**, and **Viral/Bacterial** **Pneumonia** cases can help hospitals prioritize treatment during outbreaks, provide faster results in emergency situations and take some burden off nurses and laboratory staff by minimizing the need for collecting samples for testing.

The need for such **advanced systems** arises due to the increasing possibilities of fast-spreading and highly dangerous **health pandemics**, which severely impact the elderly, individuals with weak immune systems, and those with chronic illnesses, especially in underdeveloped countries. Just like in **late 2019**, when **China** gifted the world **COVID-19** which led to a global pandemic, resulting in **millions** of fatalities.

Dataset Description

- **Original Kaggle Dataset:**
  - **COVID-QU-Ex Dataset:**
    - The **Original** Dataset that we downloaded from Kaggle.
    - Uploaded and often updated by "**The researchers of Qatar University**".
    - Consists of **33,920** chest X-ray (CXR) images of size **256x256,** including:
      - **10,701 Normal**.
      - **11,956 COVID-19**.
      - **11,263** Non-COVID infections (Viral or Bacterial **Pneumonia**).
    - We downloaded the "**Lung Segmentation Data**" **directory** which has the **full** data, consists of **Train**, **Val**, and **Test**.
- **Our Dataset:**
  - **Base Folder(CNP_DS) Structure:**

    - **Restructuring**: Created three folders: **train (70%)**, **dev (15%)**, and **test (15%)**, each contains images of the three classes. We **broke** down and **combined** the **images** within the folders (**Normal**, **COVID-19**, **Pneumonia**) from the **Original kaggle dataset directory** for each of the directory folders (**Train**, **Val** and **Test**), then **stored** in each of our **datasets' folders**.

    - **Labels CSV Creation:** We created a **labels.csv** for each dataset (**train**, **dev** and **test**), contains images' **names** and corresponding class **labels** (**Normal**, **COVID-19**, **Pneumonia**).

| Deep Learning Approach

Complex CNN Architecture

- **Convolutional Layers: Four** layers with **batch normalization** and **ReLU/Leaky ReLU** activation functions.
- **Pooling: Max Pooling** for the two **initial** layers and **Average Pooling** for **last** two layers.
- **Fully Connected Layers:** Only **one**, with **128** neurons and a **dropout** of (**30%**) for **regularization**.
- **Classification (Output) Layer: Three** neurons one per class.

Simple CNN Architecture

- **Convolutional Layers: Three** layers with **ReLU** activations.
- **Pooling: Max** and **Average** Pooling.
- **Fully Connected Layer:** Also **one**, **128** neurons with **dropout** (**30%**).
- **Classification Layer: Three** neurons.

Justification

- The **Complex CNN** to enable **deeper** feature extraction.
- The **Simple CNN** for computational **efficiency** and **comparison** purposes.
- **Both architectures** were **trained** and **evaluated** with and without **data augmentation,** and had their **results** and **feature maps visualized**.

| Evaluation Metrics

Metrics used to evaluate both models' performance:

- **Accuracy**, **F1-Score** were used alongside the **Loss** during **training** to **track** and **evaluate** the training process across phases.
- **F1-Score**, **Recall**, **Precision** were used after **evaluating** the models on the **test** set to evaluate the performance **overall** and **per-class**.
- **Confusion Matrices Heatmaps** were also used to visualize the **testing** results of each model.

| Hyperparameter Tuning

- **Tuned hyperparameters:**
    - **Optimizers:** Adam and **Momentum** SGD.
    - **Learning Rates: [0.01, 0.001].**
    - **Phases: [1, 2, 3, 4],** were tuned **dynamically with** early stopping **threshold (F1 improvement < 2%).**
- **Results:**
    - **Best configuration (based on F1-Score):** Adam **optimizer, learning rate =** 0.001**, phases =** 4**.**
    - **Note:** The resulting best values were the same as the **initial** values we used when we trained the models.

Results and Discussion

- **Models Performance (Testing results):**

Metric	Complex Model	Simple Model
Accuracy	~88-91%	~86-87%
F1-Score	~88-91%	~86-87%

- **Class-wise Analysis:**

Class \ Metric	COMPLEX Precision	COMPLEX Recall	COMPLEX F1	SIMPLE P	SIMPLE R	SIMPLE F1
Normal	~76%	~96%	~85%	~81%	~86%	~83%
COVID-19	~98%	~88%	~93%	~93%	~94%	~93%
Pneumonia	~93%	~80%	~86%	~86%	~80%	~83%

- **Data Augmentation Impact:**
  - The **Augmentation Techniques** we used (**horizontal flip**, **rotation**, **cropping**, and **resizing**) showed **marginal** improvement in **some** classes **but**, in **some cases**, **reduced** accuracy.
  - **Alternative** techniques and parameters more suited to this task **may** do **better** in enhancing the model and boosting its performance as the ones above did **not** quite **outshine** the original approach.

- **Challenges:**
  - **Overfitting: Slight** overfitting was noticed in **some** runs of **4-phase** training **compared** to other runs**, especially** those of **3-phase training.**
  - **Limited augmentation effect: Chosen** techniques did **not** achieve the **expected** results.
  - **The approach itself**, while **X-Rays** images are a great **initial** tool to detect and classify various **respiratory diseases** like **COVID-19**, they **may** not be the **most sufficient** for **definitive** diagnoses of such diseases when used as a **standalone** tool. However, combining **X-ray** images with additional data, like **blood tests** or other **medical analyses** could amplify **diagnostic accuracy** and **reliability**.
