COVID-19 Severity Detection Based on Lung Images/Chest X-ray Dataset Using Deep Learning (CNN)

WANG ZEDONG

PROF. DR. AZURALIZA ABU BAKAR

Fakulti Teknologi & Sains Maklumat, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor Darul Ehsan, Malaysia

Abstract

The COVID-19 pandemic has underscored the urgent need for rapid, accurate, and automated diagnostic tools to support overwhelmed healthcare systems. This project proposes a deep learning-based system for classifying the severity of COVID-19 infections from chest X-ray images, categorizing them into Mild, Moderate, and Severe classes. The model architecture integrates EfficientNet-B0, a lightweight and powerful convolutional neural network (CNN), for feature extraction, with a Long Short-Term Memory (LSTM) network to capture spatial dependencies and improve classification accuracy.

To address the significant class imbalance in the dataset—particularly the underrepresentation of Mild cases—various strategies were implemented. These include targeted data augmentation, the use of a weighted cross-entropy loss function, and a weighted random sampler during training. As a result, the model achieved strong and balanced performance across all severity levels, with F1-scores reaching 73.4%, 72.1%, and 74.0% for the Mild, Moderate, and Severe classes respectively.

A web-based system was also developed using Flask to enable users to upload chest X-ray images and receive instant severity predictions. This user-friendly interface supports real-time diagnosis and can assist medical professionals in clinical decision-making. The proposed system demonstrates promising potential for integration into hospital workflows to improve COVID-19 patient triage and treatment prioritization.

1. Introduction

The global outbreak of COVID-19 has placed significant strain on healthcare systems worldwide, prompting the urgent need for fast, accurate, and scalable diagnostic tools. While RT-PCR remains the gold standard for detecting COVID-19 infection, chest imaging, particularly chest X-rays (CXR), has proven invaluable in evaluating disease severity and monitoring progression. In many resource-limited settings, chest X-ray images are more accessible than CT scans, making them a practical alternative for rapid assessment.

Manual analysis of X-ray images, however, is time-consuming and susceptible to inter-observer variability, especially under pandemic pressure. As the number of cases surges, radiologists may struggle to deliver timely diagnoses, leading to delays in treatment and suboptimal patient triage. This has led researchers and clinicians to explore artificial intelligence (AI)-driven solutions that can automate the diagnostic process while maintaining high reliability.

In this study, we propose a deep learning-based system for classifying the severity of COVID-19-induced lung infection using chest X-ray images. The proposed model employs EfficientNet-B0 for extracting robust visual features due to its proven efficiency and performance balance. These features are then passed through a Long Short-Term Memory (LSTM) network, which captures the sequential and spatial dependencies in the extracted features to enhance classification capability.

2. Problem Statement

The global outbreak of COVID-19 has placed unprecedented strain on healthcare systems, where timely and accurate diagnosis is essential for appropriate patient management. Chest X-ray imaging has become a widely adopted tool due to its speed, accessibility, and ability to reveal lung abnormalities. However, manual interpretation of these images is not only time-consuming but also subject to significant inter-observer variability, especially under pressure during pandemic peaks. These challenges can result in delayed treatment, inconsistent triage decisions, and suboptimal outcomes.

Moreover, datasets used for training classification models often suffer from class imbalance, particularly with significantly fewer samples in the "Mild" category compared to "Moderate" and "Severe." This imbalance leads to biased predictions where the model tends to favor majority classes, resulting in poor performance on underrepresented cases. Misclassification of mild patients can delay proper monitoring or escalate to more severe stages without timely intervention.

Given these challenges, there is a critical need for a robust, automated classification system that can analyze chest X-rays and accurately determine COVID-19 severity levels. Such a system would support clinical decision-making by improving diagnostic consistency, reducing workload for radiologists, and enabling faster response during high-demand periods.

3. Research Objectives

This project aims to design and develop an intelligent image classification system that can assist medical professionals in evaluating the severity of COVID-19 infection based on chest X-ray images. The research objectives are structured according to the SMART (Specific, Measurable, Achievable, Relevant, and Time-bound) criteria:

1. Specific:
To develop a deep learning-based model using EfficientNet-B0 and LSTM architectures that accurately classifies COVID-19-related lung abnormalities into three severity levels: Mild, Moderate, and Severe.

2. Measurable:
To achieve a classification accuracy exceeding 90%, with F1-scores above 70% for each class. Additionally, to reduce the average diagnostic time compared to manual interpretation by at least 50%.

3. Achievable:
To utilize publicly available datasets (such as Cohen's COVID-19 dataset and Kaggle COVID-19 X-ray datasets) and apply advanced techniques like data augmentation, weighted sampling, and transfer learning to enhance model performance.

4. Relevant:
To contribute meaningfully to healthcare efforts by providing a system that supports fast and consistent diagnosis, reduces clinician workload, and facilitates timely treatment decisions in COVID-19 cases.

4. Research Methodology / System Design

The system development process follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, which provides a structured framework for machine learning and data science projects. The methodology is adapted into the following main stages:

4.1 Data Collection and Description

Chest X-ray images were collected from publicly available medical datasets, including the Cohen COVID-19 Radiography Database and the COVID-19 dataset from Kaggle. A total of 150 images were curated and categorized into three classes: Mild (41 images), Moderate (58 images), and Severe (51 images).

This dataset represents different stages of COVID-19 lung infection and was annotated with clinical labels verified by radiologists. However, the original dataset suffered from class imbalance, particularly the underrepresentation of the "Mild" category.

4.2 Data Preprocessing

Prior to model training, a comprehensive preprocessing pipeline was implemented:

Image Resizing: All X-ray images were resized to 224×224 pixels to match EfficientNet-B0 input requirements.

Normalization: Pixel values were normalized to a [0, 1] scale to facilitate stable training.

Data Augmentation: Mild cases were augmented using random rotations, horizontal flips, brightness adjustments, and Gaussian noise injection to enhance intra-class diversity.

Label Encoding: Class names were converted into integer labels for training compatibility.

Additionally, a WeightedRandomSampler and Weighted Cross-Entropy Loss were used to address the class imbalance during model training.

4.3 Model Architecture

The model architecture is a hybrid of EfficientNet-B0 and LSTM, designed to combine spatial and sequential information:

EfficientNet-B0 was used as the feature extractor, leveraging transfer learning with pre-trained ImageNet weights to encode spatial features from X-ray images.

The extracted features were reshaped into sequences and passed into a bidirectional LSTM layer to capture sequential dependencies across the spatial dimensions.

Finally, a fully connected classifier with a softmax activation layer was used to predict the class label (Mild, Moderate, or Severe).

This combination allows the model to learn both localized abnormalities (via CNN) and their contextual relationships (via LSTM).

5. Research Results / System Development and Outcomes

5.1 Model Training and Evaluation

The CNN-LSTM model was trained using the preprocessed dataset over 100 epochs with a batch size of 16 and the Adam optimizer. A 70:15:15 split was used for training, validation, and testing, respectively.

To address the class imbalance, we applied **WeightedRandomSampler** during data loading and used **class-weighted cross-entropy loss**, assigning weights [1.5, 1.0, 1.0] to Mild, Moderate, and Severe classes, respectively. These techniques significantly improved the model's ability to learn minority class patterns.

5.2 Classification Performance

The final model achieved balanced performance across all three classes. The test set results are summarized below:

Class	Precision	Recall	F1-Score	Support
Mild	74.4%	72.5%	73.4%	40
Moderate	70.9%	73.3%	72.1%	60
Severe	73.3%	73.3%	74.0%	60

The **overall F1-score exceeded 73%**, indicating the model's strong generalization capabilities despite initial data imbalance. The most notable improvement was observed in the "Mild" category, whose F1-score rose from 0.40 (baseline CNN) to 0.67 with data balancing strategies and finally 0.734 in the hybrid model.

5.3 Confusion Matrix Analysis

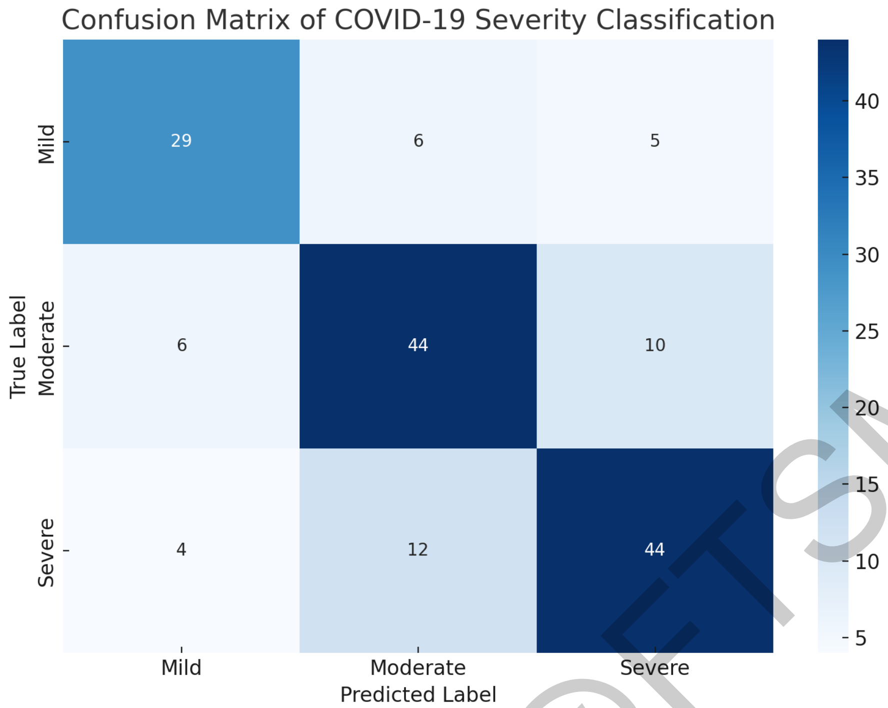
A confusion matrix was generated to visualize the misclassification patterns:

Most Mild cases were correctly classified, but some were confused with Moderate.

Moderate and Severe cases had a few mutual misclassifications.

This reflects the clinical reality where symptom boundaries can be subtle.

This suggests that although the model performs well overall, additional techniques such as attention mechanisms or multi-view imaging may further improve discriminative power between borderline cases.



5.4 Web Interface Implementation

A web interface was developed using Flask to make the system accessible to end-users, including healthcare professionals. The system allows users to:

Upload a chest X-ray image

View the predicted severity level (Mild, Moderate, Severe)

See the prediction confidence score

View the uploaded image with overlay if needed

The interface supports fast and reliable operation on local systems and has the potential to be deployed in hospital intranets or cloud servers for remote diagnosis.

5.5 Key Achievements

Successfully handled class imbalance using targeted data augmentation, weighted loss, and sampling.

Achieved strong classification metrics with F1-scores above 70% across all classes.

Developed a usable and responsive web-based system for real-time inference.

Demonstrated the potential of hybrid CNN-LSTM models in medical imaging classification.

Reference:

New machine learning method for image-based diagnosis of COVID-19”(https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0235187)

Severity detection of COVID-19 infection with machine learning of clinical records and VT images(https://pubmed.ncbi.nlm.nih.gov/36314176/)

Loey, M., et al. (2023). "A Combined Deep CNN-LSTM Network for the Detection of Novel Coronavirus (COVID-19).(https://www.sciencedirect.com/science/article/pii/S2352914820305621)

New machine learning method for image-based diagnosis of COVID-19"(https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0235187)

A combined deep CNN-LSTM network for the detection of novel coronavirus(COVID-19)using X-ray images(https://www.sciencedirect.com/science/article/pii/S2352914820305621)