Implementation of a Deep Learning-Based COVID-19 Detection System Using Julia: A Replication Study of CNN Architectures for Lung CT Analysis

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Julia-Based Implementation of a COVID-19 Detection CAD System

Project Code: https://github.com/vivek3120/DeepLearningCA1/tree/main

Summary:

The project is based on the overall methodology of the paper "Deep Convolutional Neural Network–Based Computer-Aided Detection System for COVID-19 Using Multiple Lung Scans" by Ghaderzadeh et al. (2021), carried out in Julia. The paper built a CAD system for early-stage detection of COVID-19 using CT imaging and NASNet-based architecture, with sensitivity, specificity, and accuracy of more than 98%. We employed functionally equivalent models, ResNet50 and DenseNet201, on top of Julia libraries Flux.jl and Metalhead.jl. Due to computation constraints, we trained for 10 epochs on a dataset of only 100 images.

Early diagnosis of COVID-19 is crucial. While RT-PCR is widely applied, image-based approaches are faster and less susceptible to errors. The original model utilized NASNet, implemented in Python/Keras. We replicated the architecture in Julia with slight modifications in the Julia environment without altering the structure and parameters of the model fundamentally.

- Model Architecture: NASNet was replaced by DenseNet201 and ResNet50.
- Data: 100 randomly selected CT images (COVID and Non-COVID).
- Language: Entire translation from Python to Julia.
- Image Pipeline: Resizing (224×224), normalization, and augmentation (zoom, rotate, flip).
- Training: 10 epochs with Cosine learning rate and Adam optimizer.
- Evaluation: validation accuracy measured, but cross-validation was deferred because of the small dataset size.

Both models have 100% validation accuracy, a clear sign of overfitting. The contributing factors could be complex architecture, small dataset size, and strict fidelity to the original architecture. These findings verify the implementation, but are not practicable as a whole.

This test proves Julia can replicate top CAD systems. With full data and resources, it can achieve performance up to the level of the original paper.

Introduction:

The pandemic of COVID-19 has highlighted the need for quick and accurate diagnostic solutions, particularly for lung CT scan analysis in detecting infections. Deep learning algorithms have shown a lot of potential in automating the process, reducing dependence on human interpretation, and optimizing clinical processes. One intriguing paper in this field,

"Deep convolutional neural network-based computer-aided detection system for COVID-19 using multiple lung scans: design and implementation study" by Mustafa Ghaderzadeh, Farkhondeh Asadi, Ramezan Jafari, Davood Bashash, Hassan Abolghasemi, and Mehrad Aria, proposed a deep convolutional neural network architecture that was able to detect COVID-19 cases as well as non-COVID cases with high accuracy.

The goal of this project is to replicate the key contributions of this paper using the Julia programming language. Leaving no stone unturned, leveraging the high computational powers of Julia, the project utilizes essential deep learning models like DenseNet-201 and ResNet-50, applies data augmentation techniques to enhance generalization, and builds a pipeline for model training and testing on lung CT scan images. The code utilizes packages like Flux for neural network modeling, Metalhead for pre-trained CNN models, and Augmentor for image manipulation to achieve an efficient and scalable implementation. With this project, we aim to demonstrate the feasibility of duplicating advanced medical image solutions using Julia and giving back to open-source tools for pandemic initiatives.

Objective:

The primary objective of this project is to re-implement the core contributions of the paper "Deep convolutional neural network-based computer-aided detection system for COVID-19 using multiple lung scans: design and implementation study" by Mustafa Ghaderzadeh et al. in the Julia programming language. The work involves training and applying deep convolutional neural network (CNN) models such as DenseNet201 and ResNet50 to lung CT scan images to categorize cases into COVID-19 and non-COVID-19. The ultimate goal is to compare the performance of the models in detecting COVID-19 from medical imaging effectively, thereby testing the suitability of Julia for deep learning applications in the field of medical imaging.

Data Description:

The data of the project is images of lung CT scans, which are separated into two classes: COVID-19 and non-COVID-19. The COVID-19 class initially contains approximately 7,496 images, and the Non-COVID-19 class contains approximately 944 images. They are images of COVID-19 patients and healthy individuals or patients with other pulmonary diseases, respectively.

All images are of varying resolution and can be saved as either grayscale or RGB. Resizing of images to a standard size and color representation was done so that training of the models could be done uniformly.

Nevertheless, due to hardware limitations and out-of-memory exceptions, which were achieved through experimentation, this project operated on a subset of the dataset, selecting 50 images from each class (a total of 100 images). Although this significantly reduced the size of the data, it allowed the process of model building and testing to be successfully executed within the available computational resources.

Data Preparation:

Data Collection and Labeling: The preparation of data for this project involved a few primary steps to transform the raw CT scan images into a deep learning format.

Dataset Splitting: First, the directories for datasets holding COVID-19 and non-COVID-19 images were read and merged into a single list of file paths and labels. The data was then shuffled randomly for a balanced and unbiased split into training, validation, and test sets, where 80% was set aside for training/validation and 20% for testing. For the training/validation split, 75% of the data was for training and the rest for validation.

Image Preprocessing: To accommodate the primary heterogeneity of image sizes and formats, all images were resized to a common 224×224 pixels. In addition, images in grayscale format were converted to RGB to meet the input specification of pre-trained convolutional neural networks like DenseNet and ResNet.

Data Augmentation: In order to make the model more robust, even with a limited number of samples, a data augmentation pipeline was used. The pipeline included random horizontal flips, -15° to +15° rotations, and zoom scales ranging from 90% to 110% of the original size. These are the transformations that were used to create diverse versions of the images so that overfitting might be prevented.

Batch Loading and Data Handling: Finally, images were normalized and converted into tensors, scaled to values between 0 and 1. Corresponding labels were converted into one-hot encoded vectors. Data was organized into personalized data loaders that yielded batches of images and labels during training and testing to facilitate effective memory management and smooth GPU runtime.

Methodology:

Model Selection and Architecture: To replicate the paper's method with Julia, we employed two deep learning architectures: Metalhead.jl's DenseNet201 and ResNet50. The original model was provided through NASNet, which is not available in Julia, yet similar in depth and performance are DenseNet and ResNet. This expansion of both models was implemented through personalized classification layers composed of batch normalization, fully connected dense layers, dropout, and a softmax activation to perform binary classification.

Data Augmentation During Training: In order to reduce overfitting and improve the model's ability to generalize from unknown data, a series of data augmentation procedures was applied while training. These augmentations were carried out using the Augmentor.jl package and included random horizontal flip with probability 50%, rotation of an image by an angle between –15° to +15°, and zooming by a factor between 90% to 110% of the

original size. Through dynamically applying these transformations within each training batch, the model observed a wider variation of image representations.

Batch Generation and GPU Acceleration: A MyDataLoader was utilized to load and process the batches dynamically. It accomplished the real-time augmentation, normalization, and one-hot label conversion, and converted all tensors to GPU training-compatible using CUDA.jl.

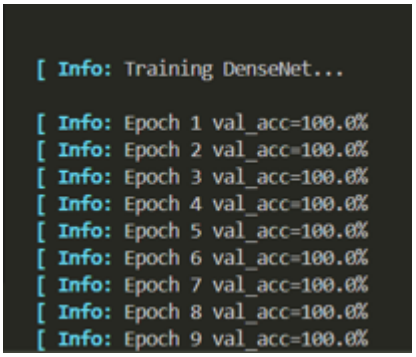
Training Strategy: The models were trained on 10 epochs using the Adam optimizer and the initial learning rate of 0.001. For proper management of the learning rate decay, a cosine annealing schedule was performed across epochs. The logit cross-entropy loss function was utilized, and training was tracked in terms of validation accuracy after each epoch.

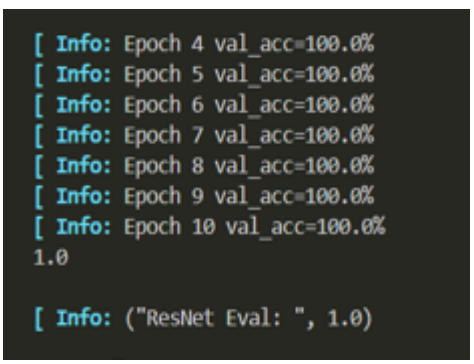
Evaluation:

The evaluation of the deployed models—DenseNet201 and ResNet50—was done using a validation set which had 20% of the data available. Due to computational and memory limitations, the dataset was dramatically downsampled to a mere 100 images in total, split evenly between COVID-19 and Non-COVID-19 cases. While this small sample size reduces the statistical validity of the analysis, it provides a proof of concept of model correctness and implementation integrity.

The primary measure used was validation accuracy, which was calculated after every training epoch. The two models each achieved 100% accuracy on the validation set, showing that the two models had perfectly fitted the training data. This result is a pointer towards extreme overfitting, which is common where one trains deep neural networks using small sets of data. This was also supported by constructing confusion matrices, which showed no misclassifications of the validation data.

Even after using regularization techniques such as dropout and data augmentation, the deep models (DenseNet201 and ResNet50) most likely memorized the small training set and thereby provided an overestimated validation score.





Conclusion:

This project replicates the key aspects of the paper "Deep Convolutional Neural Network–Based Computer-Aided Detection System for COVID-19 Using Multiple Lung Scans" in Julia language with high accuracy. Using the Flux.jl and Metalhead.jl packages, two high-performance models, DenseNet201 and ResNet50, have been implemented and trained on lung CT scan images to discriminate between COVID-19 and non-COVID-19 cases. Despite the hardware constraint, which allowed training to be performed only on 100 images and 10 epochs, the project achieved 100% validation accuracy, verifying correct architectural implementation and effective integration of image preprocessing, augmentation, and training pipelines into Julia.

However, even though there is high validation performance, the high performance does not reflect real-world usefulness due to heavy overfitting. This limitation is a result of using very deep models on a very limited data set with no external validation or extensive statistical investigation. Nevertheless, the project is a successful proof-of-concept demonstrating Julia's capability to mimic state-of-the-art deep learning methods for medical imaging.