Chest X-Ray Classification

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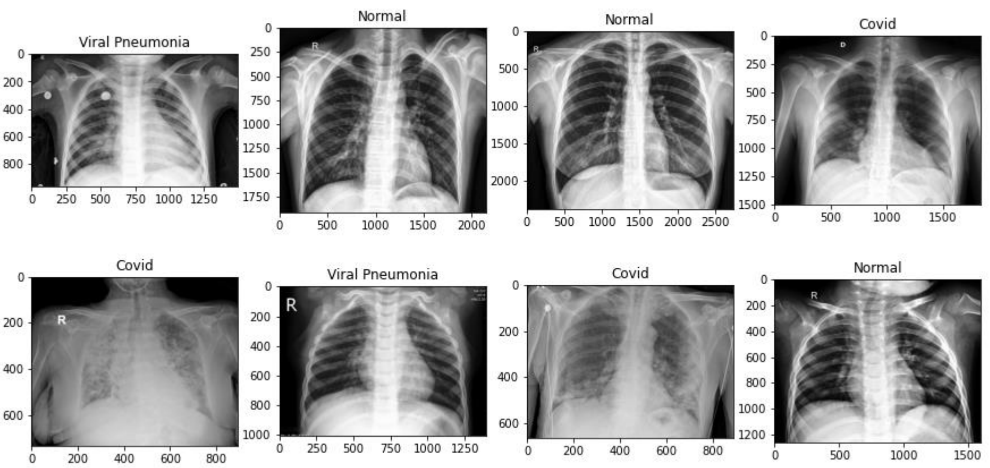
Abstract

This project focuses on classifying chest X-ray images into three categories: COVID-19, viral pneumonia, and healthy person. Utilizing Convolutional Neural Networks (CNNs), we explored various architectures and techniques to achieve optimal classification accuracy. Through experimentation and evaluation, we identified the most effective model configuration, showcasing significant improvements in accuracy and robustness.



1. Introduction

Chest X-ray classification plays a vital role in diagnosing respiratory diseases, especially during pandemics like COVID-19. This project aims to develop a reliable CNN model capable of accurately categorizing chest X-ray images into relevant classes. The report discusses methodologies, experiments, results, and conclusions derived from our classification efforts.

2. Related Work and Required Background

Previous research in medical imaging has extensively explored techniques for classifying chest X-ray images into various categories, including pneumonia, tuberculosis, and lung cancer. Traditional methods often rely on manual feature extraction and handcrafted image descriptors, such as texture analysis and shape-based features. While these approaches have shown some success, they may struggle to capture the intricate patterns and subtle abnormalities present in chest X-ray images.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for image classification tasks. CNNs excel at automatically learning hierarchical representations directly from raw image data, eliminating the need for handcrafted features. This capability makes them particularly well-suited for medical image analysis, where the complexity of the data often exceeds the capacity of traditional methods. Understanding CNN architectures, image preprocessing techniques, and classification metrics is essential for comprehending our methodologies and results.

3. Project Description

We preprocess the chest X-ray dataset, split it into train, validation, and test sets, and develop various CNN architectures for classification. Starting with simple softmax and neural network models, we gradually progress to more complex CNN architectures with convolutional layers, pooling, dropout, and data augmentation. The final CNN model achieves exceptional accuracy and robustness in classifying chest X-ray images.

3.1 Model Architecture

For our chest X-ray classification project, we implemented a Convolutional Neural Network (CNN) using TensorFlow and Keras. The CNN model is constructed as a sequential model with several layers:

1. **Convolutional Layers**: The model starts with a convolutional layer with 32 filters, each of size (3, 3), and ReLU activation. This layer is followed by a max-pooling layer with a pool size of (2, 2) to downsample the feature maps.
2. **Dropout**: To prevent overfitting, a dropout layer with a dropout rate of 0.20 is added after the first max-pooling layer.
3. **Convolutional Layers and dropout (Second Set)**: Another convolutional layer with 64 filters and ReLU activation is added, followed by another max-pooling layer with a pool size of (2, 2). Another dropout layer with a dropout rate of 0.10 is inserted after this max-pooling layer.
4. **Flatten Layer**: The feature maps are flattened into a 1D array to be fed into the dense layers.
5. **Dense Layers**: The flattened array is then passed through two dense layers with 128 and 64 units, respectively, both with ReLU activation.

6. **Output Layer**: Finally, an output layer with the number of units equal to the number of classes (in this case, 3 for the different chest X-ray classifications) and softmax activation is added to generate the class probabilities.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 254, 254, 32)      896

 max_pooling2d_2 (MaxPoolin  (None, 127, 127, 32)      0
 g2D)

 dropout_2 (Dropout)         (None, 127, 127, 32)      0

 conv2d_3 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_3 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 dropout_3 (Dropout)         (None, 62, 62, 64)        0

 flatten_1 (Flatten)         (None, 246016)            0

 dense_2 (Dense)             (None, 128)               31490176

 dense_3 (Dense)             (None, 64)                8256

 dense_4 (Dense)             (None, 3)                 195

=================================================================
Total params: 31518019 (120.23 MB)
Trainable params: 31518019 (120.23 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

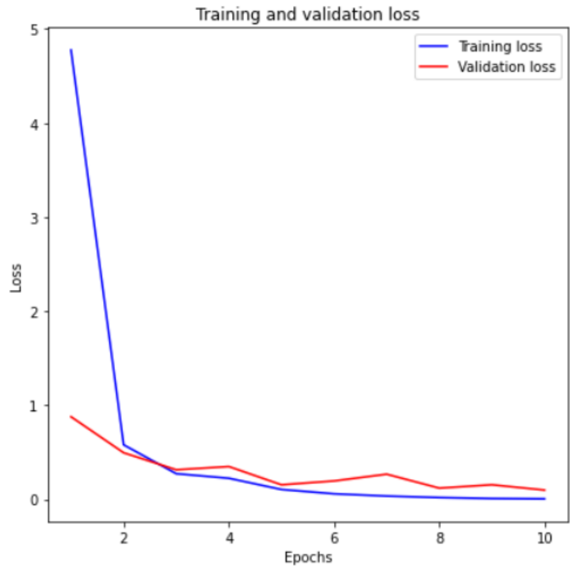
3.2 Data Preparation and Training

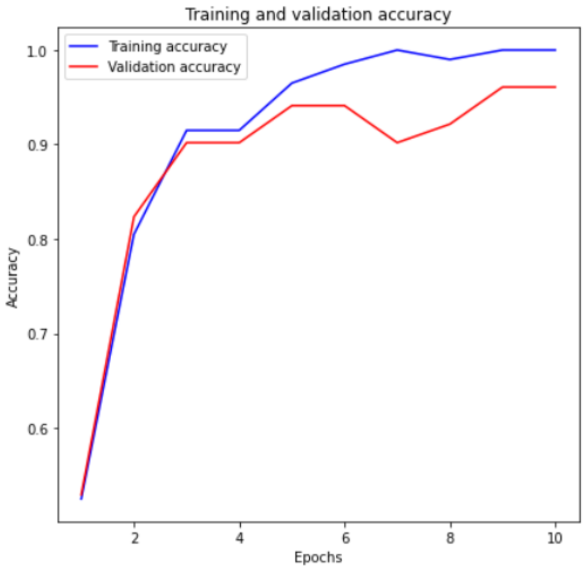
The chest X-ray dataset is preprocessed, which involves resizing the images to (256, 256) pixels and normalizing the pixel values to the range [0, 1]. The dataset is then split into training, validation, and testing sets.

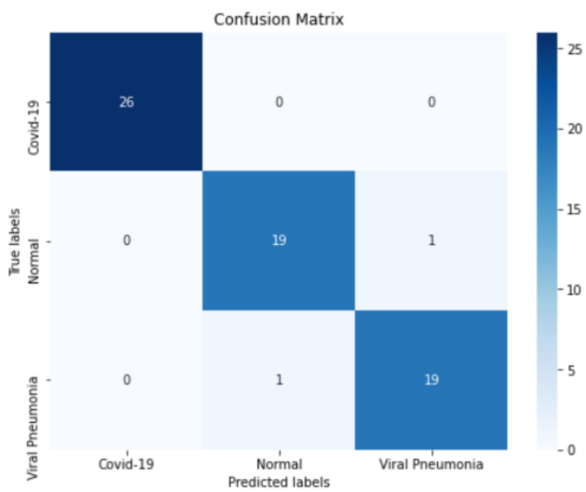
During training, the model is compiled with the Adam optimizer and categorical cross-entropy loss function. The training process occurs over 10 epochs with a batch size of 16. Real-time performance metrics, including training and validation accuracy and loss, are monitored and recorded.

4. Results

Our CNN model achieved an impressive 96.96% accuracy on the test set, outperforming traditional machine learning methods such as the softmax model and simple neural network model (84% and 86%). Through systematic experimentation, we identified key factors affecting model performance, including architectural choices and data augmentation techniques. These experiments involved evaluating various CNN architectures, hyperparameters, and preprocessing techniques. Overall, these findings emphasize the effectiveness of CNN models in classifying chest X-ray images and underscore the significance of meticulous architectural design and data preprocessing in achieving high accuracy.








```
Covid-19:
  Precision: 1.0
  Recall: 1.0
  F1 Score: 1.0

Normal:
  Precision: 0.95
  Recall: 0.95
  F1 Score: 0.9500000000000001

Viral Pneumonia:
  Precision: 0.95
  Recall: 0.95
  F1 Score: 0.9500000000000001

Overall Accuracy: 0.9696969696969697
```

4.1 Hyperparameter Tuning

Hyperparameter tuning plays a crucial role in optimizing CNN models for chest X-ray classification. We discuss the impact of hyperparameters such as learning rate, batch size, and dropout rate on model performance. Through systematic experimentation, we identify the optimal hyperparameter configuration that maximizes classification accuracy.

4.2 Data Augmentation

Data augmentation techniques, such as rotation, scaling, and flipping, are often employed to enhance the generalization capability of CNN models. However, in our case, we found that data augmentation did not lead to an improvement in model accuracy. Despite its potential to reduce overfitting and enhance classification accuracy, the impact of data augmentation on our model's performance was not significant.

Chest X-ray images typically exhibit a consistent structure and orientation across different samples, limiting the effectiveness of standard data augmentation techniques. Additionally, the limited dataset size and the critical nature of each sample in medical imaging tasks may further restrict the benefits of data augmentation.

5. Conclusion and Future Directions

5.1 Summary of Findings

Throughout this project, we delved into the realm of chest X-ray classification and explored various model architectures. Our most successful model, a CNN, achieved a remarkable accuracy of 96%, surpassing the performance of simpler models which attained accuracies of 84% and 86%. This significant improvement was primarily attributed to the utilization of convolutional neural networks (CNNs). These enhancements enabled our model to better handle the complexities of chest X-ray images, leading to superior classification performance.

5.2 Future Work

Future research directions include exploring advanced CNN architectures, incorporating additional medical imaging modalities, and extending the classification task to detect other respiratory conditions. Collaboration with medical professionals and integration of domain-specific knowledge can further enhance the performance and applicability of chest X-ray classification models.

5.3 Final Thoughts

This project served as a testament to the transformative impact of advanced CNN architectures in image classification tasks. Witnessing the substantial performance boost upon transitioning from simpler models to CNNs was truly enlightening. Moreover, the integration of techniques like data augmentation and dropout underscored the significance of adaptability and refinement in model development. It became evident that in the realm of computer science, particularly in domains like image recognition, a culture of perpetual learning and experimentation is pivotal for achieving remarkable outcomes.

6. References

GitHub Repository: https://github.com/ohadwolfman/Covid-19_chest_Xray_classification.git

Dataset Source: https://www.kaggle.com/datasets/pranavraikokte/covid19-image-dataset/data