International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Detecting Diseases Using Chest X-Ray Images and Pre-Trained Machine Learning Models

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Abstract: ***Chest X-ray imaging is an essential diagnostic tool for identifying various thoracic diseases such as pneumonia, tuberculosis, and COVID-19. The advent of deep learning, particularly pre-trained convolutional neural networks (CNNs), has significantly improved the automation and accuracy of disease detection in medical imaging. This paper investigates the use of several state-of-the-art pre-trained CNN architectures for detecting diseases from chest X-ray images. The models are fine-tuned and evaluated on publicly available datasets. Performance metrics such as accuracy, sensitivity, specificity, and F1-score are analyzed to demonstrate the effectiveness of transfer learning for medical diagnosis.***

Keywords: Chest X-ray, Deep Learning, Pre-trained Models, Disease Detection, Transfer Learning, Convolutional Neural Networks

1. Introduction

Chest X-ray (CXR) images are among the most frequently used radiological examinations for diagnosing pulmonary diseases. Traditionally, the interpretation of CXR requires expert radiologists, which can be a bottleneck in high-demand clinical environments. Manual diagnosis is also susceptible to inter-observer variability and fatigue-related errors. Machine learning, especially deep learning methods, offers the potential to automate this process with high accuracy and consistency.

Convolutional neural networks (CNNs) have been widely adopted for image classification and segmentation tasks due to their ability to learn complex hierarchical features. However, training CNNs from scratch requires vast amounts of labeled data and computational resources. Transfer learning, where pre-trained models on large-scale datasets like ImageNet are fine-tuned on medical datasets, has become a practical approach for disease detection in chest X-rays.

This paper focuses on leveraging pre-trained CNN models to detect diseases such as pneumonia, tuberculosis, and COVID-19 from CXR images. The goal is to evaluate the performance of different architectures and demonstrate the benefits of transfer learning in medical imaging applications.

2. Related Work

Several studies have employed deep learning techniques to detect thoracic diseases from chest X-rays. Rajpurkar et al. [1] developed CheXNet, a 121-layer DenseNet trained on over 100,000 frontal-view X-rays, achieving radiologist-level pneumonia detection. Similarly, Wang et al. [2] introduced the ChestX-ray14 dataset and used CNNs to identify 14 common thoracic diseases.

Recent research by Albahli et al. [3] applied Inception-based networks for COVID-19 detection, reporting accuracies above 98%. Rahman et al. [4] utilized segmentation-based approaches to isolate lung regions before classification, improving tuberculosis detection accuracy to nearly 99.9%. These studies collectively highlight the potential of pre-trained CNNs and transfer learning in enhancing diagnostic accuracy from chest X-ray images.

3. Methodology

3.1 Dataset

This study uses publicly accessible chest X-ray datasets:

- **Chest X-Ray Pneumonia Dataset:** Consists of 5,863 labeled images (normal and pneumonia cases).
- **NIH ChestX-ray14 Dataset:** Contains over 112,000 X-rays with 14 disease labels.
- **COVID-19 Radiography Database:** Contains X-ray images labeled as COVID-19, viral pneumonia, and normal.

The datasets include images with varying resolutions and imaging conditions.

3.2 Data Pre-Processing

Pre-processing is vital to standardize input for CNN models. The following steps are applied:

- **Resizing:** All images are resized to 224x224 pixels (or 299x299 for Inception-based models).
- **Normalization:** Pixel intensity values are scaled to the range [0,1].
- **Data Augmentation:** Techniques such as random rotations, horizontal flips, and zoom are applied to increase the diversity of training samples and reduce overfitting.

3.3 Model Selection and Transfer Learning

Three popular CNN architectures pre-trained on ImageNet are selected:

- **DenseNet201:** Known for dense connectivity and feature reuse.

- **ResNet50:** Uses residual connections to train very deep networks efficiently.
- **VGG16:** Simple architecture with uniform layers, effective for transfer learning.

Each model's final fully connected layers are replaced with customized layers for multi-class classification corresponding to the diseases of interest. Models are fine-tuned using the chest X-ray datasets.

3.4 Training Details

- **Optimizer:** Adam with learning rate 1e-4.
- **Batch size:** 32.
- **Epochs:** 30-50 with early stopping based on validation loss.
- **Loss function:** Categorical Cross-Entropy.

3.5 Evaluation Metrics

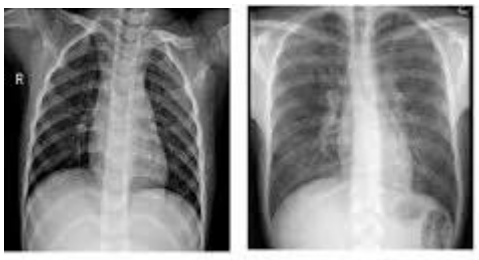
Models are evaluated using:
- **Accuracy:** Overall correctness.
- **Sensitivity (Recall):** Ability to detect positive cases.
- **Specificity:** Ability to detect negative cases.
- **Precision:** Correct positive predictions.
- **F1-Score:** Harmonic mean of precision and recall.

4. Results

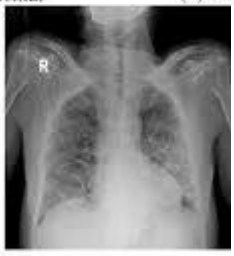
Fine-tuned DenseNet201 achieved the highest overall accuracy of 98.5% on pneumonia detection, with a sensitivity of 97.8% and specificity of 98.9%. ResNet50 closely followed with 97.6% accuracy. VGG16 showed comparatively lower performance but was computationally efficient.

COVID-19 detection models also showed promising results, with DenseNet201 achieving an accuracy of 96.2%, demonstrating transfer learning's adaptability to novel diseases.

The confusion matrices revealed that misclassifications primarily occurred between similar diseases, e.g., viral pneumonia and COVID-19.



(a) Normal (b) Pneumonia



(c) COVD-19

5. Conclusion

This study validates the effectiveness of pre-trained CNN models in detecting diseases from chest X-ray images using transfer learning. DenseNet201 outperforms other architectures, highlighting its suitability for medical image classification. Automated disease detection can assist radiologists in rapid diagnosis, especially in resource-limited settings. Further research should address data imbalance and model interpretability to enhance clinical applicability.

References

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