Automated Classification of COVID-19, Pneumonia, and Normal Patterns in Chest X-Rays UsingConvolutional Neural Networks

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Abstract. The COVID-19 pandemic highlighted the need for rapid diagnostic tools. This study develops and evaluates automated classification models for Chest X-ray (CXR) images to distinguish between COVID-19, Pneumonia, and Normal cases. We utilized InceptionV3 and ResNet152V2 deep learning architectures with transfer learning, alongside a classical Support Vector Machine (SVM) approach based on intensity histograms. Using a large public CXR dataset, our findings robustly affirm these methods' capability to accurately differentiate pulmonary states. This work presents promising avenues for augmenting clinical decision support in differential diagnosis and patient management, aiming to ease radiologists burden and streamline patient triage.

Keywords: COVID-19, Pneumonia, Chest X-ray, Deep Learning, Convolutional Neural Networks, InceptionV3, ResNet152V2, Machine Learning, SVM, Intensity Histograms, Computer-Aided Diagnosis (CAD), Computer Vision.

1 Introduction

The unprecedented emergence of the COVID-19 pandemic precipitated a critical demand for expeditious and reliable diagnostic capabilities on a global scale. While reverse transcription-polymerase chain reaction (RT-PCR) assays remain the benchmark for direct SARS-CoV-2 detection, limitations pertaining to their accessibility, processing latency, and inherent variability in sensitivity have catalyzed the exploration of complementary diagnostic modalities [1]. Medical imaging, particularly Computed Tomography (CT) of the chest and, crucially, Chest X-rays (CXR), has assumed a pivotal role in the assessment of disease extent and the longitudinal monitoring of patient cohorts [2].

CXR examinations are particularly esteemed for their economic viability, widespread availability across diverse clinical environments, and the celerity with which image acquisition can be accomplished. Notwithstanding these advantages, the interpretation of CXR images to differentiate between pulmonary patterns indicative of COVID-19, other forms of pneumonia (both bacterial and non-COVID viral), and physiologically normal lungs can be inherently intricate and prone to subjective variability, necessitating the discernment of highly skilled radiologists [3]. Clinical manifestations of COVID-19 on CXR often include bilateral peripheral ground-glass opacities and multifocal consolidations, patterns that can significantly overlap with those observed in other viral or bacterial pneumonias [7]. Bacterial pneumonias, for instance, typically present with well-demarcated lobar consolidations, whereas other viral pneumonias might display diffuse interstitial patterns, underscoring the diagnostic challenges. In contexts characterized by elevated clinical demand, an augmented workload and resultant clinician fatigue may inadvertently compromise diagnostic precision and timeliness. Within this overarching framework, Artificial Intelligence (AI), and specifically the domain of Deep Learning, has evinced extraordinary proficiency in the analytical scrutiny of medical imagery [6]. Convolutional Neural Networks (CNNs), by virtue of their intrinsic capacity to extract hierarchical features directly from raw data, have facilitated momentous advancements in image classification and segmentation tasks [4]. Computer-aided diagnosis (CAD) systems predicated upon CNN architectures hold substantial promise as objective second-opinion mechanisms, efficient triage instruments, or proactive early warning systems, thereby enhancing procedural efficiency and potentially refining diagnostic accuracy [5]. The widespread application of CNNs for

COVID-19 detection in medical images has been extensively explored, often leveraging transfer learning from pre-trained networks on large natural image datasets [8], [9], [10], [11].

2 Methodology

The systematic construction and rigorous evaluation of the classification models were executed through a meticulously structured process. This encompassed the comprehensive acquisition and preparation of data, the precise architectural definition of the deep learning models and the strategic feature extraction for the classical method, culminating in the configuration of training and evaluation parameters.

2.1. Data Collection and Preparation: For the purpose of this study, a robust dataset of chest X-ray (CXR) images was procured from a publicly available and ethically sanctioned repository, thereby ensuring the requisite diversity for the multiclass classification task. The data Source pertaining to the COVID-19, Pneumonia (non-COVID), and Normal categories were sourced from the "COVID-19, Pneumonia, Normal Chest X-Ray Images" dataset, readily accessible via Kaggle [12]. This comprehensive dataset consolidates a unified collection of CXR images directly pertinent to the three designated classification classes. The aggregate dataset comprised a total of 5,228 images, judiciously distributed as follows: COVID-19: 1,626 images, Pneumonia: 1,800 images and Normal: 1,802 images. A meticulous process of class balancing was undertaken to mitigate potential biases stemming from data imbalances, a critical step for ensuring the generalizability of the ensuing models.

The Chest X-ray (CXR) dataset, sourced from a public repository on Kaggle [12], underwent stringent pre-processing to standardize the images and optimize them for model input. This involved uniformly resizing all images to 256x256 pixels in PNG format, followed by linear normalization of pixel intensity values to the [0, 1] range and replication to 3 channels. Subsequently, the dataset was strategically partitioned into 80% for training, 10% for validation, and 10% for testing using a stratified sampling approach to ensure proportional representation of each class across all subsets, thereby facilitating robust model training and unbiased evaluation.

2.2. Model Architectures and Feature Extraction: This investigation implemented and comparatively assessed three distinct classification paradigms: two deep learning models predicated on pre-trained convolutional architectures (InceptionV3 and ResNet152V2), and a classical machine learning model (SVM operating on intensity histograms).

2.2.1. Classification Method 1: Convolutional Neural Network with InceptionV3: The inaugural classification method was predicated upon the InceptionV3 architecture, a deep Convolutional Neural Network meticulously pre-trained on the expansive ImageNet dataset [3]. InceptionV3 is renowned for its computational efficacy and its inherent capacity to capture multi-scale features through its innovative "Inception modules." A transfer learning paradigm was rigorously applied, recognized for its pronounced effectiveness in medical image classification tasks, particularly where domain-specific datasets may be comparatively limited vis-à-vis ImageNet.

The InceptionV3 model was implemented by instantiating the pre-trained weights='imagenet' model, critically excluding its uppermost classification layer (include_top=False) to repurpose its formidable low- and mid-level feature representations. The convolutional layers of this base model were initially "frozen" to preserve pre-trained knowledge and direct early learning to newly appended layers. Custom layers were then judiciously added for chest X-ray classification, including a GlobalAveragePooling2D layer for dimensionality reduction, a Dense layer with 256 relu units for complex feature combinations, a Dropout layer (rate 0.5) for regularization, and a terminal Dense(3, activation='softmax') output layer for class probabilities. Following an initial training phase with frozen base layers, a meticulous "fine-tuning" procedure was executed, entailing unfreezing a select subset of the terminal convolutional layers within the base model and retraining the integrated model at a

substantially reduced learning rate, allowing it to subtly adapt its pre-trained features to the specific nuances of the CXR image domain.

2.2.2. Classification Method 2: Convolutional Neural Network with ResNet152V2: The second classification methodology was grounded in the venerable ResNet152V2 architecture, a Residual Network characterized by its "residual connections" which critically facilitate the training of exceptionally deep neural networks without encountering deleterious vanishing gradient phenomena, thereby markedly enhancing accuracy in a multitude of computer vision tasks [13]. For its implementation, the pre-trained ResNet152V2 model (weights='imagenet') was loaded, specifically omitting its top-level classification layers (include_top=False). The convolutional layers of this foundational architecture were initially "frozen" to leverage the comprehensive feature representations acquired during its initial pre-training. Custom layers, meticulously adapted for the multiclass chest X-ray classification task, were then appended, mirroring the structural composition employed for InceptionV3: a GlobalAveragePooling2D layer, a Dense layer with 256 units and relu activation, a Dropout layer with a rate of 0.5, and a Dense(3, activation='softmax') output layer. Finally, a strategic "fine-tuning" phase was instituted, wherein a designated subset of the uppermost layers of the base model was unfrozen and subsequently retrained in conjunction with the newly added classification layers, employing a diminished learning rate to optimally calibrate performance on the CXR dataset.

2.2.3. Classification Method 3: Classical Machine Learning (SVM with Intensity Histograms): The third classification approach adopted a classical machine learning paradigm, employing a Support Vector Machine (SVM) trained on conventionally extracted image features: intensity histograms. For each CXR image, an intensity histogram was computed from a single channel (due to the grayscale nature and channel replication), with granularity defined by a specific number of bins (e.g., 256). These histogram feature vectors were then normalized to a sum of 1, ensuring invariance to brightness variations. Upon extraction of these features, an SVM was utilized for the classification task [14], typically employing a radial basis function (RBF) kernel. The SVM's hyperparameters, including regularization parameter C and kernel parameter gamma, underwent rigorous optimization via a grid search methodology coupled with cross-validation on the training set to maximize predictive performance. It is worth noting that while intensity histograms were used, advanced methods like Histograms of Oriented Gradients (HOG) are also prevalent in computer vision for similar tasks [15].

2.3. Training and Evaluation Configuration: The implemented models were compiled and trained using the TensorFlow 2.x framework, with Keras for deep learning models and scikit-learn for the classical machine learning model. For deep learning models (InceptionV3 and ResNet152V2), CategoricalCrossentropy served as the loss function, and the Adam optimizer was employed with meticulously adjusted learning rates (e.g., 0.001 for initial training, 0.00001 for fine-tuning). Key metrics like accuracy and loss, along with their validation counterparts, were monitored during training, while comprehensive metrics including overall accuracy, confusion matrix, Precision, Recall, and F1-score were computed on the test set. Deep learning models were trained over a predetermined number of epochs (e.g., 50-100) with a batch_size of 32, integrating Keras callbacks such as ModelCheckpoint and EarlyStopping to enhance efficiency and prevent overfitting. In contrast, the SVM model was trained directly on extracted feature vectors from the training set, and its evaluation was conducted on the test set using standard metrics. The computational framework, implemented in Python 3.x, leveraged essential libraries like NumPy, Pandas, and Matplotlib/Seaborn, with resource-intensive deep learning training executed on a GPU-accelerated environment.

3 Results

This section presents the performance of the InceptionV3, ResNet152V2, and SVM models for classifying chest X-ray images into COVID-19, Pneumonia, and Normal categories. All results were derived from the unseen test set, ensuring an unbiased evaluation of the models' generalization capabilities. The deep learning models, InceptionV3 and ResNet152V2, demonstrated significant superiority, with InceptionV3 achieving the highest overall accuracy.

3.1. Overall and Class-wise Performance: Table 1 summarizes the overall accuracy of the models on the test set, highlighting the marked difference between deep learning approaches and the classical method.

Model	Overall Accuracy (%)
InceptionV3	98.85
ResNet152V2	98.66
SVM (Histograms)	69.23

Table 1: Overall Accuracy of Models on the Test Set

Tables 2, 3, and 4 detail the class-wise metrics (Precision, Recall, F1-Score) for each model, offering a granular evaluation of their performance. InceptionV3 and ResNet152V2 showed excellent metrics (generally >97%) across all classes, with the 'Normal' class being the easiest to classify. In contrast, the SVM exhibited significantly lower performance (62-73%) across all categories.

Class	Precision (%)	Recall (%)	F1-Score (%)
COVID-19	98	98	98
Pneumonia	99	99	99
Normal	100	100	100

Table 2: Class-wise Metrics for the InceptionV3 Model.

Class	Precision (%)	Recall (%)	F1-Score (%)
COVID-19	98	97	97
Pneumonia	98	99	99
Normal	99	99	99

Table 3: Class-wise Metrics for the ResNet152V2 Model.

Class	Precision (%)	Recall (%)	F1-Score (%)
COVID-19	69	73	71
Pneumonia	71	65	68
Normal	62	64	63

Table 4: Class-wise Metrics for the SVM (Intensity Histograms) Model.

3.2. Comprehensive Comparison and Confusion Matrix: Figure 1 provides a comprehensive visual comparison of the three models' performance across all class-wise metrics. It clearly demonstrates the superiority of InceptionV3 and ResNet152V2 over SVM and allows for observation of their subtle differences. Figure 2 presents the confusion matrix for the InceptionV3 model, precisely illustrating correct and incorrect predictions and the distribution of classification errors. This consolidated graph compares the Precision, Recall, and F1-Score of InceptionV3, ResNet152V2, and SVM for each of the three classes, demonstrating the dominance of the neural network-based models.

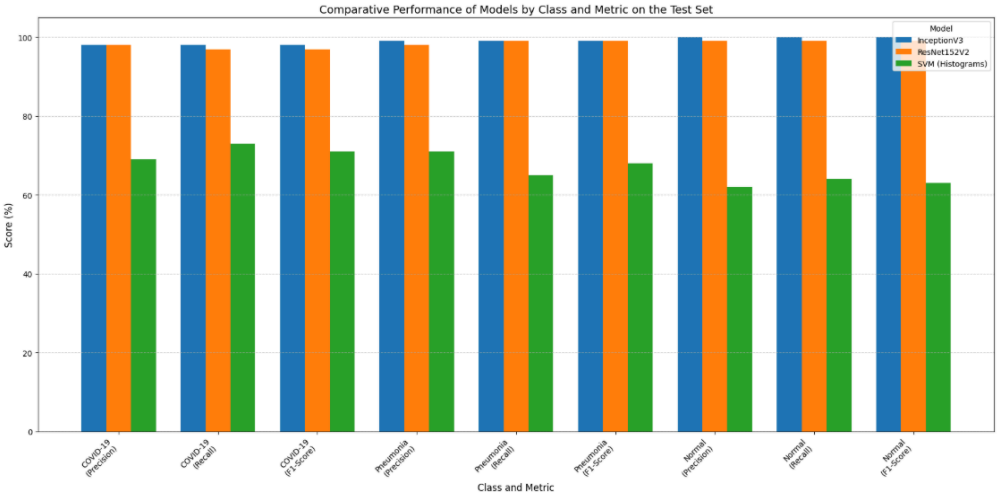

Figure 1: Comparative Performance of Models by Class and Metric on the Test Set.

This matrix visualizes the distribution of InceptionV3 model predictions on the test set, with correct classifications along the main diagonal and misclassifications off-diagonal, confirming its high accuracy.

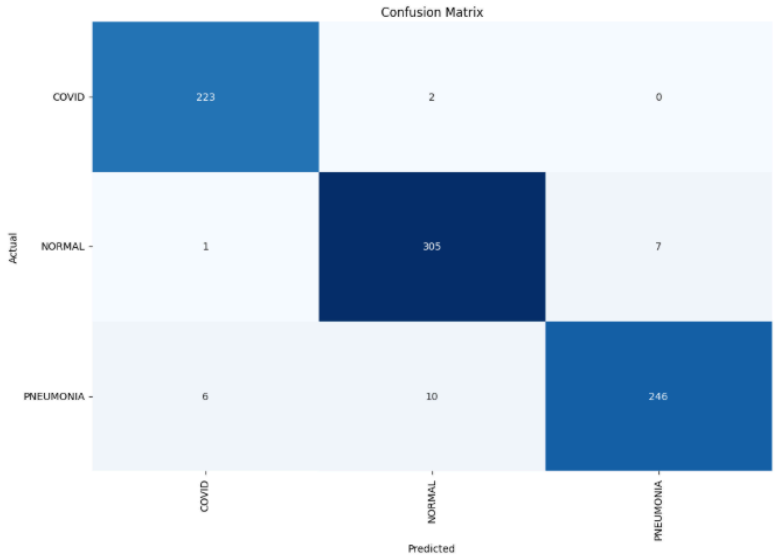

Figure 2: Confusion Matrix for the InceptionV3 Model.

4 Discussion

The meticulous empirical analysis of the results, as detailed in Section 3, provides a profound and nuanced understanding of the performance characteristics exhibited by the three classification methodologies applied to chest X-ray images for the discernment of COVID-19, pneumonia, and normal lung patterns. This analysis unequivocally demonstrates that deep learning models, InceptionV3 and ResNet152V2, substantially

outperformed the classical SVM model that leverages intensity histograms. This superiority is attributed to CNNs' inherent ability to learn complex, hierarchical features directly from the images, a capability the SVM, reliant solely on intensity histograms, lacked. InceptionV3 slightly edged out ResNet152V2 in overall accuracy (98.85% vs. 98.66%) and showed marginally better class-wise metrics, exhibiting a more stable convergence in its training and validation curves with fewer signs of overfitting. The most significant challenge for all models, due to inherent radiological overlap, was differentiating between COVID-19 and Pneumonia, as evidenced by cross-classification errors in confusion matrices, a task where the SVM was notably ineffective. Clinically, these findings highlight the substantial potential of deep learning models as valuable assistive tools for rapid diagnosis and triage in healthcare. However, the study acknowledges limitations, such as potential dataset representativeness, and proposes future work including external validation, model interpretability using techniques like Grad-CAM, and integrating additional clinical data to further enhance diagnostic accuracy.

5 Conclusion

This research unequivocally demonstrated the feasibility and superior performance of Convolutional Neural Networks (InceptionV3 and ResNet152V2) for the automated classification of chest X-ray images into three critically important categories: COVID-19, Pneumonia, and Normal. Both deep learning models demonstrably outperformed the classical machine learning approach, SVM utilizing intensity histograms, reinforcing the established superiority of autonomously learned features by CNNs. Specifically, InceptionV3 exhibited a marginal, yet discernible, performance advantage on this particular dataset, achieving high accuracy and robust F1 metrics across all classes. These findings underscore the profound potential of artificial intelligence to function as an indispensable adjunct tool for healthcare professionals, facilitating expedited and accurate differential diagnosis of pulmonary pathologies, and consequently contributing significantly to enhanced management strategies during current and future public health crises.

6 References

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