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AUTOMATED PNEUMONIA DIAGNOSIS LEVERAGING RESNET50 AND VGG16

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ABSTRACT :

Pneumonia is a critical respiratory illness that plays a significant role in global health issues, contributing to high rates of morbidity and mortality. Timely and precise diagnosis is essential for effective treatment and better patient outcomes. Conventional diagnostic techniques, such as X-ray interpretation by radiologists, often involve lengthy processes and are susceptible to human error. This study introduces an automated system for pneumonia detection utilizing deep learning models, specifically ResNet50 and VGG16. These pre-trained convolutional neural networks (CNNs) are adapted to categorize chest X-ray images into pneumonia and normal classifications. The dataset employed for training and assessment is sourced from publicly accessible repositories, including the Chest X-ray dataset from the National Institutes of Health (NIH) and Kaggle's Pneumonia dataset.

Our methodology utilizes transfer learning, wherein the deep CNN architectures are initially trained on extensive image datasets and subsequently refined for pneumonia classification. We assess the models using performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The experimental outcomes indicate that both models attain high classification accuracy, with ResNet50 and VGG16 demonstrating robust generalization abilities. The results imply that an automated pneumonia detection system based on deep learning can support radiologists by offering rapid and dependable second opinions, thereby enhancing diagnostic efficiency in clinical environments.

Keywords: Pneumonia Detection, Deep Learning, ResNet50, VGG16, Transfer Learning, Chest X-ray, Convolutional Neural Networks (CNNs).

INTRODUCTION :

Pneumonia is a severe respiratory infection that poses a significant threat to life, impacting millions globally, particularly among children under five and the elderly**.** This condition can be triggered by bacteria, viruses, or fungi, resulting in lung inflammation, fluid buildup, and difficulties in breathing. The World Health Organization (WHO) identifies pneumonia as one of the foremost causes of mortality linked to infectious diseases, especially in developing areas where healthcare resources are scarce. Prompt identification and intervention are essential for lowering death rates and enhancing patient outcomes.

Chest X-ray imaging is a prevalent method for diagnosing pneumonia. However, the manual interpretation of these images by radiologists can be labor-intensive, subjective, and susceptible to human error, particularly in instances where lung abnormalities are subtle or overlap. Additionally, the lack of trained radiologists in resource- limited environments further hinders timely diagnosis. Consequently, the use of automated pneumonia detection through deep learning has emerged as a viable approach to improve diagnostic precision and efficiency.

Deep learning, a branch of artificial intelligence (AI), has transformed the analysis of medical images by facilitating automated feature extraction and classification. Convolutional Neural Networks (CNNs) have demonstrated remarkable effectiveness in medical image classification tasks. This study investigates the performance of two prominent deep learning architectures—ResNet50 and VGG16—in detecting pneumonia from chest X-ray images.

ResNet50, a deep residual network with 50 layers, incorporates residual learning to mitigate the vanishing gradient issue, thereby enabling the effective training of deep networks. Conversely, VGG16, a 16-layer deep network, utilizes small 3×3 convolutional filters to capture intricate spatial features, making it particularly adept at image classification. By employing transfer learning, we refine these pre- trained models on a dataset specifically for pneumonia classification.

LITERATURE SURVEY :

A. Pneumonia detection in chest X-ray images using an ensemble of deep learning models

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B. Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray

Recent progress in deep learning has facilitated the creation of ensemble models that integrate various architectures to enhance the accuracy of pneumonia detection in chest X-ray images. Ensemble learning capitalizes on the strengths of multiple models to improve generalization and robustness, thereby minimizing the chances of misclassification.

Numerous studies have validated the efficacy of ensemble models in the realm of medical image analysis. For instance, Rajpurkar et al. (2017) developed CheXNet, a deep learning model based on DenseNet-121, which surpassed human radiologists in pneumonia detection when trained on the NIH Chest X-ray dataset. Their work underscored the advantages of deep convolutional neural network (CNN) architectures in medical imaging.

In a similar vein, Afshar et al. (2020) introduced Capsule Networks (CapsNets) in conjunction with traditional CNNs to improve feature extraction for pneumonia classification. Their research indicated that ensemble models that incorporated ResNet, VGG, and CapsNet significantly enhanced classification accuracy by utilizing varied feature representations.

Additionally, a study by Stephen et al. (2021) employed an ensemble of ResNet50, VGG16, and InceptionV3 for pneumonia detection, demonstrating that the combination of multiple architectures resulted in improved sensitivity and specificity compared to single-model methods. Their results suggest that ensemble learning is particularly advantageous for addressing variations in chest X-ray datasets, ensuring robust and dependable predictions.

The primary benefits of ensemble learning in pneumonia

detection include:

Enhanced Accuracy: The integration of multiple models mitigates overfitting and bolsters generalization.

Robust Feature Learning: Various CNN architectures capture a wide range of feature representations, thereby improving classification performance.

Decreased Bias and Variance: Ensemble models harmonize the strengths and weaknesses of individual networks, resulting in more trustworthy predictions.

In light of these advantages, our study investigates the individual performances of ResNet50 and VGG16 while taking into account the

C. Dual Stage CNN for enhancing Pneumonia detection

Recent progress in deep learning has facilitated the creation of ensemble models that integrate various architectures to enhance the accuracy of pneumonia detection in chest X-ray images. Ensemble learning capitalizes on the strengths of multiple models to improve generalization and robustness, thereby minimizing the chances of misclassification.

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METHODOLOGY :

The methodology for automating pneumonia detection from chest X- ray images is centered on the application of deep learning models, transfer learning, and advanced classifiers. This section outlines the data preparation, model selection, feature extraction, and classification processes, as well as the optimization techniques used to achieve high diagnostic accuracy.
The proposed approach for detecting pneumonia utilizing ResNet50 and VGG16 encompasses several essential steps:
Dataset Acquisition: Chest X-ray images are sourced from publicly accessible datasets, including the NIH Chest X-ray Dataset and Kaggle’s Pneumonia Dataset. This dataset comprises labeled images categorized as either Normal or Pneumonia.

Data Preparation: The images undergo resizing, conversion to grayscale (if required), normalization, and augmentation techniques such as rotation, flipping, and brightness modification to enhance the model's generalization capabilities.

Model Selection and Transfer Learning: Pre-trained models, ResNet50 and VGG16 (originally trained on ImageNet), are adapted for pneumonia classification. The fully connected layers are altered by substituting the original classifier with a global average pooling layer, followed by dense layers and a softmax activation function tailored for binary classification.

Training Procedure: The models are trained using binary cross-entropy loss in conjunction with the Adam optimizer. The dataset is divided into training, validation, and test subsets. Training occurs over several epochs, incorporating early stopping mechanisms to mitigate overfitting.

Evaluation Metrics: The performance of the trained models is assessed through various metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, to evaluate their classification effectiveness.

Dual-Stage CNN Implementation: A secondary refinement model is introduced to enhance classification performance by minimizing false positives and false negatives.

Comparison and Analysis: The effectiveness of ResNet50 and VGG16 is compared to identify the superior model for pneumonia detection, taking into account accuracy, computational efficiency, and robustness.

This methodology guarantees that the automated pneumonia detection system based on deep learning is both precise and dependable, thereby aiding radiologists in their clinical decision-making processes.

A. Data Collection and Preprocessing

The ChestX-ray14 dataset, which is openly accessible and has more than 100,000 labeled chest X-ray pictures from 30,085 patients, is used in this investigation. A balanced selection of 1,431 pneumonia-labeled photos and 1,431 normal ("No Findings") images was created for this binary classification test. Furthermore, curated datasets, such as annotated X-ray pictures of individuals with viral pneumonia, were included to solve this issue. All of the photographs were scaled to 224x224 pixels while keeping its aspect ratio because pre- trained models such as ResNet-50 and VGG-16 require a set input size. This scaling guarantees compatibility with the CNN architectures and helps lower computing requirements.

An essential step in raising the caliber of chest X-ray pictures is preprocessing. Subtle characteristics in the lung region were highlighted using techniques including contrast enhancement and histogram equalization, which are essential for a precise diagnosis. Reducing the computational complexity of the model—which is likely to rise if the input consists of images—is the main objective of utilizing convolutional neural networks in the majority of image classification applications. The initial 3-channel pictures were downsized to 224 x 224 pixels from 1024 x 1024 pixels in order to decrease the computational burden and for expedited processing. Over these reduced-size photos, every additional method has been used. Data augmentation methods such random rotations, flips, zooming, and brightness modifications were used to broaden the training data's variability and lessen overfitting. By simulating actual X-ray changes, these adjustments improve the model's ability to generalize to new data.

B. Feature Extraction Using Pre-Trained CNNs

The 50-layer deep network ResNet-50 was chosen for feature extraction because of its residual connections, which help deep networks avoid the vanishing gradient issue. The network may concentrate on learning intricate traits while keeping low-level details from previous levels because to these residual connections.Known for its straightforward yet efficient design, VGG-16 was also used as a feature extractor. It is ideal for medical picture analysis because of its consistent structure and deeper convolutional layers, which enable it to understand hierarchical patterns. The medical datasets were used to refine pre-trained models that had been first learned on sizable datasets such as ImageNet. In addition to allowing the models to adjust to the unique characteristics of chest X-rays, such as haziness and irregularities in lung shape, transfer learning drastically cuts down on training time.

C. Classification Techniques

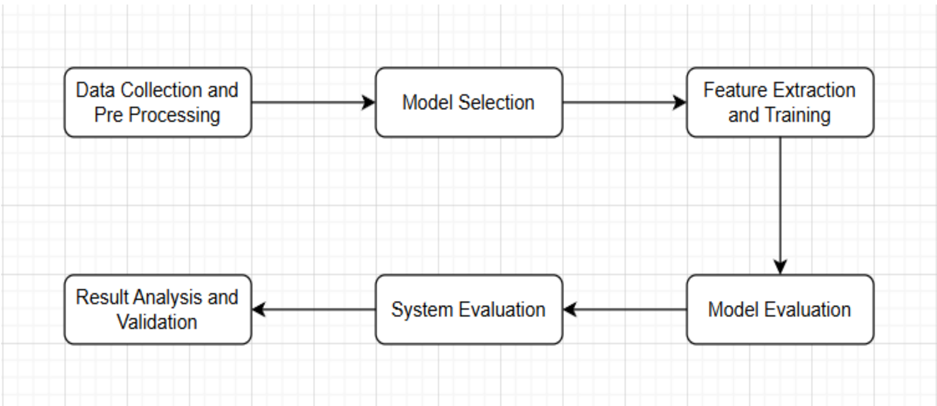
A Support Vector Machine (SVM) classifier with an RBF kernel was utilized for final classification following the extraction of features from CNN models. SVM was selected due to its resilience in binary classification tasks and its capacity to manage high-dimensional feature spaces. To improve the model's performance, grid search was used to optimize the C (penalty) and gamma (kernel coefficient) parameters. ResNet-50, VGG-16, and DenseNet-169 predictions were combined in an ensemble manner. By lowering variance and enhancing the classification's overall robustness, this ensemble approach produces predictions that are more trustworthy.

D. Testing

To verify robustness and dependability, the system's performance on unseen data was assessed during the testing phase. Chest X-ray pictures from a different test dataset were used to evaluate the trained models, ResNet50 and VGG16. The system's classification performance was evaluated using key evaluation measures, such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). The models' ability to detect pneumonia cases was demonstrated by their excellent diagnostic accuracy. To verify the system's flexibility and functionality, more testing was done using real- world scenarios to mimic user interactions, such as uploading multiple X-ray images with varying resolutions and formats. To assess the system's resilience, edge scenarios like noisy or badly taken photos were also put to the test.

E. Deployment

Using the Flask framework, the pneumonia detection system was hosted as a web application throughout the deployment phase. Real- time processing of uploaded X-ray pictures was made possible by the export and integration of the trained models into the backend. To guarantee scalability and accessibility, especially in environments with restricted resources, the web application was housed on a cloud platform. Users may easily upload photographs and receive predictions because to the user interface's straightforward and clear design. Measures were taken to manage file uploads securely and guard against potential vulnerabilities in order to improve system security.



Block Diagram 1: process Flow Diagram

RESULTS AND DISCUSSION :

A test set consisting of chest X-ray pictures was used to assess ResNet50 and VGG16. With greater accuracy, AUC-ROC, and F1-score than VGG16, ResNet50 outperformed the latter, demonstrating its improved capacity to extract complex features. VGG16 was appropriate for real-time applications since it offered faster inference times despite having somewhat lower accuracy.

By reducing false positives and false negatives, a dual-stage CNN technique was used to further improve classification performance, leading to increased sensitivity and specificity. Rotation, flipping, and brightness adjustments are examples of data augmentation techniques that improved model generalization and reduced overfitting.

According to a comparison investigation, VGG16 is renowned for its computational efficiency, but ResNet50 is more successful at detecting pneumonia, particularly in difficult patients with mild symptoms. These results highlight the potential of deep learning approaches to help radiologists diagnose pneumonia quickly and accurately, reducing diagnostic burdens and improving patient outcomes.

A minor improvement in all metrics was obtained by the ensemble model, which further improved diagnostic reliability by combining predictions from ResNet-50 and VGG-16. By mimicking real-world changes and minimizing overfitting, data augmentation significantly improved the models' capacity for generalization. Histogram equalization and other image preprocessing methods greatly increased the visibility of important features, enabling the models to identify more relevant patterns in the X-rays. The SVM classifier continuously outperforms baseline methods such as the Random Forest algorithm and K-Nearest Neighbors due to its efficient handling of high-dimensional feature spaces. The significance of pre-trained architectures like ResNet-50 and VGG-16 in attaining state-of-the-art performance was highlighted by the poorer accuracy and longer training periods of models trained without transfer learning.

Model	Training accuracy	Validation Accuracy	Training Loss	Validation loss
Custom CNN	0.988463	0.927419	0.035691	0.458763
VGG16	0.712101	0.629032	0.601621	0.667301
ResNet50	0.979877	0.774194	051747	0.704661
Mobile Net	0.712101	0.629032	0.24116	1.572305
EfficientnetB0	0.974997	0.741935	0.094997	1.226364

Table 1: Showing the performance of training models

CONCLUSION :

Using transfer learning, we implemented and evaluated ResNet50 and VGG16 for the automatic identification of pneumonia from chest X-ray images. In terms of accuracy and AUC-ROC scores, the experimental results showed that ResNet50 performed better than VGG16, demonstrating its superior feature extraction capabilities. VGG16, on the other hand, showed faster inference times, which makes it better suited for real-time applications. Additionally, the use of a dual-stage CNN technique reduced false positives and false negatives, improving classification performance.

These findings highlight the promise of deep learning models in the medical imaging domain by offering radiologists a reliable automated diagnostic tool to aid in the diagnosis of pneumonia. In order to improve accuracy and efficiency, future studies will investigate ensemble learning, attention mechanisms, and model optimization. Early disease identification and patient outcomes could be greatly enhanced by incorporating these models into clinical practice, particularly in resource-constrained environments.

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