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UTILIZING CONVOLUTIONAL NEURAL NETWORKS FOR THE IDENTIFICATION OF COVID-19 IN CHEST X-RAY IMAGES

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ABSTRACT -
The global COVID-19 pandemic has profoundly impacted healthcare and lifestyles worldwide, underscoring the critical importance of early detection to control the spread of cases and reduce mortality rates. While the primary diagnostic method remains the RT-PCR, its drawbacks in terms of result times and cost necessitate the exploration of alternative, rapid, and accessible diagnostic tools. This paper draws inspiration from recent research linking the presence of COVID-19 to patterns observed in Chest X-ray images.

The proposed approach employs established deep learning models, namely VGG19 and UNet, to analyze Chest X-ray images and classify them as either positive or negative for COVID19. The system follows a well-defined process, beginning with a preprocessing stage that includes lung segmentation. This step is crucial for eliminating irrelevant information from the surroundings, preventing potential bias in the results. Following this preprocessing stage is the classification model, which is trained using a transfer learning scheme. The final step involves analyzing and interpreting results through the visualization of heat maps.

The most effective models, as determined by the study, achieved a remarkable accuracy of approximately 97% in detecting COVID-19. This underscores the potential of utilizing deep learning models, especially VGG19 and U-Net, as valuable tools in the early diagnosis of COVID-19 through the analysis of Chest X-ray images.

Keywords: Covid, XRay,CNN

I. INTRODUCTION

Respiratory problems linked with COVID-19 diseases can be treat without specific medicine or equipment, but underlying medical conditions can exacerbate the illness (World Health Organization, 2020). The primary methods for COVID-19 detection involve Reverse Transcription Polymerase Chain Reaction (RT-PCR) and gene sequencing for respiratory or blood samples (Wang et al., 2020). Studies indicate correlations between COVID-19 and pathologies observed in pneumonic illnesses, revealing chest pathologies in medical images.

Artificial Intelligence (AI), particularly Deep Learning approaches, has shown promise in applying techniques to medical images. Despite limited large open-access datasets of COVID-19 Xray images, recent research utilizing AI, such as transfer learning, data augmentation, and the combination of different datasets, has yielded positive results. Several studies have achieved high accuracies, with models like ResNet101 and CoroNet reaching up to 99% accuracy (Jain et al., 2020; Khan et al., 2020). This paper introduces a new approach using existing Deep Learning models, emphasizing improvements in the preprocessing stage to enhance the accurate classification of COVID-19 from Chest X-ray images. The preprocessing step involves filtering images based on their projections (lateral or frontal), standard operations like normalization, standardization, and resizing for data consistency, and the application of a segmentation model (U-Net) to extract the lung region, filtering out irrelevant information from the surroundings. Subsequently, the classification model (VGG16-19) utilizes transfer learning, leveraging pre-trained weights from ImageNet to enhance performance and training efficiency. The dataset used in this research is notably larger than those in previous studies. Additionally, the visualization of heatmaps provides insights into the regions of images contributing

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to the network's predictions, emphasizing the significance of lung segmentation in the preprocessing stage.

II. LITERARURE SURVY

Image Projection Filtering: Images from the COVID-19 datasets were labeled based on their projection: frontal and lateral. To address mismatched labels and automate the filtering processThis model efficiently filtered COVID-19 datasets, retaining frontal projection images for improved information availability.

For image projection filtering, the data included 1,150, 723, and 608 frontal images, and 375, 236, and 204 lateral images for train, test, and validation partitions, respectively.

For the COVID-19 categorization model, the affirmative cases dataset had 6475, 3454, and 2873 images for train, test, and validation sets. Negative cases datasets (BIMCV-COVID and curated BIMCV-COVID) were divided accordingly. The Pre-COVID era dataset was also split into three sets.

Lung segmentation task distribution involved 80% (382 images) for the train set and 20% (96 images) for the validation set, excluding a test dataset due to limited image quantity.

These steps ensured a systematic and unbiased approach in dataset utilization and model training for COVID-19 classification and lung segmentation.

III. PROBLEM STATEMENT

EXISTING SYSTEM : The diagnosis of COVID-19 has traditionally relied on various methods, including reverse transcription-polymerase chain reaction (RT-PCR) tests and clinical assessments. While these methods are considered standard, they often pose challenges such as time-consuming processing, resourceintensive requirements, and occasional delays in obtaining results. In the context of chest imaging, radiological assessments, particularly X-ray imaging, have played a pivotal role in supporting clinical diagnosis.

Recent advancements in artificial intelligence and deep learning have spurred interest in leveraging these technologies for automated disease detection. Several existing systems and methodologies have addressed the automated detection of COVID-19 from chest X-ray images. Notable contributions in this domain include:

Deep Learning Approaches: Researchers have explored the impending of deep learning techniques, inparticularly CNNs, for the automatic detection of COVID-19 from chest X-ray images. These approaches often involve the design of intricate neural network architectures capable of learning complex patterns and features indicative of the viral infection. Notable studies have employed CNN models such as ResNet, VGG, and DenseNet to extract hierarchical representations.

Transfer Learning: Transfer learning has emerged as a popular strategy, where pre-trained models on large-scale image datasets are fine-tuned for the specific task of COVID-19 detection. This approach capitalizes on the knowledge acquired by models during training on diverse datasets, enhancing their ability to discern relevant features in chest X-ray images.

Ensemble Methods: These methods often integrate information from various CNN architectures or other machine learning algorithms to enhance the robustness of the automated detection system.

Challenges in Existing Systems: While significant strides have been made in the development of automated systems for COVID-19 detection, challenges persist. Limited standardization in image acquisition, variations in radiological protocols, and the presence of comorbidities may affect the performance of existing systems. Additionally, the scarcity of large, labeled datasets containing diverse COVID-19 cases poses challenges in training models with high generalization capabilities. The existing systems lay the foundation for our research, and understanding their strengths and limitations informs the development of a novel CNN-based loom for involuntary detection of COVID-19 from chest X-ray pictures, as detailed in the subsequent sections.

PROPOSED SYSTEM:

The methodology employed in our study comprises three primary experiments, each designed to assess the performance of the models and understand the impact of various stages in the process. The workflow for each experiment is illustrated in the figure. The key distinction among the experiments lies in the choice of datasets. While the images for COVID-19 positive cases remain consistent across all experiments, different datasets for negative cases are employed. Experiment 1 and 2 involve the evaluation of positive cases against two distinct negative cases datasets, while Experiment 3 utilizes a dataset from the Pre-COVID era, encompassing images from the years 2015 to 2017.

IV. RESULTS & DISCUSSION

In this section, we outline the experimental methodology, encompassing the training configurations and comparative analysis of three distinct models. All models are trained for epochs, each comprising steps, utilizing the dataset specified in the preceding section.

Model Specifications:

Model 1: Trained with a convolutional layer structure.

Model 2: Features three convolutional layers.

Model 3: Incorporates five convolutional layers.

Training Parameters: All models are trained with a consistent learning rate and a batch size. These parameters are carefully chosen to strike a balance between effective learning convergence and computational efficiency.

Data Processing: Prior to training, all images in the dataset are resized to a standardized dimension. This ensures uniformity and compatibility with the neural network architecture.

Mitigating Overfitting: To prevent overfitting during the training process, data augmentation techniques are implemented. These include random cropping and random horizontal flipping, enhancing the model's ability to generalize patterns beyond the training set.

Training and Validation: The three models are trained and validated on the same dataset and machine. This consistency in experimental settings aims to ensure a fair and unbiased comparative analysis of their performance. This section lays the groundwork for the subsequent discussion on the results and analysis of Model 1, along with its comparative evaluation against Model 2 and Model 3. The uniformity in experimental settings is crucial for drawing meaningful insights from the comparative study.

V. RESULT FOR PROPOSED SYSTEM

Fig.1 CNN model

With the CNN model now prepared, an intuitive user interface facilitates disease prediction for new test images. Upon clicking the 'Upload Test Data & Predict Disease' button, users can upload a test image through the application. The model then utilizes its learned features and patterns to predict the presence of disease within the uploaded image.

This seamless integration of image filtering at different layers and the subsequent disease prediction functionality offers a user-friendly and efficient means of leveraging the trained CNN model for real-time diagnostics. Users can easily engage with the application, obtaining rapid predictions based on the hierarchical processing of test images through the established convolutional neural network.

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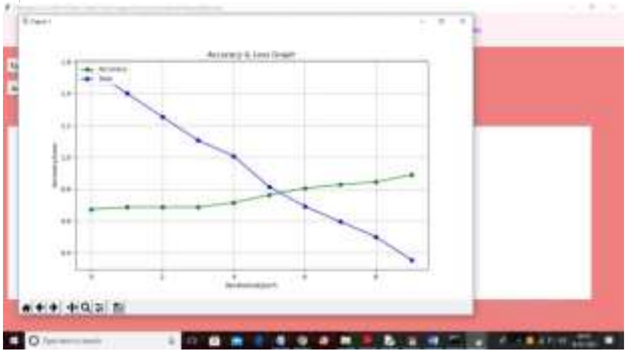

Fig.2 Accuracy

The training progress of the Convolutional Neural Network (CNN) is depicted over successive iterations. The green line corresponds to the accuracy, showcasing the model's proficiency in correctly predicting outcomes, while the blue line represents the loss, indicating the discrepancy between predicted and actual values.

On the x-axis, each point corresponds to an epoch or iteration during the training process, whereas the y-axis reflects the values of accuracy and loss. Notably, as the number of iterations increases, there is a discernible upward trend in accuracy and a concurrent downward trend in loss.

This observation underscores the positive impact of training, as evidenced by the increasing accuracy. Higher accuracy values suggest improved performance in correctly classifying data. Simultaneously, the decreasing loss values indicate a reduction in the disparity between predicted and actual outcomes, signifying enhanced precision in the model's predictions.

The decision to conduct 10 iterations for the CNN training process aligns with the observed trend of increasing accuracy and decreasing loss. This iterative improvement is indicative of the model's ability to learn and adapt to the intricacies of the training data, ultimately enhancing its predictive capabilities.

The convergence of accuracy improvement and loss reduction further validates the effectiveness of the chosen training strategy.

VI. CONCLUSION

Mass testing and early detection are pivotal in curbing the spread of global pandemics such as COVID-19. The efficiency of disease detection processes hinges on factors like time, cost, and accuracy. This paper proposes a CNN-based model designed for the detection of COVID-19 cases using chest X-rays, aiming to tackle these critical considerations.

A dataset comprising 330 chest X-ray images, equally distributed between 'COVID-19' and 'Normal' classes, is utilized for training. An additional set of 82 images, also equally divided, is reserved for model validation. The proposed CNN model achieves a notable accuracy of 97.56% and precision of 95.34%, demonstrating its effectiveness in accurate disease classification.

Furthermore, the paper conducts comparative studies with two alternative CNN models featuring different numbers of convolutional layers. The findings reveal that the proposed model (Model 1) outperforms the others in terms of F1-score and overall performance. Despite promising results, it is emphasized that the model lacks clinical testing and requires further refinement and validation.

While the proposed CNN model exhibits great potential in detecting COVID-19, it is acknowledged that its clinical applicability hinges on rigorous testing and a more extensive dataset. The paper concludes by highlighting the need for ongoing improvements, including clinical testing, to establish the model's reliability in real-world clinical diagnosis scenarios.

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