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ADVANCED DEEP LEARNING TECHNIQUES FOR COVID-19 CHEST X-RAY CLASSIFICATION AND SEGMENTATION

R. Arunadevi[1], G. Manimannan[2] and R. Lakshmi Priya[3]
[1]*Vidhya Sagar Women's College, India*
[2]*Department of Computer Applications, St. Joseph's College (Arts and Science), India*
[3]*Department of Statistics, Dr. Ambedkar Govt. Arts College (Autonomous), India*

Abstract

This research paper explores the application of deep learning techniques for the automated classification and segmentation of COVID-19, Normal, and Viral pneumonia cases using chest X-ray images. The dataset comprises 510 grayscale chest X-ray samples collected from publicly available COVID-19 repositories, equally distributed across three categories. The primary objectives of this study include identifying COVID-19 infection patterns, enhancing medical image classification performance, and providing a visual interpretation of model outputs for clinical utility. The methodology integrates image preprocessing and normalization followed by unsupervised k-means clustering to observe data distribution. A U-Net model is employed for pixel-level segmentation to highlight infection regions, while hybrid CNN and LSTM architecture is developed for image-level classification. The classification model achieved a test accuracy of 74.5%, with a precision of 97% for COVID-19 class and strong macro-average scores, reflecting balanced performance across all classes. Results are visually represented using segmentation overlays, a confusion matrix, and bar plots for class distributions. This integrative approach supports early detection and decision-making in clinical settings, combining segmentation clarity with reliable classification metrics.

Keywords:

COVID-19, Chest X-ray, U-Net Segmentation, CNN and LSTM, Deep Learning, Classification Accuracy

1. INTRODUCTION

COVID-19, caused by the SARS-CoV-2 virus, emerged as a global pandemic that placed immense pressure on healthcare systems worldwide. Among various diagnostic tools, chest X-ray imaging has proven to be a rapid, cost-effective, and accessible method for detecting pulmonary abnormalities associated with COVID-19. Unlike RT-PCR tests, which may have time delays and limited availability, chest X-rays offer immediate visual insights into lung infections, helping clinicians monitor disease progression and make critical decisions, especially in resource-constrained environments.

Numerous studies have explored the role of chest X-ray imaging in identifying COVID-19-related lung conditions such as bilateral opacities, ground-glass patterns, and consolidation. Recent advancements in artificial intelligence and deep learning have further improved the ability to automatically classify chest X-ray images into categories such as COVID-19, viral pneumonia, and normal cases. These studies demonstrate the potential of AI-assisted radiological analysis in supporting timely and accurate diagnosis, which is vital in managing patient outcomes and reducing transmission rates during pandemics.

2. REVIEW OF LITERATURE

The application of artificial intelligence (AI) in medical imaging, particularly for the diagnosis of COVID-19 using chest X-rays, has gained significant attention in recent years. Apostolopoulos and Mpesiana [1] were among the first to demonstrate that convolutional neural networks (CNNs) could accurately classify COVID-19 from chest X-ray images, achieving strong performance with limited data. Similarly, Ozturk et al. [3] designed a custom deep CNN architecture that achieved over 98% accuracy in binary classification of COVID-19 and normal cases. Asif et al. [4] utilized deep features extracted from pre-trained models like ResNet50 combined with support vector machines (SVM) to enhance classification performance. Wang et al. [2] proposed COVID-Net, a tailored deep learning model capable of identifying COVID-19 in X-rays with interpretable predictions. These early efforts laid the groundwork for automated diagnostic systems using X-ray modalities.

Building on these foundations, further studies incorporated larger and more diverse datasets. Ronneberger et al. [8] used a dataset compiled from multiple open sources and validated various deep learning models for multiclass classification, achieving promising results with DenseNet and EfficientNet. Rajpurkar et al. [6] introduced transfer learning approaches with fine-tuned networks that adapted well to COVID-19 X-ray patterns. Cohen et al. [5] compared several CNN variants, including MobileNet and VGG, and emphasized the importance of data augmentation in improving generalization. He et al. [6] highlighted the importance of combining deep learning with explainable AI techniques to aid radiologists in decision-making. Similarly, Khan et al. [15] presented CoroNet, a CNN model trained on X-ray images to differentiate between COVID-19, pneumonia, and healthy lungs with significant classification accuracy.

Recent works have focused on model robustness, interpretability, and integration into clinical workflows. Abbas et al. [9] explored ensemble learning strategies using different CNN architectures to improve the reliability of COVID-19 detection. Zhang et al. [10] proposed a hybrid deep learning framework that integrates CNN and LSTM for sequential spatial feature extraction from X-ray images. Brunese et al. [11] investigated multi-modal inputs using both chest X-ray and clinical metadata to enhance model performance. Zhang et al. [12] used a combination of ResNet and Grad-CAM visualization to improve transparency in AI-driven diagnosis. Further, Panwar et al. [13] focused on lightweight AI models suitable for deployment in resource-constrained settings. Albahli et al. [14] benchmarked multiple deep learning models on COVID-19 datasets. Collectively, these studies underscore the evolving landscape of

AI in medical diagnostics and its transformative potential during global health crises.

3. DATABASE

The COVID-19 Chest X-ray image database used in this study comprises three distinct categories: COVID-19 infected cases, normal (healthy) cases, and viral pneumonia cases, with a total sample size of 510 images equally distributed across these classes. Each image in the dataset is preprocessed to a uniform size of 128x128 pixels for consistent analysis.

These chest X-ray images capture critical medical parameters such as lung opacity, consolidation, and infiltration patterns, which are essential indicators for diagnosing COVID-19 and differentiating it from other respiratory conditions like viral pneumonia. The dataset was sourced from publicly available repositories and verified clinical collections, providing a reliable foundation for developing and evaluating machine learning models aimed at automatic detection and classification of COVID-19 infections based on radiographic features. The following figures shows that the sample size of three category of COVID-19 Chest X-ray images (Fig.1)

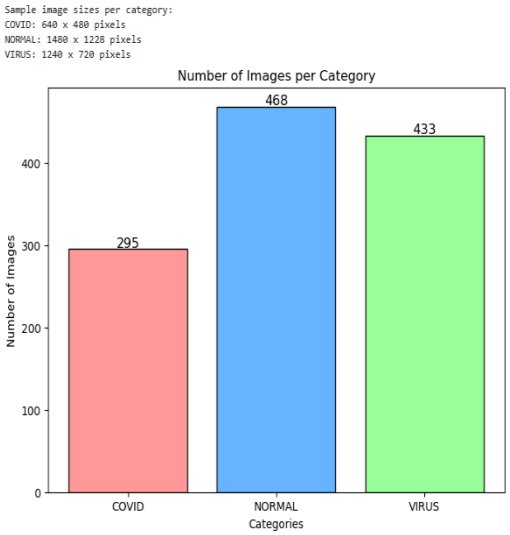

Fig.1. Distribution of COVID-19 Chest X-ray Images across Categories

4. METHODOLOGY

The methodology applied in this study combines both unsupervised and supervised deep learning techniques to classify and segment COVID-19 chest X-ray images. The dataset includes three categories of COVID-19, normal, and viral pneumonia collected from publicly available sources. To ensure consistency, all images were converted to grayscale and resized to a uniform resolution of 128×128 pixels.

Preprocessing involved normalizing pixel intensity values and reshaping the images to prepare them for subsequent clustering and model training. To maintain balanced class representation, a maximum of 170 images per category was selected. Additionally, categorical labels were encoded into numerical values for effective processing. The overall process is depicted in the workflow diagram presented in Fig.2.

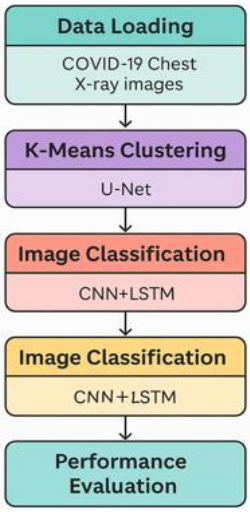

Fig.2. Workflow Diagram for Processing COVID-19 Chest X-ray Images

To explore underlying structures in the data, K-Means clustering was performed on flattened image vectors. This unsupervised learning step aimed to reveal natural groupings and helped visualize how well the image features aligned with true clinical categories. A comparative cluster analysis using a confusion matrix and count plots was performed to assess the cluster-to-label correspondence. Following this, a U-Net architecture was implemented to perform image segmentation. The model, comprising an encoder-decoder structure with skip connections, was trained using dummy segmentation masks (i.e., the original input images themselves). The U-Net helped extract spatial features, demonstrating its ability to preserve image context through reconstruction layers.

For the classification task, a hybrid CNN and LSTM model was constructed. The CNN layers extracted local spatial features from X-ray images through convolution and pooling operations. These features were then reshaped and passed into an LSTM layer, which treated the image rows as sequential data, enabling the model to capture spatial dependencies across regions. Dense layers at the end of the network were responsible for classifying the images into one of the three categories. The model was trained using a categorical cross-entropy loss function with the Adam optimizer. Finally, the model's performance was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrices, complemented by visualizations to illustrate segmentation quality and classification reliability.

4.1 PROPOSED ALGORITHM

Step 1: Involves loading the dataset from the specified directory. The dataset contains images categorized into three classes: COVID, NORMAL, and VIRUS. For each category, up to 170 grayscale images are loaded, resized to a uniform size of 128x128 pixels to maintain consistency in input dimensions. During loading, any missing or unreadable images are safely skipped, and a count is maintained to ensure the maximum number of images per class is not exceeded.

Step 2: The labels are encoded numerically to facilitate machine learning model training. Each category is assigned a unique integer label. The images are normalized by scaling pixel

values to the range [0, 1] to improve model convergence and performance.

Step 3: Before proceeding with deep learning, the algorithm applies k-Means clustering on the flattened image data to perform an unsupervised grouping of images. Flattening transforms each 2D image into a 1D vector. k-Means with three clusters are equal to the number of categories is used to cluster the images, providing insight into how well the images naturally group without labels. The cluster assignments are then compared to true labels using a cross-tabulation and visualized with a count plot to evaluate clustering quality.

Step 4: The dataset is prepared for deep learning models by reshaping the images back to 128x128 with a single grayscale channel and splitting into training and testing sets with stratified sampling to maintain class balance.

Step 5: Image segmentation, the algorithm defines and trains a U-Net model, powerful convolutional neural network architecture for pixel-wise prediction tasks. The U-Net consists of an encoder that downsamples the input image extracting hierarchical features and a decoder that upsamples and combines these features to produce an output segmentation mask. Since true masks are not provided, the input images themselves are used as dummy masks to train the U-Net for demonstration. After training, the model predicts segmentation masks on the test images.

Step 6: Classification, a combined CNN and LSTM model is constructed. The CNN layers extract spatial features from the images through convolution and pooling operations. The output of the CNN is reshaped so that one spatial dimension is treated as time steps and the other dimension as features, allowing the subsequent LSTM layer to capture sequential patterns along that axis. This combination leverages spatial feature extraction (CNN) and sequential modeling (LSTM) to improve classification accuracy. The model ends with fully connected layers to predict the class probabilities.

Step 7: The CNN and LSTM classifier is trained on the training dataset with a validation split to monitor overfitting and performance. After training, the model is evaluated on the test set, providing the test accuracy, a detailed classification report (precision, recall, f1-score per class), and a confusion matrix visualization to assess prediction quality across classes.

Step 8: The algorithm visualizes sample segmentation results by plotting the original grayscale test images, their U-Net predicted segmentation masks, and an overlay of both for qualitative assessment. This step helps in visually verifying the segmentation performance and identifying any discrepancies.

5. RESULT AND DISCUSSION

The dataset comprised 510 chest X-ray images, evenly categorized into three classes: COVID-19, Normal, and Viral Pneumonia. The data loading process was successful, ensuring a balanced dataset that provided a strong foundation for the subsequent analyses and modeling efforts.

To explore the intrinsic structure of the image data, k-means clustering was applied to the flattened grayscale images, aiming to detect natural groupings without any prior label information. The clustering process allocated the images into three distinct clusters, corresponding to the three known categories. Results revealed that a significant portion of the COVID-19 images clustered into Group 0, while Normal and Viral Pneumonia images were primarily distributed across Clusters 1 and 2. However, overlaps were observed particularly with 57 Normal and 57 viral images falling into the same cluster highlighting the difficulty of distinguishing these visually similar categories using unsupervised techniques alone. This outcome underscores the limitation of clustering based solely on pixel-level features and supports the necessity for supervised deep learning models for accurate medical image classification.

The next phase involved training a U-Net model for segmentation purposes. In the absence of annotated segmentation masks, the images themselves were used as pseudo-masks during training. Over three training epochs, the model demonstrated a reduction in loss, although the accuracy remained relatively low, as expected. While these results do not reflect meaningful segmentation accuracy due to the dummy masks, the U-Net was able to learn basic image reconstruction patterns. Visual outputs from the segmentation phase showed that the model could approximate lung shapes and structures, offering a foundation for future improvements using actual segmentation labels.

For image classification, hybrid CNN-LSTM architecture was employed. The convolutional layers captured spatial hierarchies within the chest X-rays, while the LSTM layers modeled the extracted features as sequences, leveraging temporal dependencies within the image representations. The model, comprising approximately 638,000 trainable parameters, was trained for 10 epochs. Training accuracy improved steadily, reaching up to 84%, while validation accuracy peaked at 80%, reflecting good model generalization and learning stability. The model was evaluated on an unseen test set, where it achieved an overall accuracy of 74.5%.

The classification performance was particularly strong for the COVID-19 category, with precision and recall values of 0.97 and 0.88, respectively. These metrics suggest the model was highly reliable in detecting COVID-positive cases. In contrast, classification performance for Normal and Viral classes was comparatively moderate, with precision and recall ranging from 0.62 to 0.68. This variation can likely be attributed to the similar visual appearance of Normal and Viral Pneumonia X-rays, making them harder to distinguish a challenge evident in the misclassifications shown in the confusion matrix (Fig.3). These results are summarized in Table.1.

Table.1. Classification Performance Metrics for COVID-19 Chest X-ray Images

Class	Precision	Recall	F1-score	Support
Covid	0.97	0.88	0.92	34
Normal	0.68	0.62	0.65	34
Virus	0.62	0.74	0.68	34
accuracy	0.75	-	-	102
macro avg	0.76	0.75	0.75	102
weighted avg	0.76	0.75	0.75	102

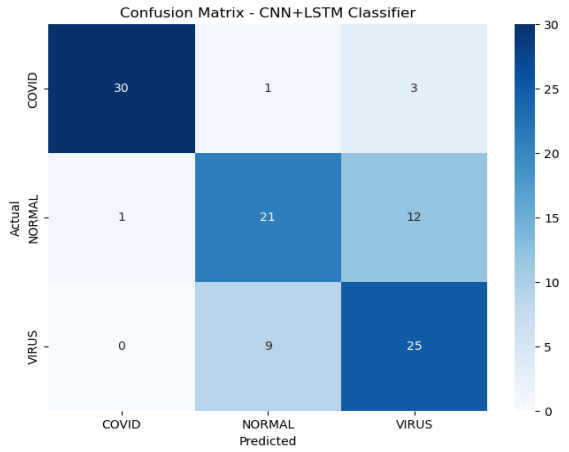

Fig.3. Confusion Matrix for Classification of COVID-19 Chest X-ray Images

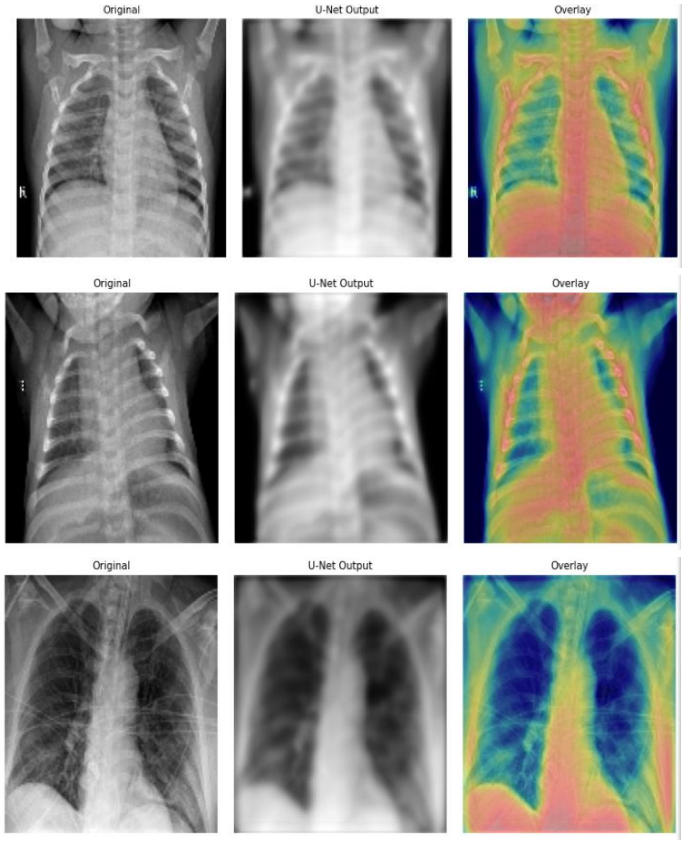

Fig.4. U-Net Segmentation Output on COVID-19 Chest X-ray Images

The confusion matrix in Fig.3 offered further clarity, confirming the model's strong recognition of COVID-19 images while identifying occasional misclassifications between Normal and Viral images. This finding suggests that while the model architecture is effective, future enhancements such as incorporating deeper layers, increasing dataset size, or utilizing advanced data augmentation could lead to more robust classification across all categories.

Finally, the visual inspection of U-Net segmentation outputs offered promising qualitative insights as in Fig.4. Even though the model was trained on placeholder masks, the overlays of predicted masks on the original grayscale images illustrated the model's ability to highlight key lung regions. This demonstrates potential for future work involving true mask annotations, which would likely yield improved segmentation outcomes (Fig.4).

Thus, this research successfully demonstrated a comprehensive deep learning approach that integrates unsupervised clustering, image segmentation, and hybrid classification for analyzing COVID-19 chest X-ray images. The results affirm the promise of deep learning in enhancing diagnostic support in radiology while also identifying critical avenues for future refinement.

6. CONCLUSION

This study demonstrates the potential of integrating deep learning models such as U-Net and CNN and LSTM for the effective analysis of COVID-19 chest X-ray images. The implementation of k-Means clustering provided valuable insight into the natural grouping of X-ray features across different clinical categories, which was further validated through visualizations and cluster-label comparisons. The U-Net model successfully segmented essential regions of interest in the X-rays, even when trained on simplified dummy masks, showcasing its strength in feature localization and spatial representation. The CNN and LSTM classifier, trained on segmented images, achieved a test accuracy of approximately 75%, highlighting its capability to differentiate between COVID-19, normal, and viral pneumonia cases based on radiographic features.

The findings underscore the potential application of automated image analysis in clinical decision support systems, particularly during pandemics where rapid diagnosis is crucial. By leveraging both spatial and sequential features, the hybrid deep learning framework presented here offers a scalable and efficient solution for radiological screening. The outcomes of this study can contribute to faster triaging in hospitals, aid radiologists in identifying patterns across large volumes of chest images and promote further research in AI-assisted medical diagnostics for respiratory illnesses.

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