Deep Hybrid Learning Approaches for COVID-19 Virus Detection Using Chest X-ray Images

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***Abstract*—This paper introduces a novel deep learning framework for highly accurate COVID-19 detection using chest X-ray images. The proposed model tackles the challenge by combining stacked Convolutional Neural Network models for superior feature extraction to potentially enhance interpretability. The proposed model achieved a high accuracy in distinguishing COVID-19 from healthy cases. The study demonstrates the potential of deep hybrid learning for accurate COVID-19 detection, paving the way for its application in real-world settings. Future research directions could explore methods to further refine the model's capabilities. Overall, this work contributes significantly to the development of robust deep-learning methods for COVID-19 detection with the potential for broader use in medical image analysis.**

Keywords*—*COVID-19 detection; deep learning; deep hybrid learning; chest X-ray analysis; machine learning classifiers; medical image analysis; convolutional networks

I. INTRODUCTION

The emergence of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) in 2019, causing the highly contagious COVID-19 disease, significantly impacted global health [1]. Coronaviruses, like SARS-CoV-2, cause respiratory illnesses ranging from mild to severe. COVID-19 primarily affects the respiratory system, with common symptoms including fever, cough, fatigue, and shortness of breath. To control the spread of the virus, preventative measures like social distancing and mask-wearing were implemented [2].

Polymerase Chain Reaction (PCR) testing is the standard method for diagnosing COVID-19, but it can be time-consuming and have limitations in accuracy. X-rays, a well-established imaging modality, offer a more accurate alternative for detection. X-ray imaging is used to assess the extent of lung infection, guide treatment decisions, and monitor patients after hospitalization [3]. In addition, recent advancements in technology allow for faster and potentially accurate diagnosis of COVID-19 using chest X-rays, compared to traditional methods.

This work proposes Deep Learning (DL) models for COVID-19 detection using chest X-rays, addressing the limitations of PCR testing by enabling faster diagnosis. DL models have shown good performance in image analysis tasks compared to traditional methods [4]. We propose a novel framework, Deep Hybrid Learning (DHL1) that leverages DL for feature extraction from X-ray images. This framework utilizes stacked Convolutional Neural Network (CNN) models to generate informative feature spaces, which are then fed into separate classifiers for COVID-19 diagnosis. Additionally, we propose a separate RENet model that employs region-based and edge-based operations to extract features. The RENet model incorporates transfer learning (TL) to further enhance COVID-19 detection accuracy. The obtained results of our suggested DHL1 model are promising.

This paper is structured as follows. Section II reviews existing COVID-19 detection methods. Section III describes our proposed schemes for COVID-19 detection in detail. Section IV discusses the experimental setup used to evaluate our methods. The results of these experiments are presented and analyzed in Section V. Finally, Section VI concludes the paper by summarizing the key findings and outlining potential future directions.

II. BACKGROUND

Since the emergence of COVID-19, researchers have actively sought effective detection methods. Therefore, several researchers have examined well-established CNNs that have shown promise in the detection of COVID-19 using X-ray images such as Xception (e.g., [5], inception (e.g., [6] GoogleNet (e.g. [7]. Researchers employed TL which has been suggested to accomplish this task [8, 9].

Overall, several Artificial intelligence (AI) driven detection methods have been utilized in the detection of Covid-19, supervised learning-based, deep learning-based, active learning based, transfer learning-based, and evolutionary learning-based mechanisms [4]. TL is emerging as a dominant paradigm in the realm of medical image analysis for COVID-19 detection [10]. This approach leverages pre-trained CNN models, honed on vast natural image datasets and adapts them for the specific task of COVID-19 classification in medical images, such as chest X-rays and CT scans [10]. This strategy capitalizes on the pre-existing feature extraction capabilities learned from natural images, promoting faster convergence and improved generalization on the often-limited medical image datasets [4].

For example, Researchers such as [11] created their COVID-Net model for the purpose of detecting cases infected with COVID-19 employing X-ray images, their model attained a high percent accuracy and sensitivity. Similarly, Afshar et al. proposed the COVID-CAPS model that reached a 98 percent accuracy and a detection rate of 80 percent [12].

Nevertheless, the above-described models could have a poor detection rate due to a shortage of COVID-19 collected and labeled datasets [13]. Accordingly, TL is now being implemented in the latest models and adjusted on an issue-specific chest X-ray dataset [14]. For instance, a cutting-edge inception model based on TL was used for screening COVID-

19 while having a low accuracy of 89.5 percent [15]. Similarly, a pre-trained ResNet-50 CNN was used mostly on small numbers of instances, and it attained a 98 percent accuracy [16].

Several researchers used approaches that are based on existent CNNs to detect COVID-19 in suspected cases, namely ResNet18 (e.g., [17], DensNet201 (e.g., [18], and squeezeNet [19]. The aforementioned models were fine-tuned on the "COVID-Xray-5k" dataset employing TL and achieved an accuracy of 98 percent [16]. Each of these models was implemented on a SoftMax (SM) classifier in order to screen COVID-19 subjects. Therefore, these models have utilized the merits of empirical risk minimization (ERM).

Likewise, DHL optimized COVID-19 detection function by employing ERM and structural minimization merits [20]. In these related research [21], the features have been generated from the existent Residual Network-50 (ResNet-50) CNN model and then subsequently fed into the ML classifier. The proposed DBHL framework attained a 95 percent detection accuracy [21]. Also, deep features, derived from the pre-trained ResNet-152, that was fine-tuned, have been extracted and then fed into ML classifiers [22]. Accordingly, COVID-19 detection utilizing the eXtreme Gradient Boost (XGBoost) and Random Forest classifiers obtained 97.3 percent and 97.7 per cent accuracy, correspondingly [24]. Despite advancements, existing methods face some key limitations:

First, Existent CNN models were mostly used on a significantly small chest X-ray dataset. This impairs these models' reliability on larger real-life datasets.

Second, these models have all been particularly created for natural images and fine-tuned for the detection of COVID-19. However, chest X-ray images of COVID-19-infected patients are distinguished from natural images by a distinct pattern and texture. Natural images are often big, basic in composition, and unique from one another [23]. COVID-19 viral infection, on the other hand, manifests a distinct pattern and texture, and its severity differs amongst patients. Indeed, the subject having COVID-19 chest infections exhibits reticulation, ground-glass opacity, and consolidation patterns [25]. Therefore, this paper aims to address the limitations of the previous Covid-19 detection DL model to improve their ability to detect Covid-19 cases accurately and effectively.

The remainder of this paper proceeds as follows: the schemes for the detection of COVID-19 are explicated in depth in Section III. The experimental setup is discussed inSection IV. Then, Section V describes the results, and finally, Section VI concludes this research.

III. SUGGESTED COVID-19 DETECTION SCHEME

The present study proposes a novel DL scheme for detecting COVID-19. Our proposal is named DHL approach that aims to detect COVID-19 virus in chest X-ray images (DHL_Covid19). As illustrated in Fig. 1, this proposed scheme consists of four modules: (1) data preprocessing, (2) feature extraction, (3) models training, and (4) the test of the models using the test dataset. Our proposal is based on deep CNN and ML techniques, and it employs three distinct experimental set-ups. Training instances are augmented during experimentation to ameliorate the models' performance. The aforementioned augmented training instances are used to perform the training of the suggested techniques. Fig. 1 depicts the workflow of the schemes for COVID-19 detection.

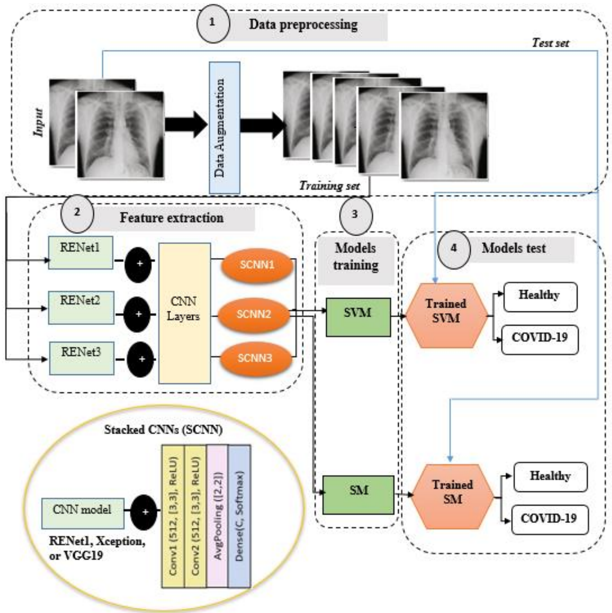

Fig. 1. DHL Covid-19 scheme.

Before exploring the COVID-19 dataset for healthy and COVID-19 classes extraction, the used dataset has to be preprocessed in order to obtain adequate input for the next module. As explained in the following section, this module aims to augment the employed data to ameliorate the ML models' performance.

A. Data Pre-processing

CNN architectures are well-known for their tendency to overfit with limited training data [26]. Large datasets are beneficial for training complex models and improving their performance. One approach to address limited data is data augmentation, a method that expands the number of training samples by applying various transformations to existing data [27]. Table I shows some of the alterations included in our data augmentation method. These transformations, such as rotation, reflection, and scaling, help the model become more robust to slight variations in the input data, mimicking real-world scenarios the model might encounter during deployment. The employed augmentation strategy involves the following operations:

- Rotation: rotate the data with (0,360) degrees.
- Scaling: scale the data with (0.5,1).
- Reflection: reflect the data with X and Y in (-1,1).

TABLE I. DEFINED HYPER-PARAMETERS

Hyper-parameter	Optimizer	Momentum	Learning rate	Weight decay	Loss	Activation function	Epoch	Batch size
value	SGDM	0.95	0.0001	0.0005	Cross-entropy	ReLU	20	16

B. *COVID-19 Detection Approaches*

In this paper, we propose several experimental frameworks for COVID-19 virus detection using DL. We introduce a novel DHL approach. Here, the deep feature learning potential of the three improved models, RENet1, Xception, and VGG-19, was improved by adding CNN layers. These models incorporate additional CNN layers within modules named stacked CNNs (SCNN1, SCNN2, and SCNN3). The proposed frameworks, DHL1 utilize these SCNN modules separately. DHL1 employs a Support Vector Machine (SVM) classifier, then it is enhanced by utilizing SM classifier for COVID-19 patient diagnosis. Finally, the RENet models are trained using two approaches, from scratch and with TL on chest X-ray datasets.

1) Suggested DHL frameworks: Three well-established CNNs are developed in the present study, namely RENet1, RENet2, and RENet3. In order to ameliorate the feature extraction methods, we proposed to modify the CNN sub-modules and add CNN layers to each one, named Stacked CNNs. Accordingly, three deep feature spaces are generated from these sub-models. Then, they are eventually fed into the SVM, and the SM classifiers as illustrated in Fig. 2. Edge-based and Region-based operations are used methodically in the sub-models to make use of region homogeneity and boundary-related features. Accordingly, we use the average pooling operator and max pooling operator, interlacing convolution operations systematically to achieve efficient learning of the COVID-19 discriminative patterns [29].

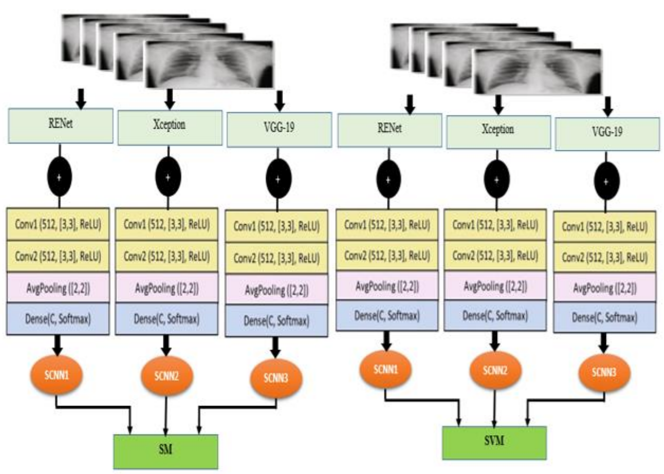

Fig. 2. DHL approach for COVID-19 virus detection.

C. *Stacked CNNs (SCNNs)*

This work proposes three modifications to established CNN architectures (RENet1, Xception, and VGG-19), named Stacked CNNs (SCNNs). As shown in Fig. 2, the outputs of these SCNNs serve as input for the classifiers. The performance of these classifiers heavily relies on the quality and quantity of extracted features for COVID-19 detection.

The proposed RENet models consist of three feature extraction blocks, each containing ReLU activation functions and convolutional layers. This design leverages spatial correlations by addressing non-linearities in the dataset. To create the SCNNs, we removed the top layers of the base CNNs and added new layers to generate new architectures. Our proposed architecture at the top of the network includes two CNN layers with ReLU activation, a Global Average Pooling layer, a fully connected layer, and a SM layer.

We utilize a deep hybrid learning approach that combines the benefits of ERM and structural risk minimization (SRM) principles to improve COVID-19 detection performance. CNNs excel at learning by minimizing training loss through ERM, which can lead to overfitting [30, 31]. However, SVMs are robust machine learning classifiers known for good classification accuracy. They achieve this by reducing structural risk factors, promoting generalization through widening the margin between classes [32]. In addition to the SVM, we also employ a SM classifier for COVID-19 virus detection. Therefore, our proposed DHL frameworks leverage SCNNs for feature extraction and utilize both SVM and SM classifiers.

2) Detection models' training scheme: Training the proposed SCNN model utilizes chest X-ray data. While the model's parameters are randomly initialized with a uniform distribution, deep CNNs generally require substantial amounts of data for optimal performance. Limited X-ray samples can hinder convergence and consequently impact COVID-19 detection accuracy [30, 31]. To address this challenge, we leverage TL to improve detection performance [34].

TL involves transferring the parameters of pre-trained convolutional layers from a large dataset (e.g., ImageNet) to the target COVID-19 X-ray dataset. This pre-training helps initialize the SCNN parameters effectively. In our hybrid framework, the convolutional layers of the developed TL-based models (RENet1, VGG-19, and Xception) extract COVID-19 image bottleneck features. These features are then fed into the SVM and SM classifiers for training.

IV. EXPERIMENTATIONS

A. *Used Dataset*

The study presents a chest X-ray dataset encompassing healthy individuals and COVID-19 patients. The new dataset was created by gathering the publicly available X-ray images from repositories like GitHub and Kaggle, which were labeled by radiologists [33-35]. These repositories provide a diverse collection of X-ray images originating from various geographic locations, medical centers, and X-ray equipment. Consequently, the images exhibit variations in patient positions, orientations, and acquisition techniques due to the differences in source institutions and detector panels. As illustrated in Fig. 3, our approach meticulously filters both COVID-19 and healthy instances from these repositories. To ensure balanced representation, we created a dataset containing 3224 X-ray images each from COVID-19 positive and healthy individuals. These images were originally of various dimensions and have all been preprocessed to a uniform size of 224 x 224 pixels.

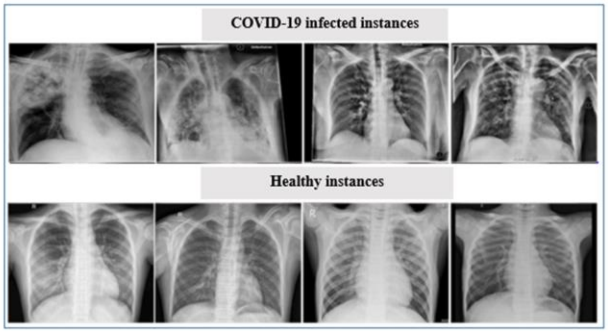

Fig. 3. Dataset instances.

B. Experimentation Process

We employed a hold-out cross-validation approach, splitting the data into an 80% training set (4126 images) and a 20% testing set (1290 images). To address potential class imbalances, stratified sampling was used during the split. The training set was further divided into an 80% inner training set and a 20% validation set (1032 images) for hyperparameter tuning. The CNN models were trained on the inner training set with the optimized.

For evaluating the performance of COVID-19 detection models, we employed conventional metrics including Accuracy (Acc), Sensitivity (Se) or Recall (R), Specificity (Sp), Precision (P), and F1-Score. While accuracy reflects the overall correct predictions, it can be misleading in imbalanced datasets like COVID-19. Therefore, we placed more emphasis on sensitivity and specificity. Sensitivity indicates the model's ability to correctly identify individuals with COVID-19 (low false negative rate), which is crucial to prevent undetected cases. Specificity reflects the model's accuracy in classifying healthy individuals without COVID-19 (low false positive rate), minimizing unnecessary treatments or interventions. The following Equations present the mathematical definitions of these metrics.

Eq. (1), represents accuracy measurement.

$$\text{ACC} = \frac{\text{Detected Covid} - 19 - \text{Detected Healthy}}{\text{Total}} \times 100$$

Sensitivity is measured using Eq. (2).

$$Sensitivity = \frac{Detected\ Covid - 19}{Total\ Covid - 19} \times 100$$

Specificity metric is measured using Eq. (3).

$$Specifictiy = \frac{Detected\ Healthy}{Total\ Healthy} \times 100$$

Eq. (4) demonstrates the precision.

$$Precision = \frac{Detected\ Covid - 19}{Detected\ Covid - 19 + Wrongly\ Detected\ Covid - 19} \times 100$$

Eq. (5) illustrates the F-score.

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100$$

V. Result and Discussion

In the present paper, a new deep learning-based framework, which is named DHL1, is suggested for detecting COVID-19 using chest X-ray images. As highlighted in Table II. The proposed DHL models achieved high performance in COVID-19 detection using chest X-rays, with all models exceeding 98% accuracy across various metrics. SCNN1-based SVM stood out with the highest sensitivity (99.13%), demonstrating its strength in correctly identifying COVID-19 cases. Conversely, SCNN2-based SVM excelled in specificity (98.00%), minimizing false positives among healthy individuals. For a balanced performance between these two aspects, SCNN1-based SVM achieved the best F1-score (98.56). Overall, these findings highlight the potential of our proposed DHL models for accurate COVID-19 detection with chest X-rays, paving the way for further research on larger and more diverse datasets.

TABLE II. DHLs Performance

	ACC	Se	Sp	P	F1-Score
SCNN1-based SVM	98.33	99.13	98	98	98.56
SCNN2-based SVM	98.19	98.55	97	97	97.79
SCNN3-based SVM	98.26	98.52	97	97	97.75
SCNN1-based SM	98.15	98	98	98	98
SCNN2-based SM	98	97	98	98	97.49
SCNN3-based SM	98.07	97	97	97	97

Many researchers have leveraged DL for robust COVID-19 detection. This study contributes to the growing body of research exploring deep learning techniques for COVID-19 detection in chest X-rays. Our proposed CNN-SVM combination (DHL1) achieved superior performance and potentially addressed limitations observed in some prior works.

Similar to previous studies employing DL for this task [28-36], we leverage the powerful feature extraction capabilities of CNNs. However, we move beyond solely relying on CNNs, which can be susceptible to over-fitting or lack interpretability. We integrate SVMs known for strong generalization ability and potential for improved model interpretability. This combined approach achieved high accuracy and offer insights into the features most discriminative for COVID-19 detection.

Our proposed DHL1 framework extracts deep features from well-established CNN architectures like VGG-19, ResNet-1, and Xception, similar to approaches used by [37], As observed in Table II, DHL1 demonstrates high performance in differentiating COVID-19 from healthy cases.

This combined CNN-SVM approach showcases very competitive performance compared to methods using only CNNs, potentially exceeding the accuracy reported in some prior studies (e.g., [38]). Furthermore, utilizing well-established CNNs provides a solid foundation for feature extraction, building upon their proven effectiveness in image recognition tasks.

The high classification accuracy achieved by DHL1 is particularly promising, especially if the model generalizes well to new data. However, as with some previous works (e.g., [39]). Further validation on larger and more diverse datasets is necessary to ensure the generalizability of our findings and mitigate the potential for overfitting.

Our proposed CNN-SVM approach (DHL1) achieves an accuracy of 98% on our dataset, higher than the 94% accuracy reported by [40]. However, DHL1 also achieves a higher sensitivity (0.98 vs. 0.92) and a comparable specificity (0.97 vs. 0.87), indicating a better balance between precision and recall. This suggests that DHL1 might be less susceptible to misclassification. Furthermore, unlike other researchers such as [41, 42] which focused on binary classification, our approach can be extended to handle multi-class scenarios with additional diseases.

An alternative approach to DL for COVID-19 detection involves TL, where pre-trained models are adapted for the specific task. Several studies in this field explore this technique [43]. Transfer learning offers a balance between accuracy and efficiency by leveraging the power of existing models like VGG-16 or ResNet-18. While chest X-rays are the most common image type used, with studies aiming for multi-class detection (normal, COVID-19, other lung issues), some research also investigates CT scans or ultrasounds with varying classification goals (binary or multi-class). The reported accuracy for transfer learning approaches varies, with some achieving impressive results exceeding 95% (e.g., [44, 45].

While there are a number of AI image detection methods used by researchers to detect Covid-19. Using an individual approach could be challenging as each model has its advantages and disadvantages. For, example, using VGG-16 could lead to faster training time and improved accuracy, but it may be suboptimal for medical images as it is trained on natural images, and it might not be suited for the specific patterns and textures seen in medical images [46].

Our study shows how multiple approaches could be utilized to solve a problem and overcome the limitations of other single approach models. Our CNN-SVM approach (DHL1) offers several potential advantages over other TL techniques. Firstly, it allows for more flexibility in feature extraction by leveraging the power of multiple CNN architectures (VGG-19, ResNet-1, Xception) compared to relying on a single pre-trained model. Secondly, the integration of SVMs potentially improves interpretability, offering insights into the features most discriminative for COVID-19 detection.

However, it's important to acknowledge that both approaches have merit. TL can be a good choice when computational resources or dataset size are limited. Further research is needed to comprehensively compare the performance and generalizability of CNN-SVM combinations like DHL1 against other TL techniques across various datasets and tasks.

VI. Limitations and Future Studies

To prevent the COVID-19 spread, patients must be identified quickly and early. The present paper suggests a new framework, DHL1, for detecting COVID-19 in chest X-ray images successfully. For the purpose of detecting COVID-19 accurately, three stacked CNN models, namely SCNN1, SCNN2, and SCNN3 were adopted for feature extraction. The experimental findings illustrate that our suggested DHL1 framework out-performs existing well-established CNNs combined with the SM classifier.

This study has presented promising deep learning frameworks, DHL1, for COVID-19 detection using chest X-rays. However, to ensure their real-world applicability and further refine their capabilities, it's important to address some limitations and explore future research directions.

One key limitation lies in the generalizability of the findings. The models were evaluated on a relatively limited dataset. To ensure they perform well on unseen data and mitigate potential overfitting, validation on larger and more diverse datasets from various institutions is necessary. Additionally, the dataset used in this study might not perfectly reflect the true prevalence of COVID-19 cases in the real world. Future work could investigate the impact of class imbalance on model performance and explore techniques to address any potential biases arising from imbalanced datasets.

While DHL1 integrates SVMs with the potential for improved interpretability, this aspect requires further investigation. Future work could involve analyzing the SVM weights or decision boundaries to understand the specific features most discriminative for COVID-19 detection. This would not only enhance our understanding of the model's decision-making process but also potentially lead to the development of more interpretable AI models in healthcare.

The current study focused on differentiating between COVID-19 and healthy individuals. Future researchers could extend the models to handle multi-class scenarios, allowing them to distinguish COVID-19 from other lung pathologies. Additionally, collaborations with hospitals or medical institutions could enable testing the models on real-world clinical data. This external validation would provide valuable insights into the practical applicability of these models in a clinical setting.

Furthermore, exploring techniques for optimizing the models for computational efficiency is important. This could involve reducing the computational resources required for training and inference. Such optimizations would be particularly relevant for deploying these models in resource-constrained settings with limited computing power. Finally, a comprehensive comparison between DHL1 and other TL approaches on various datasets and tasks would be valuable. This comparison would provide insights into their relative strengths and weaknesses, guiding the selection of the most suitable approach for different scenarios.

By addressing these limitations and pursuing the suggested future work directions, this research can significantly contribute to the development of robust and reliable deep learning methods for COVID-19 detection and potentially pave the way for their application in other medical image analysis tasks.

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