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Ensemble of Transfer Learning Techniques for Detection of COVID-19 based on CT scans

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ABSTRACT

Purpose: The rapid advancements in convolutional neural networks (CNNs) have significantly improved medical image analysis. The COVID-19 pandemic has impacted millions worldwide, with containment hindered by inadequate testing resources and inefficiencies in diagnostic methods. This study proposes and explores a novel framework employing an ensemble of advanced deep transfer learning techniques for accurate and consistent COVID-19 detection from Computed Tomography (CT) scans, reducing reliance on manual assessment.

Materials and Methods: The proposed framework integrates standardized data pre-processing with fine-tuned heterogeneous transfer learning models, including CNN- and Transformer-based architectures. An ensemble learning strategy is implemented at the feature level using Principal Component Analysis (PCA) to fuse deep representations extracted from the most effective models. The framework has been evaluated on two large publicly available CT datasets, COVID-CT and SARS-CoV-2, comprising over 1,600 COVID-19 and 1,450 non-COVID-19 images.

Results: Experiments have demonstrated that fusing five architectures—ResNet-50 v2, EfficientNet-B5, ViT, VGG16, and DenseNet-201—achieves superior diagnostic performance compared to individual models and existing frameworks, as reflected by improved F1-scores.

Conclusion: The results have confirmed that integrating transfer learning with feature-level ensemble learning within a unified framework significantly enhances the robustness and accuracy of COVID-19 detection from CT images. The proposed methodology provides a scalable and reproducible solution that can be extended to other medical image-based diagnostic tasks.

1. Introduction

In the wake of the COVID-19 pandemic, which has spread extensively across various regions worldwide, there is a pressing need to accurately identify and distinguish this novel coronavirus disease from other respiratory illnesses. Currently, a critical need exists for a reliable approach to distinguish COVID-19 from related illnesses in order to effectively mitigate its transmission and provide prompt and appropriate medical treatment. Given the limitations of PCR testing in terms of time and resource requirements, imaging techniques such as Computed Tomography (CT) scans have emerged as valuable adjuncts for identifying the pulmonary manifestations of COVID-19, thereby aiding in the early detection and differentiation of the disease [1].

Even though COVID-19 is a highly transmissible disease, early detection offers several potential benefits. Individuals diagnosed with COVID-19 can receive timely treatments, such as antiviral medications [2], which are more effective when administered during the early stages of infection. Accurate diagnosis can be challenging, as symptoms of COVID-19 often overlap with those of other respiratory illnesses or flu-like conditions [3]. Diagnostic confirmation typically requires the detection of viral genetic material or proteins

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through methods like Polymerase Chain Reaction (PCR) tests or antigen tests [4]. Early identification of COVID-19 cases is crucial for limiting the spread of the virus and improving patient outcomes. Several diagnostic techniques, including rapid antigen tests, PCR assays, chest imaging, and serological tests, are commonly employed [5, 6]. However, achieving high diagnostic accuracy depends on expert analysis and the effective interpretation of complex medical data, such as viral load and imaging results. Therefore, there is a growing demand for algorithms that can enhance the accuracy and efficiency of COVID-19 diagnostics. Among these diagnostic techniques, the CT scanning method stands out as a highly effective tool in detecting COVID-19 due to its precision and reliability [7]. Diagnosing COVID-19 relies on radiologists' assessment of CT images, a process prone to inter-observer variability and uncertainty. To address these challenges, the integration of a sophisticated machine-learning-based system is essential for automatic, consistent, and widely applicable diagnoses without dependence on expert radiologists [1]. Recent studies have extensively investigated the application of artificial intelligence for the detection of COVID-19. Traditional machine learning classification techniques have been employed to analyze various types of pulmonary images, including X-rays (CXR) and CT scans. However, the complex nature of medical imaging poses significant challenges. An effective classification methodology must identify features within similar patterns of chest images. In this context, deep learning has emerged as a particularly effective approach for classification tasks, thereby mitigating the complexities associated with medical image analysis [5]. Consequently, deep learning algorithms have demonstrated high efficiency in classifying pulmonary images at various stages of COVID-19 [8, 9]

Deep learning methodologies, particularly Convolutional Neural Networks (CNNs), demonstrate enhanced efficacy compared to conventional machine learning techniques [10], as they excel in image classification and object detection through their proficiency in automatically learning hierarchical feature representations. However, training CNNs from scratch necessitates extensive datasets and significant computational resources, posing challenges for researchers. Transfer learning has emerged as a pivotal strategy to alleviate this issue, enabling the utilization of pre-trained networks to achieve high model accuracy with smaller datasets and fewer computational requirements. This approach not only accelerates model development but also broadens access to advanced methodologies, fostering innovation. Despite its potential to enhance model accuracy, transfer learning may increase the risk of overfitting in limited datasets, making data augmentation and intensity normalization essential for enhancing model robustness.

In classification tasks, ensembles of classifiers generally enhance the performance of machine learning techniques by combining multiple models to achieve better accuracy and robustness compared to individual classifiers, as they mitigate variance in final predictions [7]. Within the framework of CNNs, an ensemble can be constructed through variations in network architecture or by training a network on datasets that have undergone distinct data normalization techniques. By integrating diverse predictive insights from various models, ensemble methods effectively mitigate individual model errors and reduce overfitting. This strategic combination capitalizes on the strengths of each model, leading to superior outcomes in complex tasks, such as medical diagnostics, where precision and reliability are crucial for effective decision-making.

This study employed transfer learning methodologies by fine-tuning high-performing pre-trained models, including VGG16, ResNet-50 v2, EfficientNet-B5, MobileNet, Vision Transformer (ViT), Swin Transformer, Xception, Inception-v3, DenseNet-201, and ConvNeXt, as well as utilizing pre-processed datasets. We further integrated ensemble learning techniques, particularly a PCA-based feature fusion method, to enhance the accuracy of the final predictions. To our knowledge, this research is the first to combine data pre-processing, transfer learning, and feature fusion ensemble learning within a single framework to improve diagnostic performance for COVID-19. The research introduces a novel methodology that utilizes an ensemble deep transfer learning approach, incorporating multiple pre-trained CNN architectures. The proposed system is applied to a combination of two of the largest publicly available CT image datasets for COVID-19 diagnosis, namely the COVID-CT and SARS-CoV-2 datasets. We systematically devise an optimal combination of the outputs from deep transfer learning models by integrating an additional ensemble module. In this study, we introduce a novel ensemble technique utilizing feature fusion based on Principal Component Analysis (PCA). This method involves the integration of feature representations extracted from the final convolutional layers of distinct pre-trained models. By consolidating diverse learned features into a single, unified vector, it provides a comprehensive data representation. Unlike linear feature fusion, which offers a weighted feature sum, PCA transforms these learned features from pre-trained models into a reduced-dimensional set of uncorrelated features and principal components. This enhanced, multidimensional feature set significantly improves classification accuracy. While recent studies such as Ohno et al. [1] have demonstrated the utility of quantitative CT analysis for assessing disease severity and treatment response in COVID-19 patients, their focus is primarily on handcrafted radiomic features and clinical outcomes. In contrast, the present study addresses the problem of automated COVID-19 detection from CT scans through an end-to-end deep learning methodology. Specifically, our approach integrates fine-tuned heterogeneous transfer learning models with ensemble learning at the feature level, employing PCA-based fusion. This approach enables the extraction of complementary deep representations, avoiding predefined quantitative descriptors. Such a fundamental methodological distinction clearly differentiates the proposed framework from existing CT-based analytical approaches.

The principal contributions and innovations of this research are summarized as follows:

- This study introduces a comprehensive and reproducible framework specifically tailored for COVID-19 detection utilizing CT scans that systematically integrates data preprocessing, transfer learning, and ensemble learning within a single pipeline.
- Distinct from prevalent methodologies that depend on decision-level ensemble strategies, this research employs a novel PCA-based feature-level ensemble approach that integrates deep features derived from heterogeneous pre-trained models including both CNN- and Transformer architectures.
- The proposed methodology rigorously assesses and identifies an optimal subset of fine-tuned models, resulting in a robust ensemble configuration (Ens-5), which yields enhancements in robustness and diagnostic accuracy across two extensive public CT datasets.
- To facilitate further scholarly inquiry and verify reproducibility, we have made our entire implementation publicly accessible to the research community.

2. Background and related research

COVID-19, caused by the SARS-CoV-2 virus, primarily affects the respiratory system with symptoms like cough, fever, and difficulty breathing, potentially leading to severe pneumonia and respiratory distress [4]. The lungs are the most impacted organ, with complications including organ damage, blood clots, and neurological issues. Severe cases require intensive medical care. As there is no definitive cure for COVID-19, developing reliable automated systems for early detection is essential, while research on treatments and vaccines continues.

Biomarkers serve as quantifiable indicators for objectively and consistently assessing disease progression and diagnosing conditions. In the context of COVID-19, several biomarkers have emerged, including chest imaging modalities (such as CXR and CT scans), polymerase chain reaction (PCR) assays, levels of antigens and antibodies, inflammatory markers (notably C-reactive protein and cytokines), and oxygen saturation levels [2, 4]. Chest CT scans are particularly significant for COVID-19 diagnosis, offering non-invasive insights into pulmonary alterations like ground-glass opacities and lung consolidation, characteristic of COVID-19 pneumonia. Advanced quantitative CT analysis further elucidates lung damage and disease severity, thereby enhancing early detection and monitoring capabilities.

The most commonly used datasets for COVID-19 research focusing on CT scans include the COVID-CT dataset [11]; the SARS-CoV-2 CT-Scan dataset; and the COVID-CT-MD dataset [12]. Among these, COVID-CT and SARS-CoV-2 CT-Scan datasets are widely utilized for COVID-19 diagnosis. These datasets contain annotated CT scans from patients with confirmed COVID-19, enabling researchers to identify key features and patterns associated with the disease [13]. They provide a diverse range of cases, including mild, moderate, and severe infections, and may include metadata such as clinical outcomes and demographic details. It has been extensively used in studies to develop and validate automated diagnostic systems, often in combination with other datasets to enhance diagnostic accuracy.

2.1. Related work on utilizing transfer learning for COVID-19 detection

Human beings bring extensive prior experience to challenging tasks, whereas neural networks often start from scratch due to random weight initializations. Transfer learning addresses this gap by pre-training a network on a different task and applying those learned weights to the new task. Recent studies on lung infections, including COVID-19, have utilized deep transfer learning techniques on CXRs and CT scans. A notable method for diagnosing COVID-19 using CT scans was developed for resource-limited devices. Das and Kumar implemented an automated approach with the Xception model to screen COVID-19 using chest CXR images [14]. Subhash et al. in [15] combined CNNs with transfer learning to automatically classify CXR images of infected and uninfected individuals across several experiments using various classifiers like Random Forest and SVM. Panwar et al. discusses popular deep learning configurations for feature identification to categorize subjects into COVID-19 cases or controls from CXR and CT images [16]. The models used several deep CNNs, with DenseNet-121 as the best feature extractor and Bagging tree classifier on publicly available datasets. Das and Kalam, [17], proposed CovXNets for identifying the virus from CXRs of various resolutions, incorporating advanced convolution techniques and fine-tuning layers.

2.2. Related work on automatic detection of COVID-19 using ensemble deep learning

Ensemble techniques involve the integration of multiple transfer learning models in various ways to leverage their complementary strengths and reduce individual weaknesses. During our literature review, we examined various studies that leverage transfer learning and ensemble learning for the diagnosis of COVID-19 [6]. In this section, a comparative analysis is conducted between our research and three prominent studies from the existing literature.

The first study [18] proposes an automated methodology that leverages an ensemble of deep transfer learning techniques for improved detection of COVID-19, addressing challenges such as the inefficiency of medical tests and variability in radiologist assessments. The authors utilized five pre-trained CNN architectures, including MobileNetV2, Shufflenet, Xception, Darknet53 and EfficientNet-B0. These models were fine-tuned and combined using a kernel support vector machine (KSVM) ensemble method to improve performance. To validate the proposed system, a publicly available dataset consisting of 349 CT scans labeled as COVID-19 positive and 397 CT scans classified as negative or indicative of other lung conditions was utilized. The ensemble of these models achieved promising results, with precision, recall, and accuracy scores of 0.857, 0.854, and 0.85, respectively. This demonstrates that ensemble-based deep transfer learning is effective for diagnosing COVID-19 using CT scans.

Mouhafid et al. in [19] address the challenge of automating COVID-19 detection from lung CT scans using the strengths of multiple deep neural network architectures to enhance prediction accuracy for COVID-19 detection. The methodology incorporates several pre-trained models, including VGG16, VGG19, Inception-v3, ResNet50, ResNet-50 v2, InceptionResNetV2, Xception, and MobileNet, all of which are fine-tuned using lung CT scan images and integrated into a robust ensemble classifier. The experimental results demonstrated that this ensemble approach outperformed existing methods, achieving an F1 score of 98.65 and an accuracy of 98.59, and stablished a new state-of-the-art for detecting COVID-19 from lung CT scans, showcasing its potential for rapid and reliable diagnosis.

Table I. Comparison of this study with the studies by Abraham et al. [18], Islam et al. [19], and Mouhafid et al. [20].

	[18]	[19]	[20]	The Present Study
Dataset	COVID-CT	SARS-CoV-2 CT-Scan	SARS-CoV-2 CT-Scan and COVID-CT	SARS-CoV-2 CT-Scan and COVID-CT
Preprocessing Technique	No pre-processing	Contrast Limited Histogram Equalization	No pre-processing	Resizing and Z-score normalization
Transfer Learning	MobileNetV2, Shufflenet, Xception, Darknet53 and EfficientNet-B0	Gaussian Naive Bayes, Support Vector Machine, Decision Tree, Logistic Regression, and Random Forest	VGG19, ResNet50, and DenseNet-201	VGG16, ConvNeXt, EfficientNet-B5, Xception, MobileNet, ResNet-50 v2, DenseNet-201, GoogleNet, Inception-v3, and ViT
Ensemble Learning	kernel support vector machine (KSVM)	Voting	Stacking and Weighted Average Ensemble	PCA-based Feature Fusion

Islam et al. propose ET-NET, a fully automated framework for COVID-19 detection using chest CT scan images [20]. Recognizing the limitations of RT-PCR tests and the sensitivity of CT imaging, the authors developed a method grounded in deep learning techniques, employing a bootstrapped aggregating or bagging ensemble of three transfer learning models: Inception-v3, ResNet34, and DenseNet-201. This configuration aims to enhance the performance metrics of individual models involved in the classification task. The framework was evaluated on a publicly available dataset and achieved an accuracy of 97.81%, precision of 97.77%, sensitivity of 97.81%, and specificity of 97.77% in a k-fold cross-validation setup. ET-NET outperformed existing state-of-the-art methods by 1.56% on the same dataset, demonstrating its effectiveness in fast and accurate COVID-19 screening.

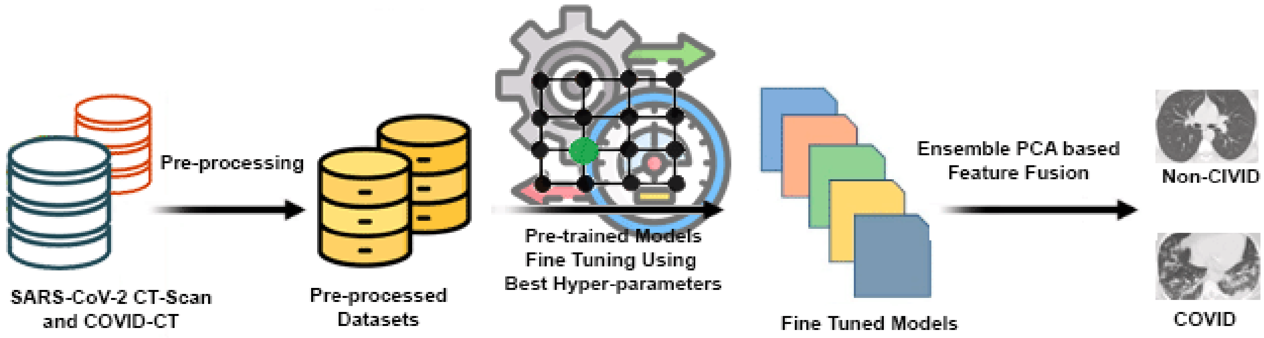
Table I provides a comparative overview of our proposed methodology against those put forth by [18, 19, 20]. Notably, in contrast to Abraham et al., who exclusively utilized COVID-CT images, our approach integrates both COVID-CT and SARS-CoV-2 CT-Scan images, employing intensity resizing and Z-score normalization, and multiple pre-trained architectures for transfer learning, thereby ensuring diversity through integration. Compared to Islam et al. [20], whose focus was restricted to SARS-CoV-2 CT-Scan images , and who did not exploit extensive preprocessing, our research uniquely combines both datasets while utilizing various pre-trained architectures in transfer learning, achieving diversity through ensembling different models. Furthermore, unlike Mouhafid et al. [19], who employed stacking and weighted averaging techniques for ensemble learning at a high computational cost, our methodology leverages PCA-based feature fusion to efficiently integrate the outputs of pre-trained models. Our proposed ensemble learning technique utilizes PCA-based feature fusion, in contrast to the methods introduced in [18], which rely on kernel methods to combine features for handling nonlinear feature distributions.

3. Methodology

The proposed methodology consists of a series of sequential steps, as depicted in Fig. 1. First, the CT scan datasets, particularly SARS-CoV-2 CT-Scan and COVID-CT, undergo comprehensive pre-processing using various techniques to enhance image quality and standardize input formats. Next, the pre-processed data is used with pre-trained neural networks to perform a hyperparameter search, aimed at identifying the optimal configurations for the applied pre-trained models. Following this, fine-tuning is carried out using both datasets in conjunction with the identified hyperparameters. The fine-tuned models are subsequently combined using PCA-based feature fusion, which enhances the robustness and accuracy of the classification process. Finally, the ensembled model predicts whether the input CT scan corresponds to a COVID or non-COVID case, thereby improving diagnostic performance. Each step of the process is thoroughly explained in detail in the following sections. The code implementing this methodology is publicly available at https://github.com/ghsofia/PCAEnsemble COVID.

Unlike conventional ensemble approaches that primarily operate at the decision level through voting or averaging mechanisms, the proposed methodology performs ensemble learning at the feature level through PCA. Deep feature representations extracted from the final convolutional layers of heterogeneous pre-trained models are fused into a compact and uncorrelated feature space, enabling more discriminative and robust classification. This approach enhances further discrimination and robustness in classification tasks by harnessing complementary information across various architectures while reducing redundancy and overfitting.

Fig. 1. Workflow of the proposed ensemble of fine-tuned pre-trained models for improved COVID-19 detection performance.



3.1. Database

The primary dataset employed in this study was the SARS-CoV-2 CT-Scan collection, comprising 1,252 COVID-19-positive CT scans and 1,230 negative scans, which include images of normal lungs and other lung diseases. This dataset serves as a crucial resource for our investigation, providing a diverse range of chest CT images that are essential for the accurate diagnosis and analysis of COVID-19, and is making it the largest dataset of its kind. In addition to this primary dataset, we utilized the COVID-CT dataset [11], recognized as one of the most widely used datasets in the domain. This dataset includes 349 COVID-19-positive CT scans from 216 patients and 397 negative scans from 171 patients. Further details about the SARS-CoV-2 CT-Scan and COVID-CT datasets are available in [11], respectively. It is worth noting that the CT images in these datasets exhibit varying dimensions, with average heights of 491 pixels, maximum heights of 1,853 pixels, and minimum heights of 153 pixels. The average width is 383 pixels, with a maximum of 1,485 pixels and a minimum of 124 pixels.

The SARS-CoV-2 CT-Scan dataset comprises CT scans from early COVID-19 cases identified during the beginning of the pandemic, while the COVID-CT dataset was assembled from patients diagnosed in the initial outbreak. Since both datasets reflect primarily the early strains of COVID-19, the model's effectiveness on newer variants, such as Omicron, remains untested. This limitation highlights the need for future research to evaluate the model against datasets that include more recent COVID-19 variants in order to enhance its applicability and relevance in ongoing pandemic management efforts.

A crucial aspect of COVID-19 CT image analysis is the stage of the disease at the time of imaging. While the COVID-CT dataset and SARS-CoV-2 CT-Scan dataset include metadata on patient demographics, medical history, radiological metadata, and scan reports, both lack explicit documentation about the timing of CT scans in relation to symptom onset. This absence of temporal information may introduce uncertainty in model generalizability, as COVID-19 lesions progress over time. To enhance automated detection systems, future research should aim to utilize datasets with well-documented intervals between symptom onset and imaging, ensuring a better alignment between imaging features and pathophysiological evolution over time.

3.2. Pre-Processing Techniques

In the domain of CNNs, constructing an ensemble of classifiers can be achieved either by varying network architectures or by training a single network on datasets preprocessed with different data normalization techniques. This study employs a preprocessing pipeline comprising key steps, including image intensity resizing and Z-score normalization, to prepare the data for training and evaluation.

All models were initially pre-trained on images maintaining consistent dimensions in terms of height and width. However, our applied datasets contained images of varying dimensions. To address this discrepancy, images were symmetrically padded along their width to achieve uniform dimensions in both height and width. These padded images were then resized to a standardized dimension of 456×456 pixels for EfficientNet-B5, 299×299 pixels for Inception-v3 and Xception, and 224×224 pixels for the other models using bilinear interpolation. After resizing, Z-score normalization was applied as part of the preprocessing pipeline.

Z-score normalization is a widely-used technique in machine learning that standardizes data by transforming it to have a zero mean and unit variance. This approach offers several benefits, including eliminating the influence of varying scales across features, enabling faster and more stable convergence during training, and improving model performance by ensuring consistency in feature contributions. In this study, Z-score normalization of the CT image data was performed using the mean and standard deviation calculated from the datasets. This ensured consistency and alignment between the pre-training and fine-tuning phases, thereby enhancing the effectiveness of the preprocessing stage.

After pre-processing, the dataset was systematically divided into training, validation, and testing subsets. Specifically, 80% of the data was designated for training and validation, while the remaining 20% was allocated for testing [7]. This strategic division facilitated balanced class representation, culminating in 2,437 images reserved for training and validation purposes and 610 images set aside for testing. The partitioning was performed using the train_test_split function from the scikit-learn library, which enabled the implementation of a validation split while isolating the test set, ensuring 80% of the original dataset was utilized for training and validation.

Within the training and validation data, a stratified k-fold cross-validation (k=5) strategy was employed to split the dataset. This approach enhanced the robustness of the training process by enabling the model to be evaluated across multiple data splits.

Hyperparameter optimization was subsequently performed using the pre-processed dataset, employing a grid search methodology to ascertain the most effective hyperparameters, including batch size, learning rate, and optimizer. The optimal hyperparameters identified through this process were systematically documented and utilized in subsequent analyses to ensure reproducibility and enhance model performance (Table III).

3.3. Deep learning and Convolutional Neural Networks

Deep learning algorithms have gained significant popularity in medical imaging, offering substantial performance improvements over conventional machine learning methods for disease diagnosis [16]. Among deep learning techniques, CNNs have emerged as one of the most widely used and effective approaches in this field of medical imaging. CNNs represent a state-of-the-art deep learning approach characterized by their layered architecture designed to automatically extract and classify features from input images.

The structure of a typical CNN includes several key components: convolutional layers, pooling layers, non-linear activation layers, batch normalization layers, fully connected layers, and a softmax layer. Convolutional layers form the backbone of the network, extracting features from input images using convolutional filters. Pooling layers, such as max or average pooling, reduce the spatial dimensions of feature maps while enhancing translational invariance. Non-linear activation functions, primarily the ReLU, introduce nonlinearity to tackle complex problems. Batch normalization stabilizes training and improves convergence. Fully connected layers process the features for classification by the softmax layer, which outputs class probabilities. This architecture enables CNNs to efficiently learn hierarchical representations, making them fundamental in medical image analysis [6].

3.3.1 Pre-Trained Neural Networks Used

Transfer learning leverages pre-trained models, originally trained on large-scale datasets, to enhance performance on target tasks with limited data, such as diagnosing COVID-19 from CT scans [15]. The main idea is to transfer learned features from the pre-trained model to the specific problem, effectively addressing data scarcity by utilizing expressive features from a diverse dataset. A key challenge is the domain difference between pre-trained and target datasets; features learned from general images on datasets like ImageNet may not fully capture the characteristics of medical images. To mitigate this, pre-trained models are fine-tuned on the target dataset, adapting their parameters to the specifics of the new task. This process is far less time-consuming than training a CNN from scratch, which requires extensive datasets and computational resources.

Utilizing pre-trained networks offers researchers advantages including reduced training duration, diminished hardware demands, lower computational expenses, and facilitating more efficient experimentation. Incorporating multiple pre-trained models enhances COVID-19 image classification by leveraging their unique architectures and methodologies. This approach promotes diversity in feature extraction, capturing the multifaceted nature of lung images and improving overall robustness.

Table II lists the selected pre-trained deep learning models selected from the ImageNet dataset, employed in our study for fine-tuning on CT scan images, detailing their initial training accuracy, input image size, and number of parameters. This information is crucial for understanding the baseline capabilities of these pre-trained models and how they may need to be adapted for the specific task of COVID-19 diagnosis from CT scans. Each model listed has been selected for its proven performance and efficiency on the ImageNet dataset, demonstrating strong capabilities in image classification tasks. Their architectural innovations and robustness are essential for achieving high diagnostic accuracy in the context of medical imaging. The selection spans classical CNNs (e.g., VGG16, ResNet-50 v2, DenseNet-201), efficient architectures (e.g., EfficientNet-B5, MobileNet), transformer-based models (e.g., ViT, Swin Transformer), and neural architecture search-based networks (e.g., Xception, Inception-v3, ConvNeXt). The diversity of model types and performance characteristics presented in this table allows a thorough evaluation of the trade-offs between model complexity, accuracy, and computational efficiency when fine-tuning for the target medical imaging application . This comprehensive set of pre-trained models provides a solid foundation for developing an accurate and practical COVID-19 detection system.

3.3.2 Training of CNNs

The After training an extensive set of 10 transfer learning models, including prominent architectures such as ViT, Swin Transformer, ResNet-50 v2, DenseNet-201, MobileNet, ConvNeXt, VGG16, Xception, Inception-v3, and EfficientNet-B5, we focused on optimizing performance through hyperparameter tuning . Each model underwent a rigorous training process on comprehensive datasets comprising diverse CT scans, which facilitated effective understanding and representation of the underlying features. The careful selection and tuning of hyperparameters were critical, enabling each model to learn effectively from the data and perform optimally on the given tasks.

Table II. Specifications of the pre-trained models selected for the study.

Model	Accuracy for the Dataset	Input Image Size	Parameters (Millions)
ViT	88.3%	224 × 224	86.6 M
Swin Transformers	83.3%	224 × 224	88 M
ResNet-50 v2	76.13%	224 × 224	25.6 M
DenseNet-201	77.3%	224 × 224	20.2 M
MobileNet	70.6%	224 × 224	4.2 M
ConvNeXt	82.9%	224 × 224	28.6 M
VGG16	71.3%	224 × 224	138 M
Xception	79.0%	299 × 299	22.9 M
Inception-v3	77.9%	299 × 299	23.8 M
EfficientNet-B5	83.6%	456 × 456	30 M

The performance of these pre-trained CNNs was assessed through individual fine-tuning on our various clinical datasets, enabling a detailed evaluation of their efficacy in this context. Instead of applying data augmentation, which may produce synthetic images that do not fully replicate real-world characteristics, an additional training dataset was used to address overfitting. These supplemental datasets were integrated during training to enhance model generalization and reduce overfitting in deep CNNs.

During the fine-tuning process, only the convolutional layers of each pre-trained model were retained, while all fully connected layers, which are specific to the original task for which the model was trained , were removed. These removed layers were replaced with new ones tailored to our specific task as follows. A global average pooling layer was added on top of the last convolutional layer, followed by a final classification layer utilizing an RBF layer to compute class probabilities, which may provide better uncertainty estimation in medical diagnosis than the conventional softmax activation function. All models were fine-tuned for 50 epochs using the hyperparameters specified in Table III, with Binary Cross-Entropy employed as the loss function. The hyperparameters were further optimized on the validation set to ensure robust performance.

Each CNN architecture required input images of different sizes, as listed in Table II. Therefore, as part of the data preparation process, all images were resized to match the respective input size requirements of the models and stored in separate folders. Table II provides a comparative summary of the pre-trained deep learning models, including their architectural differences and baseline performance. All models were trained under consistent initialization and learning rate policies to ensure a fair comparison.

3.4. Ensemble Techniques

To further enhance the accuracy of our final predictions, we adopted an ensemble learning approach, leveraging multiple strategies to improve overall performance. Ensemble methods are widely recognized in machine learning for their ability to combine the strengths of individual models, leading to improved predictive accuracy, reduced overfitting, and increased robustness to noise and anomalies in the data. Ensemble learning benefits from the diversity of pre-trained models described earlier, mitigating individual model weaknesses. Each model offers distinct advantages; ResNet-50 v2 addresses the vanishing gradient problem, EfficientNets optimizes scalability, DenseNet-201, Inception-v3, and Xception enhance feature extraction efficacy, as well as transformer-based models like ViT and Swin Transformer leverage self-attention mechanisms to capture global dependencies and improve generalization.

The proposed ensemble technique we employed was a PCA-based feature fusion method, which involved concatenating the feature representations extracted from the last convolutional layers of the individual models along with those from the global average pooling layer. By combining the various learned features from each model into a single, unified feature vector, this approach allowed us to capture a more comprehensive understanding of the data. Instead of using simple linear feature fusion, which provides a weighted sum of features, we employed PCA to transform the learned features derived from pre-trained models into a new set of lower-dimensional, uncorrelated features and principal components.

The resulting rich, multidimensional feature set can ultimately lead to improved classification accuracy. While concatenation maintains the integrity of the original features, it may produce high-dimensional representations. Thus, the concatenated feature vector is subsequently subjected to a linear transformation based on PCA function. To address this issue and effectively reduce the dimensionality of the integrated feature representation without substantially sacrificing information from the original features, we project the feature vectors from various sources into a unified feature space. This methodology for our proposed feature fusion is articulated in (1).

$$F = PCA(N(f_1) \oplus N(f_2) \oplus \dots \oplus N(f_{10})) \quad (1)$$

We represent the result of the extracted feature vector by each model as F. Besides, f1, f2, ⋯, f10 are the features vectors extracted by our 10 pre-trained models. The ⊕ operator denotes the concatenation of the vectors extracted from each pre-trained model. This operator forms a single high-dimensional feature representation for each image. It is noted that this high-dimensional feature space may contain redundant and correlated features due to the overlapping knowledge of our different pre-trained models.

As PCA works best when features have zero mean and unit variance, we centered each feature vector by subtracting the mean and then scaled it using the standard deviation of fi for model i, as depicted by N(.) in equation (1). To understand how features vary together, the covariance matrix is calculated. In case where two features are highly correlated, PCA combines them into a single eigenvector as the principal component associated with an eigenvalue. Eigenvalues indicate how much variance each principal component captures. The top k principal components that retain the most variance from a compressed vector representation while maintaining most of the original information [21]. This compressed representation captures the most significant patterns in the data with fewer dimensions, making our classification task more efficient. The output of PCA transformation is fed into the activation function in an RBF layer , which replaces the conventional softmax to compute class probabilities.

By employing this ensemble of models through PCA-based feature fusion, we aimed to create a robust prediction system that leverages the strengths of each architecture while compensating for their weaknesses. This integrated approach led to improved performance on the target classification tasks, demonstrating the effectiveness of ensemble learning in enhancing the predictive capability of transfer learning models.

4. Results

In this study, each model underwent training and evaluation utilizing computational resources optimized for deep learning experiments, specifically through Google Co-laboratory with the Keras and TensorFlow libraries. The training duration for each model generally ranged from several hours until convergence; however, explicit benchmarking was not conducted due to the design of certain system components, such as the data loader, which prioritized experimental flexibility over speed. This approach facilitated the efficient use of resources while preserving the scalability necessary for our experimental framework. Consequently, the setup was conducive to rigorous exploration within the context of our research objectives. The experiments were performed using the Python 3.8 programming language.

Table III. Systematically established hyperparameters employed for fine-tuning the pre-trained models.

Model	Batch Size	Learning Rate	Optimizer
ViT	32	0.0001	Adam
Swin Transformers	16	0.0001	Adam
ResNet-50 v2	64	0.001	SGD
DenseNet-201	32	0.0001	Adam
MobileNet	64	0.0001	RMSProp
ConvNeXt	32	0.0001	Adam
VGG16	32	0.0001	SGD
Xception	32	0.001	Adam
Inception-v3	32	0.0001	Adam
EfficientNet-B5	16	0.0001	Adam

Our We utilized 10 different pre-trained CNN models trained on the ImageNet dataset, with the goal of transferring their learned representations into our domain despite the limited amount of training data. Independently, our experiments fine-tuned the following models: ViT, Swin Transformers, ResNet-50 v2, DenseNet-201, MobileNet, ConvNeXt, VGG16, Xception, Inception-v3, and EfficientNet-B5 using the feature extraction technique with the pre-processed datasets of COVID19-CT and SARS-CoV-2 CT-Scan described in Section 3.1. Since predefined standardized splits of training, validation and test sets are not provided for either dataset, a fixed validation strategy, in accordance with that suggested in previous studies [7] was employed. Specifically, we allocated 80% of the data for training and validation purposes and 20% for testing. Following the approach used in recent studies, we performed an image-wise split on these datasets to ensure consistency and enable a fair comparison with existing works. Additionally, the implementation of a stratified k-fold cross-validation setup (k = 5) serves to mitigate the potential impact of data imbalance and variability in our model evaluations and enhance the robustness of the model.

We empirically determined the values of various hyperparameters by monitoring model performance while setting parameters within certain ranges. The hyperparameters investigated for training these models include the learning rate (ranging from 10^{-5} to 10^{-2}), batch sizes (ranging from 4 to 64), and optimizer choice (Adam, SGD, and RMSProp). Following the execution of a grid search augmented by a stratified k-fold cross-validation approach with k = 5, to fine-tune the specified range of hyperparameters, the systematically optimized values presented in Table III were identified. The metrics reported in Table III were derived using the validation dataset, thereby ensuring the robustness of the model's performance assessments.

The selected models, including CNN-based architectures (e.g., ResNet-50 v2, DenseNet-201, MobileNet, VGG16, Xception, and Inception-v3) and transformer-based architectures (e.g., ViT, Swin Transformer, ConvNeXt), were fine-tuned over 50 epochs utilizing the Binary Cross-Entropy Loss function as the criterion and different batch sizes, learning rates, and optimizers to achieve optimal classification accuracy. The batch size varied between 16 and 64, indicating a balance between computational efficiency and gradient stability. The learning rate was primarily set to 0.0001, except for ResNet-50 v2 and Xception, which used 0.001, suggesting a more aggressive learning strategy for these models. Adam is the most frequently employed optimizer, known for its adaptive learning rate adjustment, whereas SGD and RMSProp are used for specific architectures like ResNet-50 v2, VGG16, and MobileNet, to optimize performance based on gradient updates.

The outcomes of transfer learning across various architectures are typically evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and AUC, facilitating a comprehensive assessment of model performance. While each of these metrics offers valuable insights, the F1-score stands out as a balanced and informative measure, particularly for binary classification tasks involving imbalanced or critical-class dataset. In this study, we have employed the F1-score because it combines precision and recall into a single metric, offering a holistic evaluation of model performance.

In binary image classification, accurate identification of positive cases (recall) and the reliability of positive predictions (precision) are crucial. This is particularly important in medical image classification tasks, such as detecting COVID-19, where false positives can lead to unnecessary interventions, and false negatives can result in missed opportunities for timely and accurate treatment, both of which can have severe clinical consequences.

Table IV presents the F1-scores achieved by various fine-tuned pre-trained models on COVID-CT and SARS-CoV-2 datasets, evaluating their performance across different training and testing configurations. The table highlights the effectiveness of each model when trained on a single dataset (COVID-CT or SARS-CoV-2) and tested on either the same or an alternate dataset, as well as when trained and tested on a combined dataset (COVID-CT and SARS-CoV-2).

ResNet-50 v2 and EfficientNet-B5 achieved the highest overall performance, with F1-scores of 98.15% and 97.71% , respectively, when trained and tested on the combined datasets. ViT and VGG16 also demonstrated strong generalization, with F1-scores of 97.36% and 94.8% , respectively, on the combined dataset. Swin Transformer and ConvNeXt, while performing well on the individual datasets, showed slightly lower generalization ability compared to ViT and EfficientNet-B5. MobileNet and Xception exhibited the lowest F1-scores across all settings, indicating potential limitations in feature extraction for COVID-19 CT scan classification. A noticable performance drop was observed when models were trained on one dataset and tested on the other, suggesting domain differences between the datasets. The results in Table IV highlight the effectiveness of increasing dataset size and variability in improving model performance. The F1-score values reported in the table were obtained using the results of a thorough grid search conducted on the validation dataset, summarized in Table III.

Table IV. Comparison of Fine-Tuned Pre-Trained Models on the COVID-CT and SARS-CoV-2 Datasets Used in This Study.

MODELS		F1-SCORE				
	Trained on	COVID-CT	SARS-CoV-2	COVID-CT	SARS-CoV-2	Both DS
	Tested on	COVID-CT	SARS-CoV-2	SARS-CoV-2	COVID-CT	Both DS
VIT		91.65%	96.31%	87%	94.14%	97.36%
SWIN TRANSFORMERS		89%	92.22%	81.56%	89.7%	92.1%
RESNET-50 V2		97.31%	98.1%	86.21%	96.8%	98.15%
DENSENET-201		86.2%	94.66%	81.3%	88.67%	93.8%
MOBILENET		84.05%	87.82%	78.6%	85.32%	91.05%
CONVNEXT		87.12%	91.07%	83.53%	87.83%	90.23%
VGG16		94.33%	95.79%	92.17%	93.14%	94.8%
XCEPTION		84.38%	87.49%	82.1%	83.37%	86.6%
INCEPTION-V3		91.16%	93.46%	90.89%	93%	92.19%
EFFICIENTNET-B5		96.74%	97.1%	93 %	93.27%	97.71%

This table presents a comparative analysis of the performance of various fine-tuned using the selected datasets within this research. It systematically evaluates the models' performance, providing insight into how they adapt to and refine their representations on the specialized data utilized in this study. Through this assessment, the table provides a comprehensive understanding of the models' strengths and weaknesses, thereby contributing valuable insights into the potential applications and advancements in the field of medical image analysis and deep learning–based classification.

The efficacy of the proposed ensemble models, Ens-5 and Ens-10, is demonstrated through a comprehensive comparison with state-of-the-art deep learning architectures on two benchmark datasets: the SARS-CoV-2 dataset and the COVID-CT dataset. Table V summarizes the F1-scores of the proposed ensemble models alongside existing methods, highlighting their superior performance in COVID-19 detection tasks. The application of ensemble learning techniques, specifically PCA-based feature fusion on the predictions of the pre-trained models, significantly improved the overall performance metrics. To examine the potential detrimental impact of weaker models on the performance of stronger models within ensemble methodologies, we compared our ensemble approaches against all individual models. Two ensemble approaches were evaluated: Ens-5, which includes the five best-performing models out of ten, and Ens-10, which utilizes all ten pre-trained models through the proposed feature fusion ensemble method. This comparison, alongside evaluations of widely used ensemble approaches such as Max Voting, Averaging, and Random Forest Bagging Classifier, is also detailed in Table V. Notably, the results demonstrate that the proposed ensemble approach, Ens-5 and Ens-10, outperform existing ensemble techniques for the task of COVID-19 detection on the SARS-CoV-2 dataset and most of the existing methods on the COVID-CT dataset, achieving an F1-score of 98.67% and 91.40%, respectively.

On the SARS-CoV-2 dataset, Ens-5 achieved the highest F1-score of 98.67%, followed closely by Ens-10 with an F1-score of 98.11%. These results indicate that ensemble learning significantly enhances classification performance compared to individual models. Among the baseline models, XDNN and WAE [19] performed the best, achieving F1-scores of 97.31% and 98.65%, respectively, while DenseNet-201, VGG16 [22], and ResNet34 also demonstrated strong performance with F1-scores of 96.29%, 96%, and 94.95%, respectively.

For the COVID-CT dataset, Ens-5 again outperformed all other models, except for WAE, obtaining an F1-score of 91.40%, while Ens-10 followed closely with 91.21%. Among the existing models, Silva [23] and DECAPS+Peekaboo [24] demonstrated competitive performance, achieving F1-scores of 86.19% and 87.1%, respectively. However, other models, such as DenseNet-169 and CRNet, recorded lower F1-scores of 80.01% and 76%, respectively.

This comparative study highlights that the novel ensemble technique effectively reduces misclassifications, thereby producing more generalized predictions for COVID-19 detection. By utilizing processed chest CT scan images as input for the candidate models, the ensemble framework integrates these predictions to further enhance the overall reliability of COVID-19 diagnostics.

Table V. Comparison of the Proposed Ensemble Models with Existing Deep Learning Methods on the SARS-CoV-2 and COVID-CT Datasets Used in This Study.

Tested on SARS-COV-2 Dataset		**Tested on COVID-CT Dataset**	
MODELS	**F1-Score**	**MODELS**	**F1-Score**
ENS-5	98.67%	**Ens-5**	91.40%
ENS-10	98.11%	**Ens-10**	91.21%
XDNN	97.31%	**Silva**	86.19%
DENSENET-121	92.18%	**DECAPS+Peekaboo**	87.1%
DENSENET-201	96.29%	**DenseNet-121**	80.01%
RESNET50	91.61%	**CRNet**	76%
RESNET34	94.95%	**WAE**	94.93%
VGG16	96%	**KSVM**	91%
WAE	98.65%		

5. Discussion

This study centers on identifying COVID-19-related lesions in CT scans, rather than classifying cases by severity or differentiating COVID-19 from other pulmonary infections. Our dataset comprises both COVID-19 and non-COVID-19 cases; however, it lacks severity labels (e.g., mild or severe) or detailed distinctions between other pulmonary infections. Thus, the model has been optimized for lesion detectability but is not specifically designed to assess disease severity or distinguish between various infections. Future research should focus on datasets with severity annotations to improve the clinical applicability of automated detection models.

In clinical practice the F1-score serves as a pivotal metric that integrates both precision and recall, thereby providing a comprehensive assessment of a model's classification performance. The F1-score, calculated as the harmonic mean of precision and recall, serves as a singular metric that reflects the overall diagnostic performance of a model. A notably high F1-score, such as the 0.94 achieved by the linear transformation-based feature fusion model for COVID-19, demonstrates a well-balanced trade-off between identifying positive cases (high recall) and minimizing the misclassification of non-COVID-19 cases (high precision). This is essential in medical applications, as high precision ensures that healthy individuals are correctly classified as non-COVID, reducing unnecessary medical interventions and associated psychological distress. Moreover, the model's high recall rate emphasizes its efficacy in capturing the majority of the disease, which is vital for timely intervention and effective disease management.

This study investigates the efficacy of an ensemble deep learning framework for the automated detection of COVID-19 using two prominent publicly available datasets of CT images. We evaluated 10 state-of-the-art pre-trained architectures that have previously demonstrated superior performance on the ImageNet dataset. These pre-trained models were subsequently fine-tuned for the specific task of COVID-19 detection, which is characterized by a limited training dataset. Among the assessed networks, the ResNet-50 v2 and EfficientNet-B5 models achieved the highest F1-scores of 98.15% and 97.71% for CT image classification.

To further enhance classification performance, we developed an ensemble approach grounded in PCA-based feature fusion, integrating outputs from distinct deep transfer learning architectures. The efficacy of this proposed feature fusion approach is particularly noteworthy and can be attributed to its ability to effectively integrate complementary features from multiple models, enhancing the robustness and discriminative power of the final classification. The approach demonstrates a significant enhancement in performance and generalization when compared to the baseline performance of individual transfer learning models. Our findings reveal that the ensemble model, integrating the predictions from deep transfer learning architectures, outperformed individual models with superior F1-scores of 98.67% and 91.40% on the COVID-CT and SARS-CoV-2 datasets, respectively. This underscores the potential of ensemble methods in improving diagnostic accuracy in medical imaging contexts and highlights the potential of ensemble methods in optimizing the predictive performance of machine learning models within the domain of disease detection.

The comparative analysis of various fine-tuned pre-trained models on the COVID-CT and SARS-CoV-2 datasets demonstrates that ViT, EfficientNet-B5, VGG16, DenseNet-201, and ResNet-50 v2 are the most effective architectures for COVID-19 diagnosis using CT scans, particularly when trained on a combined dataset. These findings suggest that these models are well-suited for medical image classification tasks, leveraging transfer learning to enhance diagnostic accuracy. The Ens-5 ensemble, comprising five pre-trained models—ResNet-50 v2, EfficientNet-B5, ViT, VGG16, and DenseNet-201—exhibited exceptional performance, attaining overall F1-scores of 98.67% and 91.40% on the COVID-CT and SARS-CoV-2 datasets, respectively. This model demonstrates a strong capability in managing high-dimensional data while effectively mitigating overfitting, as reflected in its high precision and recall scores for COVID-19 diagnosis. Conversely, the Ens-10 ensemble, achieving F1-scores of a 91.21% on COVID-CT and 98.11% on SARS-CoV-2, still represents robust performance, as illustrated in Table V. The F1-scores for all diagnostic evaluations under this model are commendable, highlighting a well-balanced performance across assessments.

Table V presents a comparative analysis of the performance of the proposed ensemble model against several transfer learning architectures that utilize the same datasets, evaluated in terms of the F1-score. Notably, deep learning models such as WAE [19] and DenseNet-201 demonstrate strong performance on both datasets including COVID-CT and SARS-CoV-2. However, our ensemble approach achieves substantially superior results on the classification of SARS-CoV-2 compared with DenseNet-201, ResNet34, XDNN, DenseNet-121, and VGG16 [22].

A similar trend is observed with the COVID-CT dataset, where existing models yield satisfactory results. In contrast, when employing an ensemble of these advanced deep architectures, specifically through ensemble methods such as KSVM [18], WAE [19], and PCA the performance surpasses that of the individual models. The proposed ensemble approach not only outperforms most of the existing ensemble models documented in the literature but also establishes a new state-of-the-art accuracy of 91.40% for the COVID-CT dataset. It demonstrates better performance on the COVID-CT dataset in comparison with the methods proposed in [23], DECAPS+Peekaboo [24], DenseNet-169, CRNet.

A critical factor in evaluating the performance of lesion detection models involves comparing their outputs against expert radiologist evaluations. The datasets employed in this study lack both lesion annotations and qualitative assessments by clinical experts, complicating direct comparison of our outputs with thoracic radiologists interpretations. While previous studies have established the efficacy of deep learning approaches for COVID-19 detection using annotated datasets, this study faces limitations in its validation process. Future investigations should integrate radiologist-annotated CT scans to enable direct benchmarking against human expertise and to enhance the clinical reliability and diagnostic utility of automated detection systems in medical imaging applications.

6. Conclusion

The present study introduces a robust methodology for improving the classification of COVID-19 CT images for diagnostic applications. Through the integration of sophisticated machine learning techniques—encompassing data pre-processing, fine-tuning of transfer learning models, and ensemble learning—the research attains exceptional accuracy and reliability, both of which are essential for clinical diagnostic use. To mitigate the challenges associated with the limited availability of training data, the study employs fine-tuning of pre-trained models. Diverse neural network architectures were systematically trained on various datasets, such as COVID-CT and SARS-CoV-2, utilizing distinct pre-processing approaches. The research highlights the efficacy of employing pre-trained models, namely ResNet-50 v2, EfficientNet-B5, ViT, VGG16, and DenseNet-201, demonstrating the advantages of transfer learning in leveraging large-scale datasets for feature extraction relevant to medical imaging. Fine-tuning these models for targeted applications enables adaptation to the specific characteristics of novel medical data, leading to notable improvements in classification performance.

To further enhance diagnostic performance, we implemented an ensemble of models for the binary classification of COVID-19 CT images into COVID and Non-COVID categories. The application of PCA-based feature fusion yielded particularly strong performance, demonstrating the advantages of combining multiple predictive models. This method achieved an F1-score of over 98.60%, emphasizing the significance of a collaborative approach in predictive modeling. The results highlight the effectiveness of ensemble learning in improving classification performance. The proposed Ens-5 model consistently outperforms other approaches, demonstrating its robustness in handling medical imaging datasets related to COVID-19 diagnosis. These findings suggest that incorporating multiple deep learning models through ensemble learning can enhance the reliability and accuracy of automated diagnostic systems for infectious diseases. In conclusion, this study establishes a comprehensive framework for deploying machine learning in the diagnostic analysis of COVID-19 via CT scans. The integration of transfer learning and ensemble methodologies represents a substantial advancement in medical diagnostics, improving accuracy and yielding a scalable model for broader applicability in healthcare imaging tasks.

7. References

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