Ensemble-Based Classification of COVID-19 Radiographic Images Using Spatial, Textural, and Intensity-Based Features

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Abstract: The COVID-19 pandemic has underscored the critical need for precise diagnostic tools. Radiographic imaging, particularly chest X-rays and CT scans, has emerged as a vital modality for detecting COVID-19-related lung abnormalities. Several machine learning techniques exist to diagnose Covid-19 from such imaging modalities. In this article, an innovative approach is introduced using multimodal features extracted from CT scan images and ensemble learning to enhance the COVID-19 diagnosis. The dataset used here encompasses a wide range of COVID-19-positive and non-COVID-19 cases. To improve image quality and information extraction, preprocessing techniques like resizing, Gaussian blur, and dilation are employed. These steps enhance the ability to capture informative image features. Intensity-based, spatial, and textural features have been exploited for enhanced classification. Intensity-based features capture statistical properties of pixel intensities, while spatial features quantify geometric characteristics of image regions, and texture features leverage the Gray-Level Co-occurrence Matrix (GLCM) to encompass essential texture attributes of the images. The classification strategy used I this paper revolves around ensemble learning, utilizing three diverse base classifiers: Random Forest, Support Vector Machine, and Light Gradient Boosting Machine, each with unique strengths in image classification. These base classifiers are trained on standardized feature vectors from the training dataset, and their predictions are aggregated through averaging the decisions. This ensemble approach yields a robust model for COVID-19 image classification, achieving an overall test accuracy of 92.42%. The performance of the ensemble model is assessed using a dedicated test dataset, demonstrating its superiority (in terms of accuracy) over other methods that utilize hand crafted as well as deep features. Moreover, the potential clinical implications of our research and outline avenues for future enhancements are also discussed.

Keywords: Ensemble Learning, Gray-Level Co-occurrence Matrix, Random Forest Classifier, Support Vector Classifier (SVC), Light GBM Classifier.

1. Introduction

The COVID-19 pandemic demands fast and accurate diagnostics. Radiographic imaging, including chest X-rays and CT scans, is essential for detecting COVID-19 lung issues. Interpreting these images accurately is challenging, prompting the need for advanced machine learning models. Our research aims to bridge this gap, introducing a novel approach that combines ensemble learning integrating various feature extraction for COVID-19 image classification. Our methodology starts with acquiring and preprocessing a diverse dataset, including both COVID-19-positive and negative cases, setting the foundation for model training and evaluation. The preprocessing steps applied to the radiographic images, including resizing, Gaussian blur, and dilation, are carefully designed to enhance feature extraction, thereby subsequently improving the accuracy of the diagnostic model. Feature extraction [1,2] constitutes a pivotal component of the present methodology, encompassing three distinct categories: intensity-based, spatial, and texture features. These features collectively capture essential information from the images, reflecting statistical characteristics, geometric properties, and textural details, and thus enabling a more comprehensive analysis of the radiographic data.

From traditional machine learning [3] to bio-inspired [4-6] methods the field of image analysis evolved across ages. Recently, deep learning approaches have gained wide applicability in various domains due to their automatic feature extraction capabilities [7-10]. However, the bottleneck of such methods is to handle overfitting issues as the networks are having a huge number of parameters and making the model complex and computation intensive. In the present work, we have tried to exploit low resource constraint environments. The core of our approach lies in ensemble learning, where we combine the predictions of multiple base classifiers, each trained on the extracted feature vectors. By aggregating the outputs of these classifiers and applying a consensus-based decision-making strategy, we aim to enhance the diagnostic accuracy and reliability of our model. Furthermore, our research explores the potential clinical impact of this approach in aiding healthcare professionals in the timely and accurate identification of COVID-19 cases, particularly in resource-constrained settings.

In recent years, the application of machine learning techniques to medical image classification tasks has witnessed significant advancements. In particular, the use of ensemble learning and feature extraction methods have been explored in the context of diagnosing various medical conditions, including COVID-19. This section provides a brief overview of related research in this domain. Ensemble learning techniques have gained popularity for improving the accuracy of medical image classification. Habib et al. [11] discusses the global impact of COVID-19, emphasizing its effects on health, mortality rates, and the economy. They combine deep learning and handcrafted features, showcasing a good accuracy. [12] addresses the importance of chest disease diagnosis, especially in detecting COVID-19, achieving 90.22% accuracy in classifying 15 types of chest diseases. [13] introduces a lesion-attention deep neural network (LA-DNN) to predict COVID-19 status using chest CT images and textual radiological reports. The model could perform binary classification for COVID-19 while also identifying specific lesions associated with the virus. Another work [14] also presents a deep learning based model for COVID-19 diagnosis using chest CT scans. Here, the lung region is segmented through a pre-trained UNet; afterwards, a 3D DNN predicts COVID-19. The model does not require lesion annotations for training; a weakly-supervised approach with 3D CT volumes is employed to classify COVID-19 cases and locate lesions achieving 0.959 ROC AUC and 0.976 PR AUC, along with an accuracy of 0.901. In [15] DL is used to create an early screening model for distinguishing COVID-19 from influenza-A viral pneumonia (IAVP) and healthy cases based on pulmonary CT images. A 3D DL model is used to segment candidate infection regions, classify these regions into COVID-19/ IAVP/ irrelevant to infection groups and obtained an overall accuracy of 86.7%. In [16] a multi-view fusion model (DL based) is employed to screen patients with COVID-19 from CT images. The authors considered lung regions in axial, coronal and sagittal views. While these studies have made significant contributions to the field of medical image classification, our research builds upon these foundations by introducing a comprehensive ensemble learning approach that leverages various feature extraction strategies. We aim to provide a novel and effective methodology for COVID-19 image classification, addressing the challenges posed by this critical healthcare application.

Section 2 provides an in-depth explanation of our methodology, which includes the extraction of features from radiographic images and the ensemble learning strategy we employ. We describe the three categories of features: intensity-based, spatial, and texture features, emphasizing their relevance to image classification. Furthermore, we detail the selection and training of base classifiers, the aggregation of predictions, and the rationale behind our ensemble mechanism. The preprocessing approach and the critical parameter specifications have also been mentioned here. The methodology described in Section 2 serves as the foundation upon which our experimental approach is built. It sets the stage for Section 3, where we provide comprehensive insights into our experimental setup. This includes a detailed account of the dataset used, the specific evaluation metrics employed to assess model performance. This section is also dedicated to the thorough analysis of the results obtained through experimentation. In section 4, conclusions are drawn.

2. Proposed Methodology

In our research on accurate COVID-19 image classification, we employ a methodology (as shown in Fig. 1) combining feature extraction and ensemble learning. As mentioned, the preprocessing of radiographic images is vital for enhancing feature extraction and dataset quality. Our approach includes standardizing all images to 128x128 pixels, applying a Gaussian blur with a 5x5 kernel and sigma of 3 to reduce noise, followed by a 3x3 dilation operation to enhance image structures and boundaries.

For feature extraction, we categorize features into three groups: intensity-based (mean and standard deviation of pixel intensities), spatial (area and perimeter of image regions), and texture (quantified using the Gray-Level Co-occurrence Matrix, yielding contrast, correlation, energy, and homogeneity).

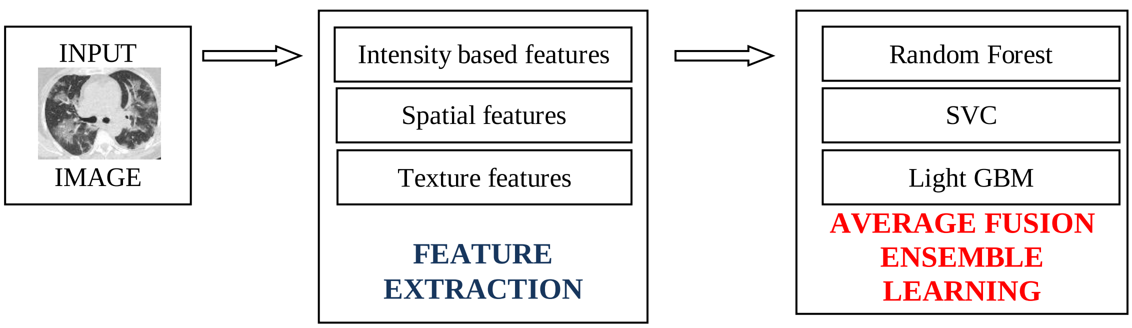
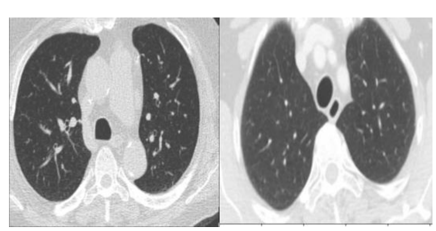


Fig. 1: Block diagram for the proposed method.

To enhance robustness of the developed model, we utilize ensemble learning by combining predictions from various base classifiers, such as Random Forest, Support Vector Machine, and Light GBM classifiers. These base classifiers are trained on standardized feature vectors from the training dataset and aggregated using an average fusion technique.

Table 1. Images from SARS-CoV-2 CT scan dataset [17].

Different Classes	Total Images for each class
NON COVID-19	1230
COVID-19	1252
Total Images	**2482**



(a) (b)

Fig. 2: Images acquired from SARS-CoV-2 CT scan dataset. (a) Covid-19, (b) Non Covid-19.

3. Analysis of Results

We evaluated our approach using the SARS-CoV-2 CT scan dataset [17], splitting it into training and testing sets with a 20% test size while ensuring class balance. The dataset used consists of 1252 COVID-19 images and 1230 non-COVID-19 images from the SARS-CoV-2 CT scan dataset (Table 1). Sample images from both the categories are displayed in Fig. 2.

To assess our proposed method, we conducted 20 simulations, presenting the average results in Table 2. The ensemble model yielded promising outcomes across various performance metrics, achieving an impressive 92.4% accuracy. We evaluated the performance of the model using metrics such as Accuracy, Precision, Recall, F1-score, Top-1% error, and visualized results with a Confusion matrix and ROC curve (see Fig. 3). In the classification task, the model correctly identified 209 COVID-19 cases (true positives) but missed 34 COVID-19 cases (false negatives). It accurately classified 242 non-COVID-19 cases (true negatives) but incorrectly labeled 14 non-COVID-19 cases as COVID-19 (false positives) (see Fig. 3). Overall, our model demonstrates its potential for COVID-19 image classification, with room for further fine-tuning to reduce false negatives. Its robust specificity suggests effectiveness in distinguishing non-COVID-19 cases, a critical aspect of medical image diagnostics. Our results are also compared with state-of-the-art methods and are summarized in Table 3.

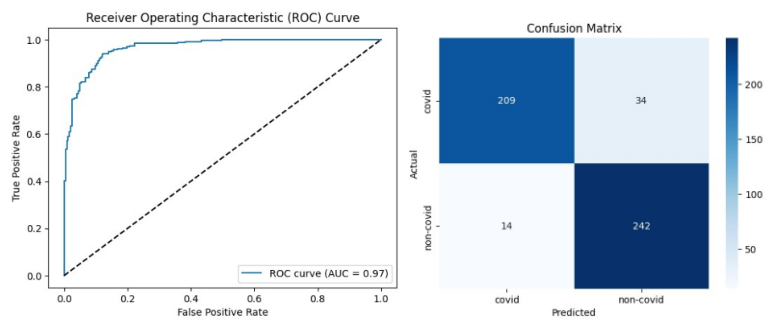


Fig. 3: ROC curve and confusion matrix for the proposed method

TABLE 2. Results from SARS-CoV-2 CT scan dataset.

Metrics	Ensemble Model (rounded)
Recall	0.93
Precision	0.92
F1-score	0.92
Accuracy (%)	92.42
AUC (%)	96.62

4. Conclusion and Future Works

In this research, we aimed to advance COVID-19 diagnosis via radiographic imaging. We extracted three key categories of features: intensity-based, spatial, and texture features, capturing vital insights from images. Ensemble learning played a pivotal role in this work. We chose diverse base classifiers, including Random Forest Classifier, Support Vector Classifier (SVC), and Light GBM Classifier, and used fusion techniques to combine their outputs. This boosted the robustness and accuracy of our classification model. We achieved high accuracy in distinguishing COVID-19 from non-COVID-19 cases, underlining its potential for real-world clinical use.

TABLE 3. Performance comparison using SARS-CoV-2 CT scan dataset.

Method	Approach	Accuracy (%)
Liu et al.	VGG16 based lesion attention DNN [13]	88.60
Wang et al.	UNet [14]	90.10
Xu et al.	UNet 3D Deep Architecture [15]	86.70
Wu et al	Use of axial coronal [16]	76.00
Proposed Method	**Ensemble-Based Method**	**92.42**

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