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Research Article

Innovative Hybrid CNN+SVM Model for Accurate Covid-19 Detection From CT Images

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ABSTRACT

The advent of advanced deep learning techniques has revolutionized various fields, including healthcare, where accurate and efficient diagnostic tools are of paramount importance. In the context of the COVID-19 pandemic, the need for rapid and precise diagnosis is critical to managing and mitigating the spread of the virus. In this study, we propose a decision support system for the diagnosis of COVID-19 using CT images, employing deep learning algorithms. To evaluate the performance of our models, we create a unique dataset that is meticulously curated and tailored to the task at hand. This dataset consists of a large number of CT images categorized into COVID-19 positive and negative classes, allowing for a robust evaluation of our models' capabilities. Our approach involves the development of novel CNN models as well as the exploration of pre-trained architectures, such as ResNet50v2 and VGG16, in a comprehensive modelling study. Additionally, we introduce a hybrid model by combining CNN models with the SVM algorithm. Hyperparameter optimization is performed using the grid search method, and the modelling process utilizes an original dataset with two classes (COVID-19 and Normal). Performance evaluation involves dividing the dataset into training and test sets (85%-15% ratio) and employing 5-fold cross-validation. Proposed novel CNN models achieve an accuracy rate of 99.93% and 99.86%, while the hybrid CNN+SVM model achieves an accuracy rate of 100% and 99.77%, respectively. Successful application of these proposed deep learning models in healthcare demonstrates their potential to improve diagnostic accuracy and patient outcomes.

Keywords: *CNN, deep learning, hybrid model, grid search, CT images*

BT Görüntülerinden Hassas Covid-19 Tespiti için Yenilikçi Hibrit CNN+SVM Modeli

ÖZ

Gelişmiş derin öğrenme tekniklerinin ortaya çıkışı, doğru ve etkili teşhis araçlarının büyük önem taşıdığı sağlık hizmetleri de dahil olmak üzere çeşitli alanlarda devrim yaratmıştır. COVID-19 salgını bağlamında, hızlı ve kesin teşhis ihtiyacı, virüsün yayılmasını yönetmek ve azaltmak için kritik öneme sahiptir. Bu çalışmada, BT görüntülerini kullanarak COVID-19 teşhisi için derin öğrenme algoritmaları kullanan bir karar destek sistemi öneriyoruz. Modellerimizin performansını değerlendirmek için, titizlikle düzenlenmiş ve eldeki göreve göre uyarlanmış benzersiz bir veri kümesi oluşturuyoruz. Bu veri kümesi, modellerimizin yeteneklerinin sağlam bir şekilde değerlendirilmesine olanak tanıyan COVID-19 pozitif ve negatif sınıflarına ayrılmış çok sayıda BT

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görüntüsünden oluşmaktadır. Yaklaşımımız, kapsamlı bir modelleme çalışmasında ResNet50v2 ve VGG16 gibi önceden eğitilmiş mimarilerin keşfedilmesinin yanı sıra yeni CNN modellerinin geliştirilmesini de içermektedir. Ayrıca, CNN modellerini SVM algoritması ile birleştirerek hibrit bir model sunuyoruz. Hiperparametre optimizasyonu ızgara arama yöntemi kullanılarak gerçekleştirilir ve modelleme sürecinde iki sınıflı (COVID-19 ve Normal) orijinal bir veri kümesi kullanılır. Performans değerlendirmesi, veri kümesinin eğitim ve test kümelerine bölünmesini (%85-%15 oranı) ve 5 kat çapraz doğrulama kullanılmasını içerir. Önerilen yeni CNN modelleri %99,93 ve %99,86 doğruluk oranına ulaşırken, hibrit CNN+SVM modeli sırasıyla %100 ve %99,77 doğruluk oranına ulaşmaktadır. Önerilen bu derin öğrenme modellerinin sağlık hizmetlerinde başarılı bir şekilde uygulanması, teşhis doğruluğunu ve hasta sonuçlarını iyileştirme potansiyellerini göstermektedir.

Anahtar Kelimeler: *CNN, derin öğrenme, hibrit model, ızgara arama, BT görüntüleri*

I. INTRODUCTION

The coronavirus disease (COVID-19), which emerged in December 2019 in Wuhan, China, as pneumonia of unknown aetiology, spread rapidly in two months and was designated an international public health problem on January 30, 2020 [1]. As of December 7, 2022, the SARS-CoV-2 virus had infected more than 600 million people worldwide, resulting in the deaths of more than six million [2]. With its contagiousness and severe symptoms, the COVID-19 epidemic, one of the largest health crises of the 21st century, has caused millions of cases and deaths worldwide. In the pandemic that has been ongoing for more than two years, there have been both positive and negative developments, such as the availability of the COVID-19 vaccine and the advancement of vaccination efforts, as well as the advent and rapid spread of new SARS-CoV-2 variants. The real-time reverse transcription polymerase chain reaction (RT-PCR) test, which analyses the sample from the upper respiratory tract, is widely used for the diagnosis of COVID-19. Nonetheless, the sensitivities of RTPCR tests can vary considerably between "60% and 90%" and frequently produce false-negative results, particularly in initial positive cases [3], [4]. Although microbiological methods such as RT-PCR are commonly used in the diagnosis of COVID-19, medical imaging methods are crucial for supporting the diagnosis, assessing the severity of the disease, detecting potential complications, and monitoring the treatment response [5]. Computerised tomography (CT) and chest x-ray (chest x-ray) are examples of information-providing medical imaging techniques used to detect infected individuals [6]. The cost of data and the availability of devices at the relevant healthcare institution or laboratory are the primary factors in selecting these imaging techniques. Prior to the onset of clinical symptoms, COVID-19 can be detected on CT scans of patients, according to published research [7],[8]. Despite the fact that it has been demonstrated in the literature that CT scanning tests are more sensitive than conventional RT-PCR tests [9][10], numerous obstacles persist. These obstacles include the dearth of well-trained radiologists and the increased labour caused by the pandemic influx of patients [4]. In addition, because COVID-19 is a new disease, radiologists must obtain new interpretation skills and update their knowledge. In areas with limited access to educational resources, diagnosis becomes more challenging. Therefore, it is crucial to develop Artificial Intelligence (AI) systems that will aid in the diagnosis of COVID-19.

Automated analysis technologies based on artificial intelligence (AI) can provide valuable assistance to radiologists in the analysis of COVID-19 from CT scans. Deep learning signifies a major breakthrough in the realm of artificial intelligence [11], with Convolutional Neural Networks (CNN) being one of the most commonly utilized designs [12]. CNNs have gained prominence in the healthcare sector due to their powerful capabilities [13]. Many studies have been submitted to literature by using artificial intelligence methods on the medical systems [14]–[20]. By combining CNN approaches with radiological imaging, it becomes possible to achieve accurate detection and classification of COVID-19 [21]. Kuldeep et al. presented an automated approach to detect covid-19 patients using a convolutional neural network model [22]. The dataset consists of covid-19 and non-covid-19 pneumonia x-ray images. As a result of the study, the proposed model reached an average of 97.92% accuracy, 99.69% sensitivity and 98.48% specificity. Pedro et al. [23] proposed a classification model called Wavelet Convolutional Neural Network (WCNN) based on wavelet transform, which aims to improve the differentiation of images of patients with Covid-19 from images of patients with other lung infections. The model proposes a new input layer called Wave layer added to the neural network. WCNN was applied to chest CT images from two internal and one external storage. The average accuracy obtained is 98.19%. Mahmud et al. [24] proposed a new approach to diagnose covid-19 from x-ray images using capsule neural networks. The data set consists of covid-19, pneumonia and normal classes. As a result of testing the model, they reached an accuracy rate of over 95%. Nadiah et al. [25] proposed the Sparrow search algorithm (SSA) on pre-trained model and CT lung images to perform automatic and accurate Covid-19 classification using Convolutional Neural Network. SSA has been used to find the best configuration for the models and optimize different CNN and transfer learning hyperparameters to improve performance. Two data sets were used in the experiments. There are two classes in the first dataset and three in the second. they achieved the best accuracy results of 99.74% with MobileNetV3Large in the two-class dataset of the proposed framework and 98% with SeNet154 in the three-class dataset. Avinandan et al. [26] used CNN models in conjunction with ensemble methodology to detect Covid-19 from chest X-rays. The DenseNet-201 model was trained and then combined with the Random Forest classifier model. They used two separate data sets, one large and one small. The proposed approach achieved an accuracy rate of 94.55% with the large dataset and 98.13% with the small dataset. Sujithra et al. [27] designed a real-time interactive system for the diagnosis of Covid-19. Recommended system, UI, analytics, cloud, etc. The system consists of multiple components, including a preliminary evaluation of medical data, such as pulse oxygen rate and RT-PCR results, to identify potential COVID-19 cases. If a positive indication is detected, the system prompts the user to upload X-ray or CT images for further disease severity evaluation. These images are then transmitted to a custom-built artificial intelligence module. The proposed AI system can classify patients according to whether they have COVID-19, pneumonia, or other viral infections. For medical image analysis, the classification task employs CNN architectures including ResNet-50, ResNet-100, ResNet-101, VGG 16, and VGG 19. From the experiment, it was observed that VGG 19 with an accuracy of 97% for CT images and ResNet101 with an accuracy of 98% for X-ray images outperformed. Muhammed et al. [28] used three pre-trained alternative CNN architectures for COVID-19 diagnosis and the grid search method to improve network performance. They used two different datasets of X-ray and CT images for model training. Resnet achieved the highest classification accuracy, reaching 98.98% for X-ray images and 98.78% for CT images. Afamefuna et al. [29] proposed a two-stage transformative model for COVID-19 diagnosis. This model is implemented using transfer learning, which allows efficient use of pre-trained models to speed up the training of the proposed model. The experimental results of the study provided an accuracy in the range of 0.76–0.92 for CNN-based deep learning networks, and the proposed model with transfer learning provided a significantly higher accuracy of 97.35%. Abul et al. [30] applied learning approaches to classify x-ray images consisting of COVID-19, normal, lung opacity, and viral pneumonia classes. Local binary patterns (LBP) and pre-trained convolutional neural networks are used for feature extraction. Extracted features were classified by support vector machine (SVM), decision tree (DT), random forest (RF), and k-nearest neighbours (KNN) classifiers. As a result of the classification of features obtained by a set of CNN models from four-class x-ray images by the SVM classifier, the metric values for the best performing ensemble (CNN +SVM) are 97.41% accuracy, 94.9% precision, 94.81% recall, and F1 achieved a score of 94.86%. Aleka et al. [31] used a hybrid model to classify x-ray images as normal or COVID-19. SVM was used for classification using information from the learning model, CNN, to classify images according to a predefined class (Covid-19 or Normal). The findings of the study show a training accuracy of 99.8% and a test accuracy of 99.1%. Hareem et al. [32] used two ResNet architectures, ResNet18 and ResNet50, for feature extraction from the x-ray dataset consisting of COVID-19 and normal classes. A multi-core SVM classifier, including Quadratic, Linear, Gaussian, and Cubic, is used to classify the extracted features. The experimental results demonstrate that the proposed framework successfully identifies COVID-19 from x-ray images and achieves a remarkable 97.3% accuracy through the use of ResNet50. CNN structures incorporate a variety of design decisions, such as the selection of the loss function, which, when optimally optimised, can have a substantial effect on the network's performance [33], [34] and different network hyperparameters such as the number of convolution layers, number of filters, filter size, batch size, number of training periods, learning rate, and momentum. As a result, the performance of a CNN in a particular task is heavily influenced by the values of its hyperparameters. This study centers around the optimization of CNN hyperparameters with the aim of achieving the highest possible diagnostic accuracy for COVID-19. The CNN hyperparameters will be optimised using a grid search method in order to increase the obtained accuracy. An overview of study is given in Figure 1. The following is a summary of this article's primary contributions:

- Within the scope of the study, an original dataset is created and presented to the literature. In particular, our study is important in this respect, among the limited number of studies in the literature.
- New CNN models are designed and presented for the classification process. In addition to the proposed models, pre-trained (ResNet50v2 and VGG16) models in the literature are also used in the study.
- Using a grid search method, CNN hyperparameters are optimized to reduce model losses and achieve the highest COVID-19 diagnostic precision.
- The optimized CNN architectures are also hybridized with the SVM algorithm to classify CT images of COVID-19. The extracted features of CNN architectures are categorized using the SVM classifier. This hybrid method speeds up classification without degrading the performance of CNN architectures.
- Cross-validation is used to obtain maximum precision by keeping the models away from the overfitting curve in the study.
- The accuracy values of the results obtained are 99.93% and 99.86% CNN models, 100% and 99.77% CNN+SVM models, and it is seen that the proposed models can classify the CT images of COVID-19 patients and make the diagnosis of COVID-19 with high accuracy.
- A comparison of our work is presented by presenting a comparison table with the studies carried out in the literature.

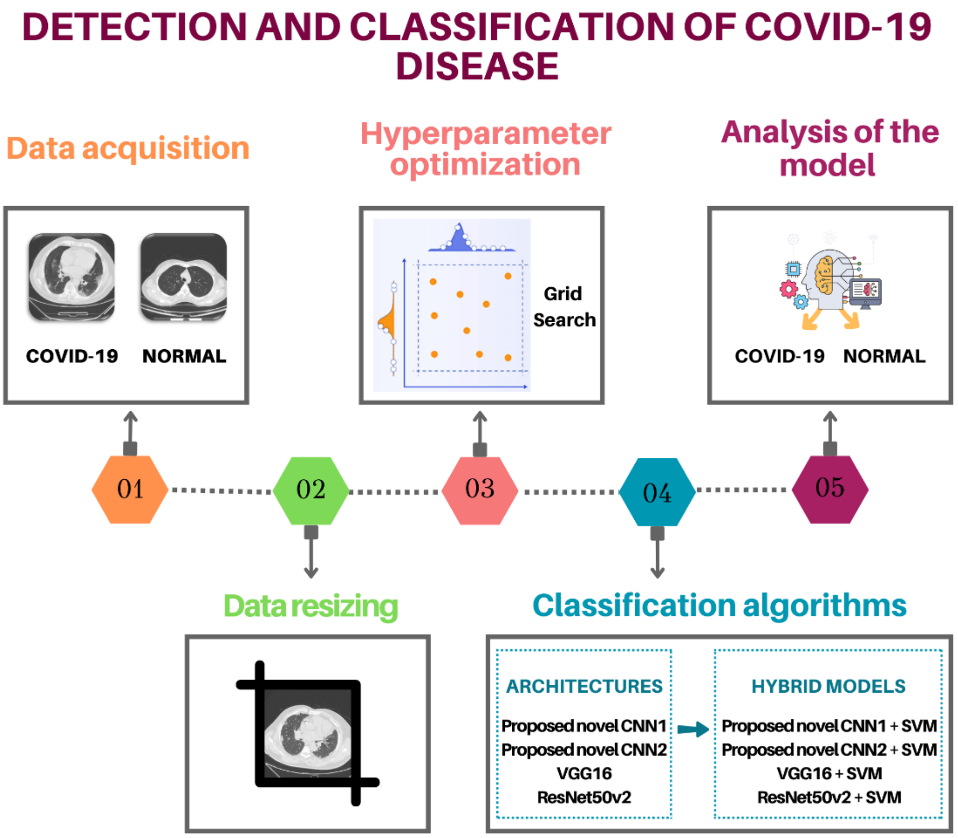


Figure 1. *An overview of study*

The paper is structured to provide a comprehensive overview of deep learning methods and their implementation, along with a summary of the employed algorithms. Section 2 offers a detailed background on the proposed CNN models. Additionally, this section covers essential aspects such as the dataset used, data preprocessing techniques applied, and the evaluation parameters utilized for assessing the performance of deep learning models. These evaluation parameters include accuracy, recall, precision, F1-scores, and ROC analysis. Moving forward, Section 3 presents the study's results, encompassing the outcomes of the deep learning models and the corresponding evaluation findings. It delves into the results obtained from cross-validation, emphasizing the contrasting performance between the proposed CNN and hybrid CNN+SVM models. Section 4 concludes the study by summarizing the findings and discussing their significance within the field. Lastly, Section 5 emphasizes the study's contributions, which encompass the development of novel CNN models and the creation of ensemble structures that offer swift training times and superior classification performance.

II. MATERIAL AND METHODS

A. DEEP LEARNING

Deep learning is a sophisticated subset of machine learning that leverages multiple layers of nonlinear computing to extract and transform intricate features from data. Unlike traditional machine learning models that rely on handcrafted feature engineering, deep learning algorithms autonomously learn hierarchical representations of data through an iterative process. Each successive layer in a deep learning architecture takes the output of the previous layer as input, allowing the model to progressively capture higher-level abstractions and gain a deeper understanding of complex patterns and relationships within the data [35].

A. 1. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) represent the most commonly used architecture in deep learning, particularly in the domain of image and video processing. CNNs consist of two main components and have gained widespread adoption due to their remarkable capabilities. In a CNN, the neurons in the initial layer are responsible for extracting features from the input data, while the subsequent layers combine these extracted features to form higher-level representations [36]. The success of CNNs can be attributed to their hierarchical feature extraction capability, enabling them to effectively capture intricate patterns and structures in the data at various levels of abstraction.

A. 2. Proposed CNN Models

In this study, Figures 2 and 3 depict, respectively, the CNN models utilised to address the research objectives. These figures depict the architectural designs of the proposed CNN models for this research. The visual representations aid in comprehending the structural components and information flow of CNN models. Architecture details of these models is provided in Table 1. During the design phase, notable differences are introduced between the two models. Specifically, in CNN1, a batch normalization layer is added to enhance the model's performance. The inclusion of this layer plays a crucial role in normalizing the distribution of activations across different layers in the neural network. The batch normalization layer offers several advantages for model training. By normalizing the activations, it helps to mitigate the issue of internal covariate shift, which refers to the change in the distribution of layer inputs during training. This stabilization facilitates more efficient and consistent model optimization. Moreover, the batch normalization layer can accelerate the training process by reducing the dependence on careful weight initialization or learning rate tuning. By enabling faster convergence, it aids in achieving better results overall. The addition of a batch normalization layer to CNN1 signifies our deliberate effort to improve the model's performance and address potential challenges during the training process. This enhancement aligns with best practices in deep learning model design and contributes to the robustness and effectiveness of the proposed CNN models in the context of COVID-19 diagnosis using CT images.

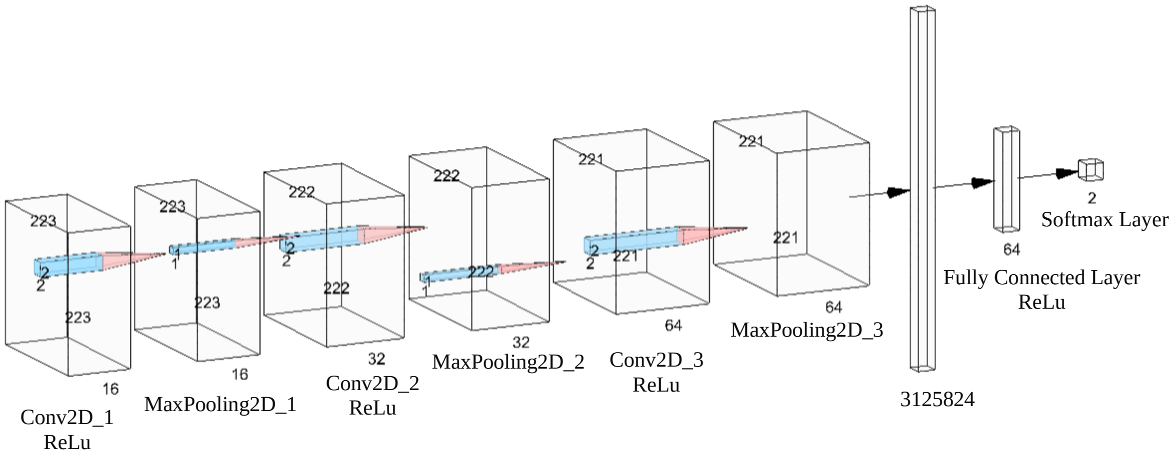


Figure 2. *CNN1 network model structure*

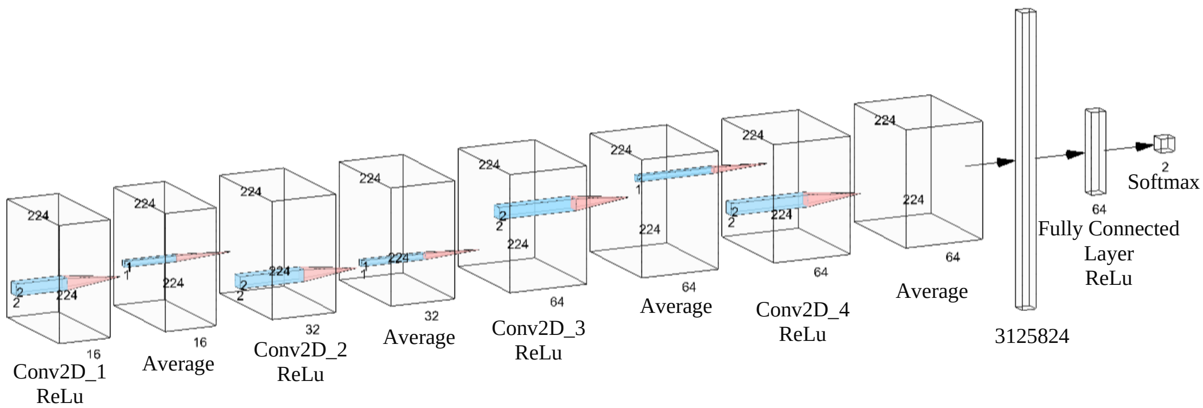


Figure 3. *CNN2 network model structure*

Table 1. *Architecture details of CNNs*

CNN1			CNN2		
Layer (type)	**Output Shape**	**Parameter**	**Layer (type)**	**Output Shape**	**Parameter**
Conv2D	223 x 223 x 16	208	Rescaling	224 x 224 x 3	0
batch_normalization	223 x 223 x 16	64	Conv2D	224 x 224 x 16	208
MaxPooling2D	223 x 223 x 16	0	AveragePooling2D	224 x 224 x 16	0
Conv2D	222 x 222 x 32	2080	Conv2D	224 x 224 x 32	2080
batch_normalization	222 x 222 x 32	128	AveragePooling2D	224 x 224 x 32	0
MaxPooling2D	222 x 222 x 32	0	Dropout	224 x 224 x 32	0
Conv2D	221 x 221 x 64	8256	Conv2D	224 x 224 x 64	8256
batch_normalization	221 x 221 x 64	256	AveragePooling2D	224 x 224 x 64	0
MaxPooling2D	221 x 221 x 64	0	Conv2D	224 x 224 x 64	16448
Flatten	3125824	0	AveragePooling2D	224 x 224 x 64	0
Dropout	3125824	0	Dropout	224 x 224 x 64	0
Dense	64	200052800	Flatten	3211264	0
batch_normalization	64	256	Dense	64	205520960
Dropout	64	0	Dense	2	130
Dense	2	130			
Total Params: 200,064,178 Trainable Params: 200,063,826 Non-trainable Params: 352			Total Params: 205,548,082 Trainable Params: 205,548,082 Non-trainable Params: 0		

B. DATASET

Various datasets have been developed by data scientists and machine learning practitioners for the purpose of diagnosing COVID-19 disease. In this study, a unique data set was created using CT images obtained retrospectively from the data of COVID-19 patients taken from Yozgat Bozok University Faculty of Medicine. It's worth noting that the dataset used in this study was ethically approved, ensuring adherence to ethical guidelines and regulations regarding patient data privacy and usage. To ensure the integrity and reliability of the dataset, all image labeling was performed by a radiologist who was blinded to the clinical condition of the patients. By conducting the labeling process in this manner, it guarantees that the dataset is labeled in an objective and unbiased manner. This approach minimizes any potential bias or subjective interpretations that could influence the accuracy and generalizability of the machine learning models developed using the dataset. The use of an ethically approved dataset and the involvement of an expert radiologist in the labeling process enhance the quality and credibility of the dataset, making it a valuable resource for training and evaluating machine learning models for COVID-19 diagnosis. The objective and unbiased nature of the dataset labeling provides a solid foundation for developing reliable and accurate diagnostic models in the context of COVID-19 detection and classification. Cases and image number of the dataset are given in Table 2 and an example of dataset is shown in Figure 4.

Table 2*. Cases and image number of the dataset*

No	Case Name	Total Cases	Used Images
1	COVID-19	104	3000
2	NORMAL	115	3000

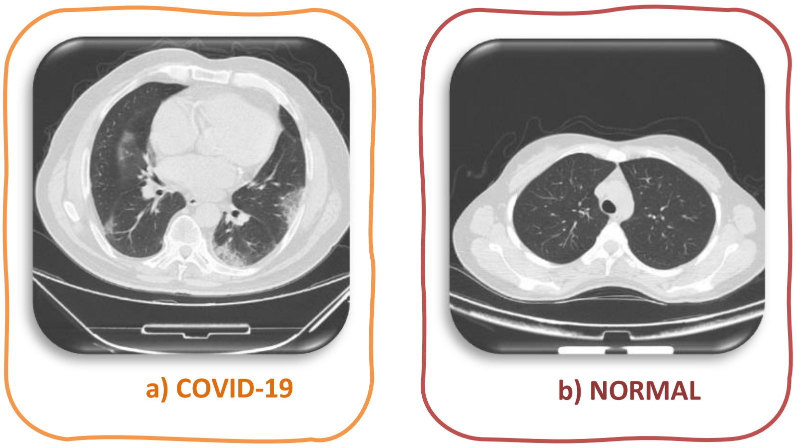


Figure 4. *Examples of dataset*

C. DATA PRE-PROCESSING

Image pre-processing plays a crucial role in deep learning as it involves preparing the input images for effective analysis by the model. This step encompasses a range of techniques, including but not limited to resizing, normalization, data augmentation, and more. The primary objective of image pre-processing is to enhance the quality of the input data and facilitate improved learning by the model. By applying appropriate pre-processing techniques, the input images are optimized to reduce noise, standardize features, and enhance relevant details, thereby enabling the model to learn more effectively from the data. At this stage, the raw data obtained from the hospital underwent pre-processing steps to prepare it for model training. The data, initially acquired in the 'DICOM' format, were visualized and inspected using the Weasis (DICOM viewer) program, an open-source and versatile medical imaging software. Weasis facilitated the display, analysis, and processing of various medical images, such as MR, CT, PET, mammography, among others.

To facilitate further processing and compatibility with machine learning algorithms, the data was converted from the 'DICOM' format to the more commonly used 'png' format. This conversion ensured that the data could be easily accessed and manipulated for subsequent analysis. Additionally, during the conversion process, the data was resized to a standardized dimension of 224 x 224 pixels, maintaining the aspect ratio and preserving the essential details present in the images. Subsequently, the data was divided into training and testing sets using an 85%-15% split. The training set comprised 85% of the data, while the remaining 15% was set aside as the test set for evaluating the performance of the trained model. By following these preprocessing steps, including image format conversion, resizing, and appropriate dataset splitting, the data was prepared and organized for subsequent model training and evaluation. This systematic approach ensured the availability of a well-prepared dataset and facilitated reliable and comprehensive analysis for the development of accurate COVID-19 detection models.

D. HYPERPARAMETER OPTIMIZATION

In classification problems, hyperparameters play a crucial role in determining optimal decision boundaries that effectively divide classes. In machine learning or deep learning algorithms, hyperparameters are tunable settings or configurations that influence the learning process and the efficacy of the resulting model. These parameters are set by the user prior to training the model and are not learned from the data. The selection of appropriate hyperparameters is crucial for attaining the utmost levels of precision and generalisation in classification tasks. Machine learning algorithms rely on an iterative process to determine the best hyperparameter values that yield the most accurate and reliable models. This process, known as hyperparameter tuning or optimization, involves systematically searching through different combinations of hyperparameters to find the optimal configuration. Various techniques, such as grid search, random search, and Bayesian optimization [17], [37], are commonly employed to explore the hyperparameter space and identify the settings that maximize the model's performance. When it comes to hyperparameter optimization, factors such as the magnitude and characteristics of the data play a significant role in determining the appropriate method to use. Among the popular optimization techniques, grid search stands out as one of the most commonly employed approaches. In grid search, a grid of hyperparameters is created, and the learning model is trained and evaluated on each combination within the grid.

E. CROSS-VALIDATION

Cross-validation methods are widely employed in machine learning to assess and validate the performance of models. The k-fold cross-validation is a frequently used technique that involves dividing the dataset into k subsets or folds of roughly equal size. The model is trained on k-1 folds and validated on the remaining fold. Each fold serves as the validation set only once. This process is repeated k times, each time using a different fold for validation. In this work, k is chosen as 5, which means the dataset is divided into five subsets. The model is trained and validated five times, each time leaving out a different subset for validation. The performance metrics obtained from each fold are averaged to provide an estimate of the model's overall performance, ensuring a robust evaluation of the model's ability to generalize to unseen data [38]. K-fold cross-validation helps to mitigate issues related to overfitting and provides a more robust evaluation of the model's

F. EVALUATION METRICS

Metrics for evaluation are used to assess the effectiveness and quality of machine learning algorithms. Effective evaluation metrics are essential for comprehending the performance of a trained deep learning model on test data, i.e., new, invisible data. The literature provides a variety of evaluation criteria for testing models. Using multiple assessment metrics to evaluate the performance of a trained deep learning model is advantageous in numerous ways, as a model may perform well with one benchmark metric but poorly with another.

Classification estimates must have one of the following four base units, and they are as follows
True Positive (TP): When the model correctly predicts the positive class.
False Positive (FP): When the model incorrectly predicts the positive class.
True Negative (TN): When the model correctly predicts the negative class.
False Negative (FN): When the model incorrectly predicts the negative class.
The evaluation metrics, denoted by Equations (1)-(4), provide quantitative measures to assess the model's performance [17]:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 - Score\ = 2x\frac{Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

III. EXPERIMENTAL RESULTS

In this section, to classify the COVID-19 original dataset in this study, two approaches are adopted. Firstly, novel CNN models and pre-trained models are proposed and utilized. These models are specifically designed to handle the task of COVID-19 classification. Secondly, a hybrid deep learning method is employed, which involved combining the proposed CNN models with the SVM algorithm. This hybrid approach aimed to enhance the classification performance by leveraging the strengths of both CNN and SVM. In various studies, datasets are obtained from public sources such as Kaggle or GitHub repositories, while in others, hospitals and universities provide private datasets. In this study, a hybrid deep learning approach is used to classify the COVID-19 dataset, which has been meticulously annotated by a clinical expert. Figure 5 displays the total number of images used in the study.

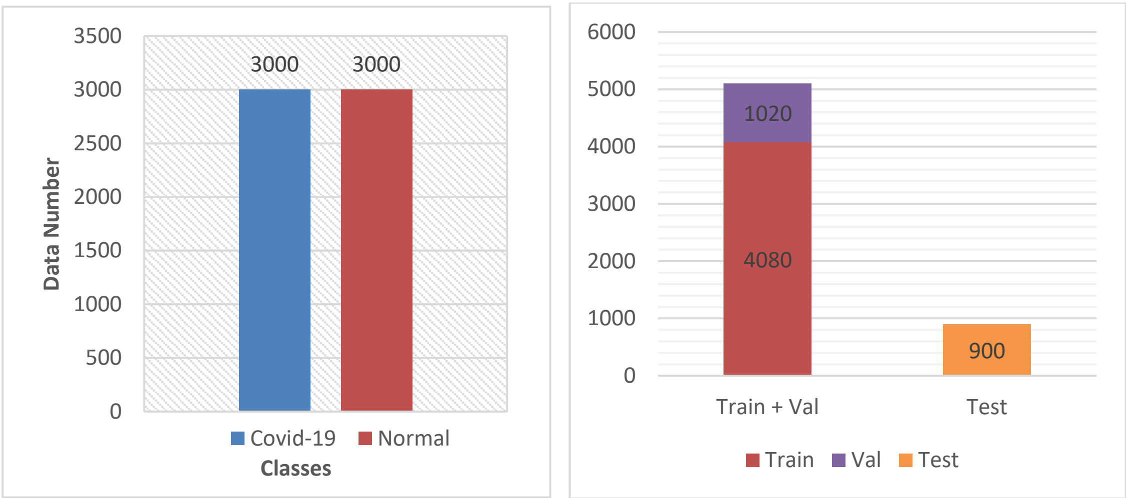


Figure 5. *Number of used images*

A. CLASSIFICATION WITH CNN MODELS

Results of proposed CNN models and pretrained models are analysed in this section. The hardware information utilized in the study is provided in Table 3. This table offers valuable insights into the computational resources employed during the experimentation process, shedding light on the hardware specifications used for training and evaluation. Size of the used models are 224x224x3. This information provides details on the architecture and structure of the CNN models, such as the number of layers and the size of each layer. Understanding the dimensions of these models aids in comprehending their complexity and the level of abstraction they can achieve.

Table 3. *Configuration of the hardware*

Name	Parameter
Memory	64 GB
Processor	Intel(R) Xeon(R) Silver 4114 CPU @ 2.20GHz 2.19 GHz (2 processor)
Server model	Hp z6 g4
Graphics	NVIDIA GeForce RTX 3090 Ti
OS	Windows 10 Pro for Workstations
Language	Python 3
Framework	Jupyter Notebook

Table 4 displays the hyperparameter values employed in the study. Hyperparameters play a crucial role in shaping the behavior and performance of deep learning models. The table provides specific values for hyperparameters used in the proposed CNN models, enabling reproducibility and facilitating further experimentation.

Table 4. *Hyperparameters of models*

Model	Learning rate	Kernel size	Activation	Pool size	Pool type	Epoch	Optimizer	Batch size
CNN1	0.0001	2 x 2	ReLu	1 x 1	maxPooling	14	Adagrad	8
CNN2	0.001	2 x 2	ReLu	1 x 1	averagePooling	15	Adam	6
ResNet50v2	0.0001	3 x 3	ReLu	3 x 3	maxPooling	10	Adam	6
VGG16	0.0001	3 x 3	ReLu	3 x 3	maxPooling	9	Adam	8

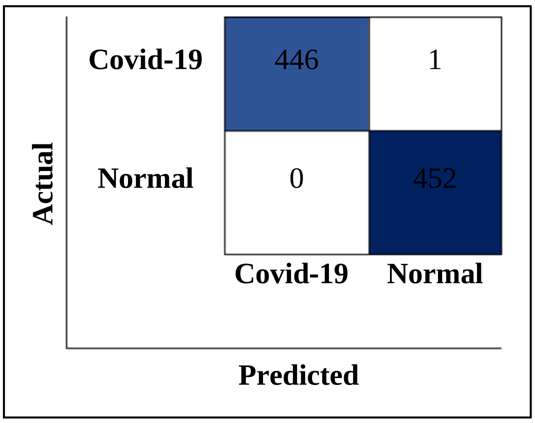
Moving on to Table 5, it presents a comprehensive analysis of the CNN models used, showcasing various performance metrics such as training, validation, and test accuracy, precision, recall, and F1-score. Additionally, the table includes information on the number of parameters, training time, and the number of epochs utilized. This detailed summary allows researchers to evaluate the performance and efficiency of the CNN models under investigation.

Table 5*. Training, validation and test accuracy, precision, recall, and F1-score along with the number of parameters, training time, and epochs required to train deep learning architectures of CNN models*

Models	Parameters	Storage	Epochs for Training	Training Time (min)	Training Accuracy	Validation Accuracy	Testing Accuracy	Precision	Recall	F1-score
ResNet50 v2	26,776,162	306 MB	10	18	99.94	99.19	99.17	99.2	99.2	99.2
VGG16	15,517,602	177 MB	9	6	100	99.05	99.26	99	99	99
CNN1	200,064,178	1.49 GB	14	23	99.27	99.84	99.93	100	100	100
CNN2	205,548,082	2.29 GB	15	29	99.67	99.96	99.86	100	100	100

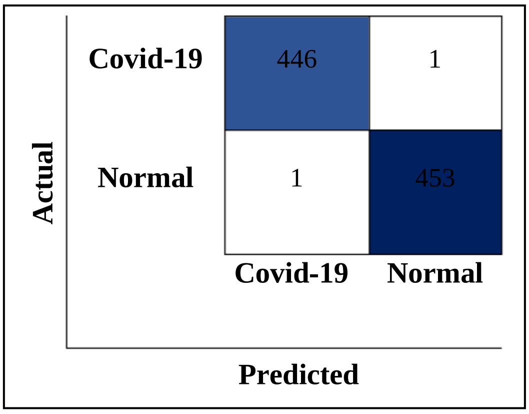
Table 6. *Classification reports and confusion matrix of models*

CNN1



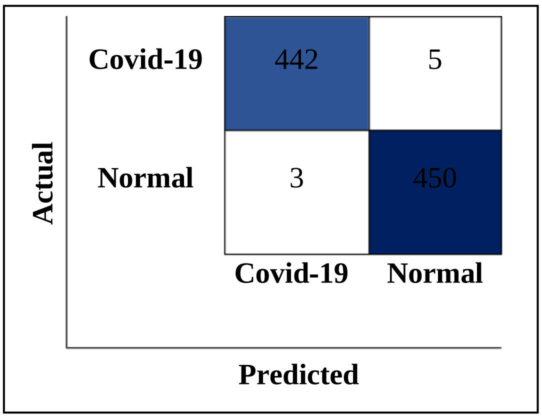
	precision	recall	f1-score	support
Covid-19	1.00	1.00	1.00	447
Normal	1.00	1.00	1.00	453
Accuracy			1.00	900
Macro avg	1.00	1.00	1.00	900
Weighted avg	1.00	1.00	1.00	900

CNN2



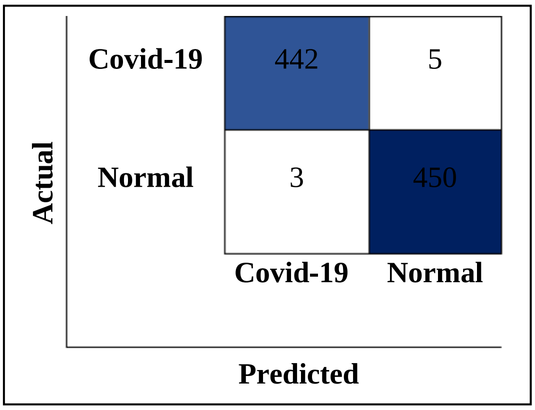
	precision	recall		support
Covid-19	1.00	0.99	1.00	447
Normal	1.00	1.00	1.00	453
Accuracy			1.00	900
Macro avg	1.00	1.00	1.00	900
Weighted avg	1.00	1.00	1.00	900

VGG16



	precision	recall	f1-score	support
Covid-19	0.99	0.98	0.99	447
Normal	0.98	0.99	0.99	453
Accuracy			0.99	900
Macro avg	0.99	0.99	0.99	900
Weighted avg	0.99	0.99	0.99	900

ResNet50v2



	precision	recall	f1-score	support
Covid-19	0.99	0.98	0.99	447
Normal	0.98	0.99	0.99	453
Accuracy			0.99	900
Macro avg	0.99	0.99	0.99	900
Weighted avg	0.99	0.99	0.99	900

A confusion matrix is a widely used tabular representation that provides valuable insights into the performance of classification models when evaluated against a set of known-true test data. It presents the results in a structured format, enabling a comprehensive analysis of the model's predictive capabilities. The classification reports and confusion matrices for each CNN model are generated using 5-fold cross-validation and the mean values of these reports are presented in Table 6. By studying the confusion matrices, researchers can gain insights into various performance metrics such as accuracy, precision, recall, and F1-score for each class. These metrics provide a comprehensive evaluation of the model's ability to correctly classify instances from different classes. Additionally, the classification reports offer a concise summary of these performance metrics, making it easier to assess the strengths and weaknesses of the CNN models under investigation.

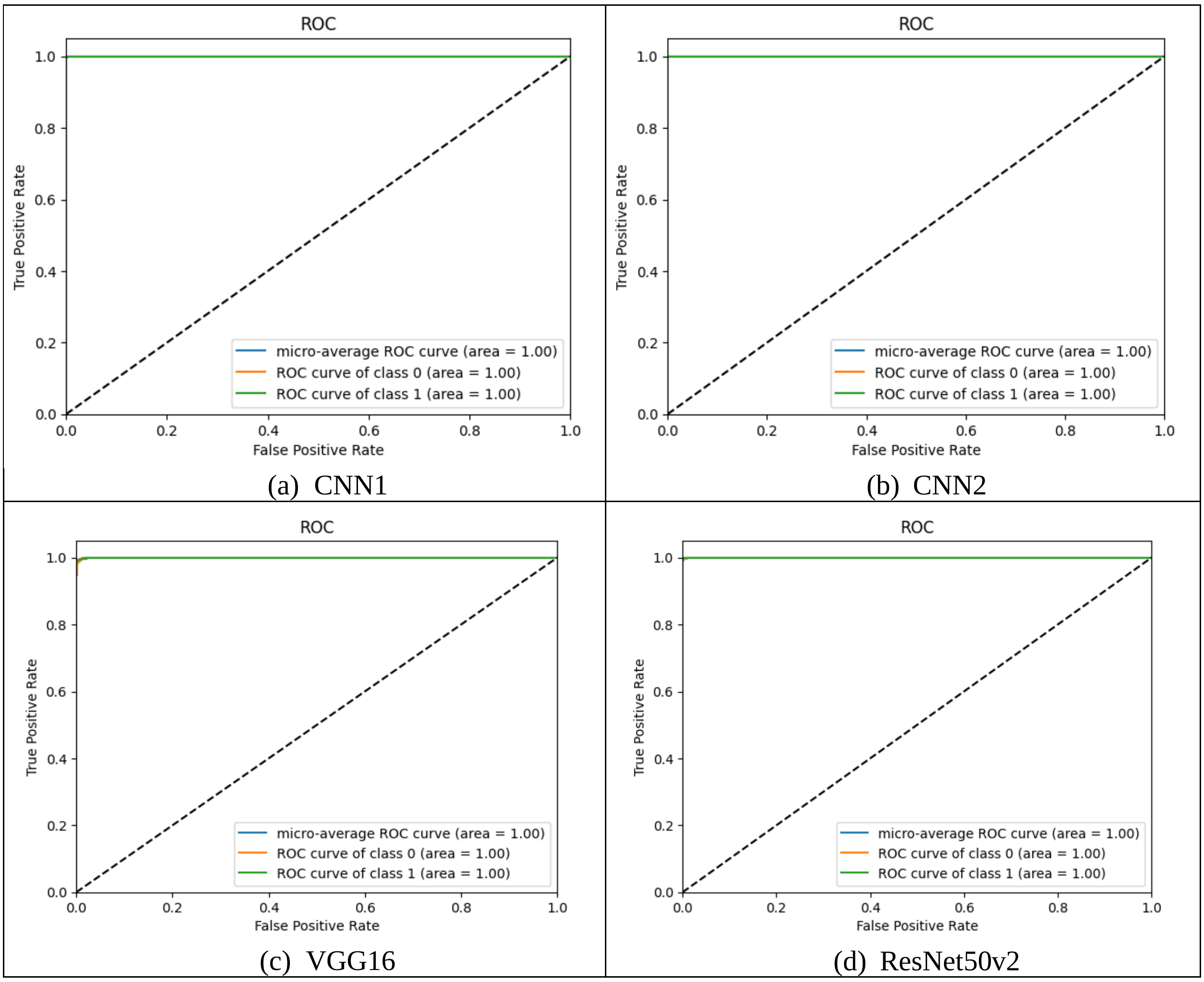
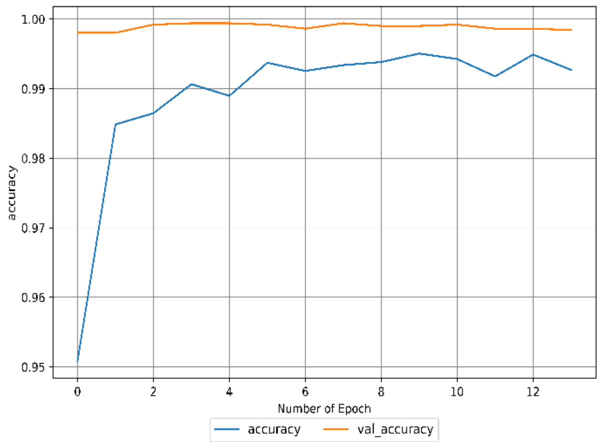


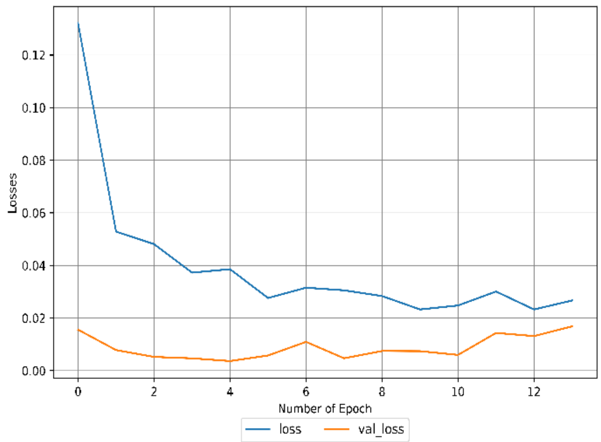
Figure 6. *ROC curves of CNN1 with 5 fold cross validation*

Figure 6 showcases the Receiver Operating Characteristic (ROC) curves for each CNN model utilized in the study. ROC curves provide a visual representation of the performance of classification models across different discrimination thresholds. By analyzing the ROC curves, researchers can gain insights into the models' ability to accurately distinguish between positive and negative instances. The curves depict the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) at various classification thresholds. A well-performing model is characterized by a curve that closely hugs the top left corner of the graph, indicating high sensitivity and low false positive rate.

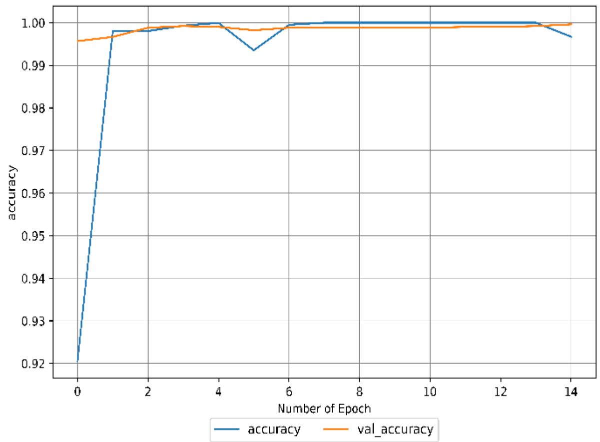
Figure 7 presents the accuracy and loss graphs of the proposed CNN models, specifically designed for k = 5 cross validation method. These graphs offer a visual representation of the models' performance and shed light on important aspects of their training process. Upon examining the accuracy graph, it becomes evident that the proposed CNN models exhibit consistent and desirable accuracy rates throughout the training phase. This implies that the models effectively learn the underlying patterns and features of the training data. Notably, the absence of overfitting is observed, which indicates that the models do not excessively memorize the training data, thus enabling them to generalize well to unseen instances. Additionally, the absence of underfitting suggests that the models are capable of capturing and leveraging the key characteristics of the data, rather than oversimplifying the problem. The loss graph, on the other hand, provides insights into the models' optimization process. The loss values decrease steadily, indicating that the models are successfully minimizing the discrepancy between their predicted outputs and the actual labels. The smooth and continuous decline in the loss signifies that the models are steadily improving their performance and converging towards an optimal state. A novel approach is proposed for developing new CNN models and utilizing pre-trained models, which involves two main components.



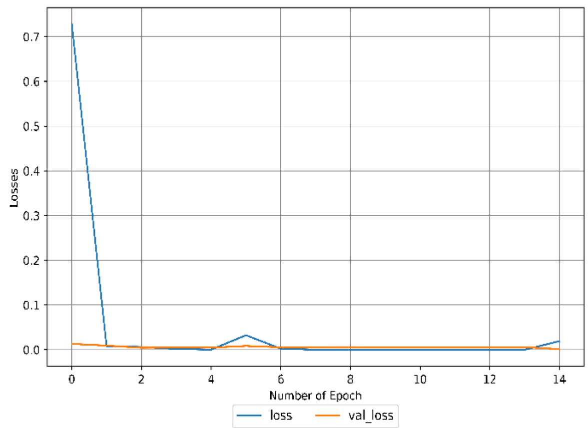
(a)



(b)



(c)



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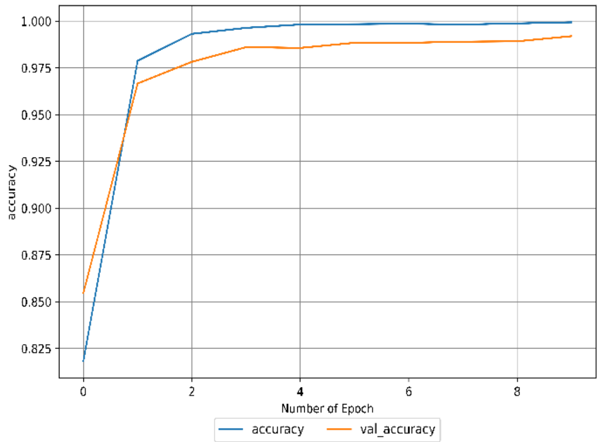
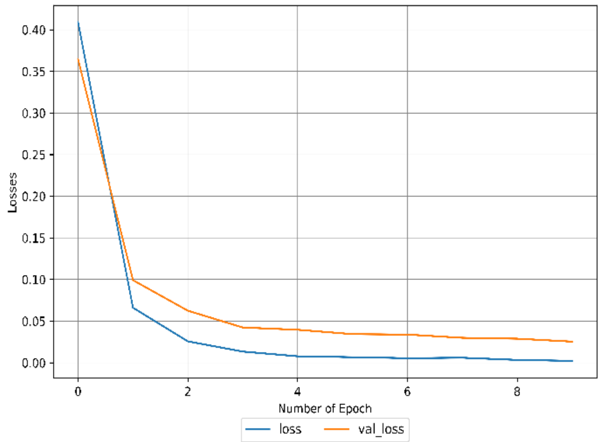
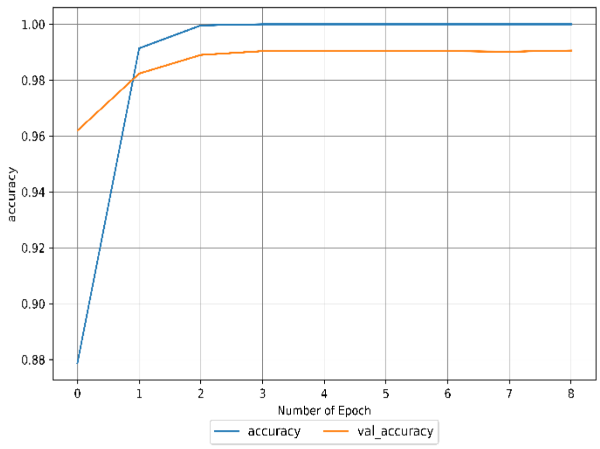


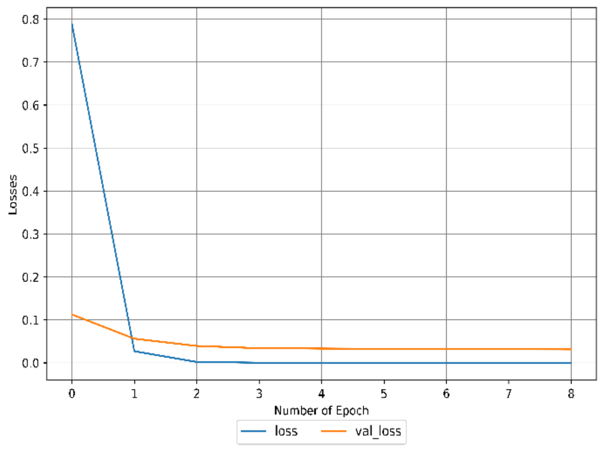
(e)



(f)



(g)



(h)

Figure 7. *Accuracy and loss graphs of the models (a) CNN1, (c) CNN2, (e) ResNet50v2 and (g) VGG16, Loss graph of the models (b) CNN1, (d) CNN2, (f) ResNet50v2 and (h) VGG16*

B. CLASSIFICATION WITH HYBRID MODELS

This section presents detailed results of the hybrid models used. The first component of the 2-stage model is a CNN network structure consisting of six layers, designed to generate feature vectors during the study. The CNN network is capable of processing high-dimensional data and extracting relevant features. The second component involves employing an SVM classifier layer for predicting outcomes. By combining these two techniques, the proposed hybrid approach aims to enhance the performance of CNN models and make them applicable in various image detection domains. However, traditional training of CNN models requires a significant amount of time and a large number of samples, imposing limitations on experimental conditions. On the other hand, SVM has demonstrated its effectiveness in regression, pattern classification, and prediction tasks [39], [40]. Unlike CNN, SVM does not require an extensive number of examples for training, but it faces challenges when it comes to identifying multiple classifications simultaneously [40], [41].

In this research, CNN1, a specific CNN model employed, comprises three convolution layers, three pooling layers, a fully connected layer, and a softmax classifier layer. Additionally, an SVM classifier is integrated into the CNN + SVM hybrid model for the classification process after the initial fully connected layer. The operational flow of CNN models involves several key stages. Initially, CT data images are inputted into the convolution layer to extract feature vectors, followed by the pooling layer to reduce data dimensionality. Finally, the fully connected layer is employed to further extract the feature vectors. The convolution layer utilizes a 2x2 kernel size, while the pooling layer employs a 1x1 convolution kernel size. Dropout is applied to mitigate overfitting. The error function is determined using cross-entropy, and optimization of the error function is achieved through the use of either the Adam or Adagrad Optimizer algorithm. A flowchart of the hybrid model is given in Figure 8.

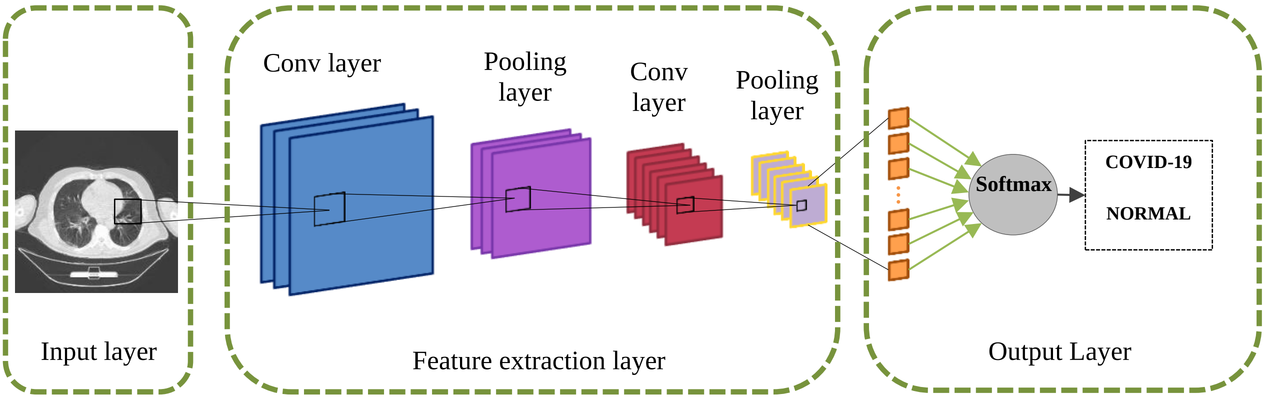


Figure 8. *A flowchart of the hybrid model*

Table 7 presents an in-depth analysis of the hybrid model utilized in the study. It includes crucial performance metrics such as training and validation accuracy, precision, recall, and F1-score. Additionally, the table provides information on the number of parameters, training time, and the number of epochs employed. The results in Table 7 demonstrate that the proposed new CNN models exhibit high accuracy in diagnosing COVID-19, with exceptional performance observed in the CNN1+SVM model, achieving 100% accuracy. The accuracy metric reflects the ability of the models to correctly classify instances of COVID-19, indicating their effectiveness in capturing the relevant patterns and features in the dataset. Furthermore, Table 8 presents a comparison between the training time of the CNN models and the SVM model. It highlights the advantage of the SVM model over the hybrid model in terms of training time. SVM is known for its efficiency in training, as it does not require a large number of examples. This characteristic is particularly advantageous when dealing with limited resources or time constraints. The table emphasizes the time-saving benefit of incorporating SVM in the hybrid model, demonstrating its superiority over training CNN models alone.

Table 7. *Training and validation accuracy, precision, recall, and F1-score along with the number of parameters, training time, and epochs required to train deep learning architectures of CNN+SVM*

Models	Parameters	Storage	Epochs for Training	Training Accuracy	Matthews corrcoef	Testing Accuracy	Precision	Recall	F1-score
ResNet50v2 + SVM	26,776,162	8 KB	10	99.99	97.11	98.55	99	99	99
VGG16 + SVM	15,517,602	4 KB	9	99.99	99.11	100	100	100	100
CNN1 + SVM	200,064,178	3 KB	14	100	100	100	100	100	100
CNN2 + SVM	205,548,082	2 KB	15	100	99.55	99.77	100	100	100

Table 8. *Training time of CNN and SVM models*

Architectures	CNN Training Time (s)	SVM Training Time (s)	Total Time(s)
ResNet50v2	504	0.1743	504.1743
VGG16	752.4	0.1704	752.5704
CNN1	682.2	0.0408	682.2408
CNN2	1677.6	0.0484	1677.6484

Classification report and confusion matrix of hybrid models are given in Table 9. In addition, the ROC curve, loss and accuracy curves of the models are also shown in Figures 9 and 10.

Table 9. *Classification reports and confusion matrix of models*

CNN1+SVM

Actual \ Predicted	Covid-19	Normal
Covid-19	447	0
Normal	0	453

	precision	recall	f1-score	support
Covid-19	1.00	1.00	1.00	447
Normal	1.00	1.00	1.00	453
Accuracy			1.00	900
Macro avg	1.00	1.00	1.00	900
Weighted avg	1.00	1.00	1.00	900

CNN2+SVM

Actual \ Predicted	Covid-19	Normal
Covid-19	445	2
Normal	0	453

	precision	recall	f1-score	support
Covid-19	1.00	1.00	1.00	447
Normal	1.00	1.00	1.00	453
Accuracy			1.00	900
Macro avg	1.00	1.00	1.00	900
Weighted avg	1.00	1.00	1.00	900

VGG16+SVM

Actual \ Predicted	Covid-19	Normal
Covid-19	445	2
Normal	2	451

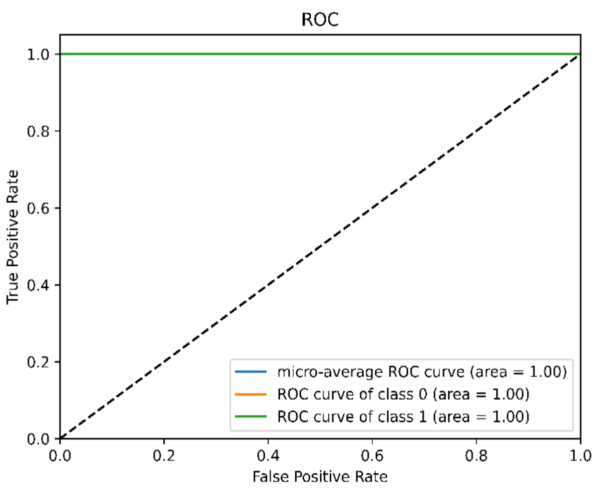
	precision	recall	f1-score	support
Covid-19	1.00	1.00	1.00	447
Normal	1.00	1.00	1.00	453
Accuracy			1.00	900
Macro avg	1.00	1.00	1.00	900
Weighted avg	1.00	1.00	1.00	900

ResNet50v2+SVM

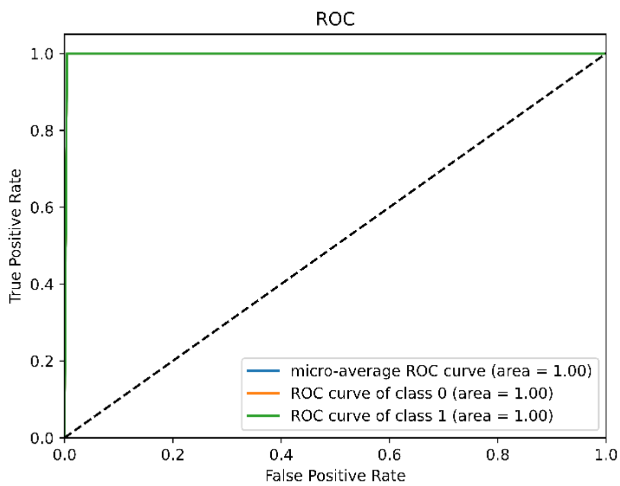
Actual \ Predicted	Covid-19	Normal
Covid-19	440	7
Normal	3	450

	precision	recall	f1-score	support
Covid-19	0.98	0.99	0.99	447
Normal	0.99	0.98	0.99	453
Accuracy			0.99	900
Macro avg	0.99	0.99	0.99	900
Weighted avg	0.99	0.99	0.99	900

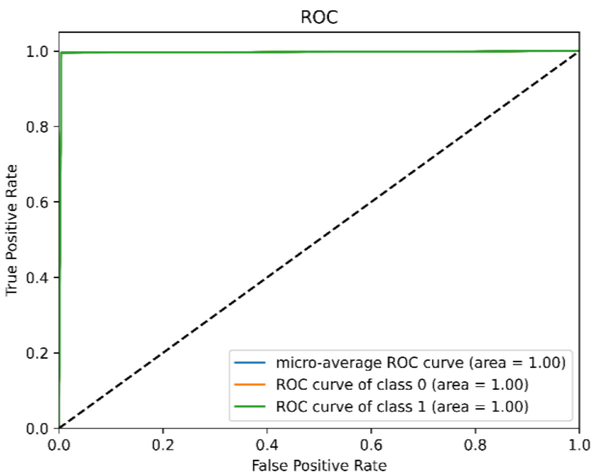
Figure 9 shows the ROC curves of used models. The ROC curve in the CNN1+SVM demonstrates perfect classification performance, with an AUC (Area Under the Curve) of 1.00 for all curves, including the micro-average, class 0, and class 1. This indicates that the model achieves 100% accuracy, correctly classifying all instances of both classes without any false positives or false negatives. The curve adheres to the upper-left corner of the plot, which represents the ideal performance of a classifier. The ROC curve for CNN2+SVM exhibits the same classification performance with CNN1+SVM, achieving an AUC (Area Under the Curve) of 1.00 across all metrics, including the micro-average, class 0, and class 1. This indicates that the model attains perfect accuracy, successfully identifying all instances of both classes without any errors, such as false positives or false negatives. The curve aligns perfectly with the upper-left corner of the plot, representing the optimal performance of a classifier. Similar to the first graph, VGG16+SVM graph reflects perfect classification performance, achieving an AUC of 1.00 for all curves. The ROC curve closely aligns with the upper-left corner, signifying that the model makes no classification errors for either class. This level of performance indicates the model's ability to completely differentiate between the two classes without overlap or ambiguity. The ResNet50v2+SVM graph shows a nearly perfect ROC curve, with an AUC of 0.99 for all curves (micro-average, class 0, and class 1). This suggests that the model performs exceptionally well but might misclassify a small number of instances. The slight deviation of the curve from the upper-left corner indicates minor imperfections in classification, but the model still achieves highly reliable performance.



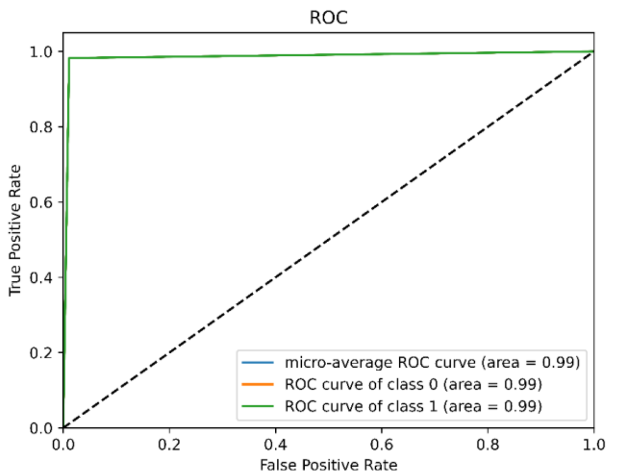
(a) CNN1+SVM



(b) CNN2+SVM



(c) VGG16+SVM

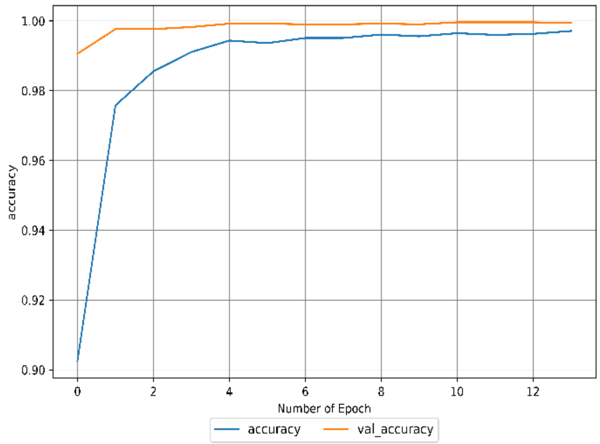


(d) ResNet50v2+SVM

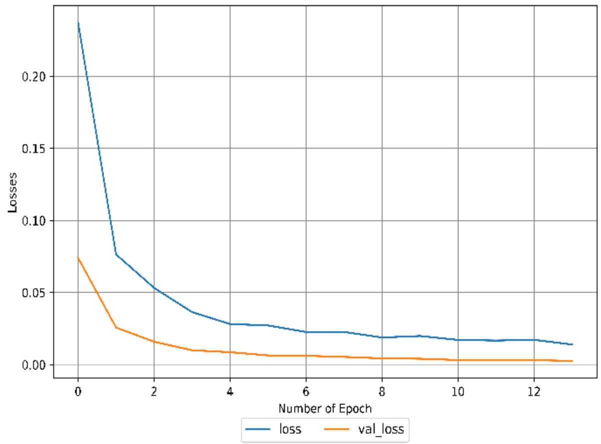
Figure 9. *ROC curves of the used models*

Figure 10 illustrates the accuracy and loss graphs of the proposed used hybrid models, these graphs provide a visual overview of the models' performance and highlight key aspects of their training process. The accuracy graph reveals that the proposed hybrid models maintain consistent and favorable accuracy levels throughout the training phase, demonstrating their ability to effectively learn the underlying patterns and features of the training data. Importantly, there is no evidence of overfitting, suggesting that the models avoid excessively memorizing the training data and can generalize well to unseen instances. Furthermore, the absence of underfitting indicates that the models successfully capture and utilize the critical characteristics of the data without oversimplifying the problem.

The loss graph, in contrast, offers insights into the optimization process of the models. It shows a steady decline in loss values, signifying that the models are effectively minimizing the difference between their predicted outputs and the actual labels. The smooth, continuous reduction in loss indicates that the models are progressively improving their performance and converging toward an optimal state. A novel methodology is introduced for developing new hybrid models and leveraging pre-trained models, consisting of two key components.



(a)



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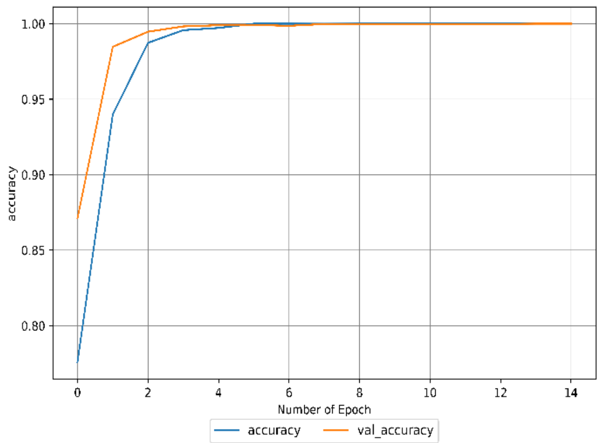

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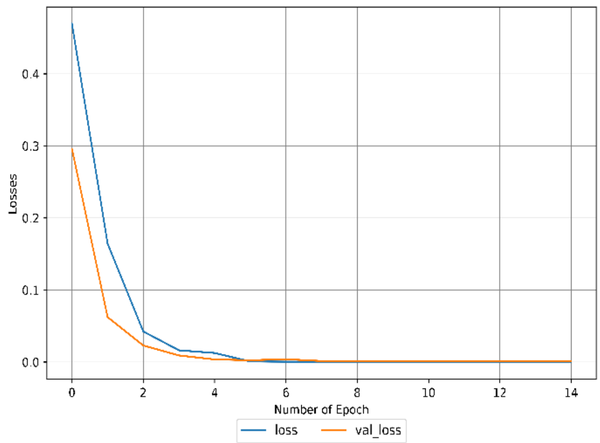

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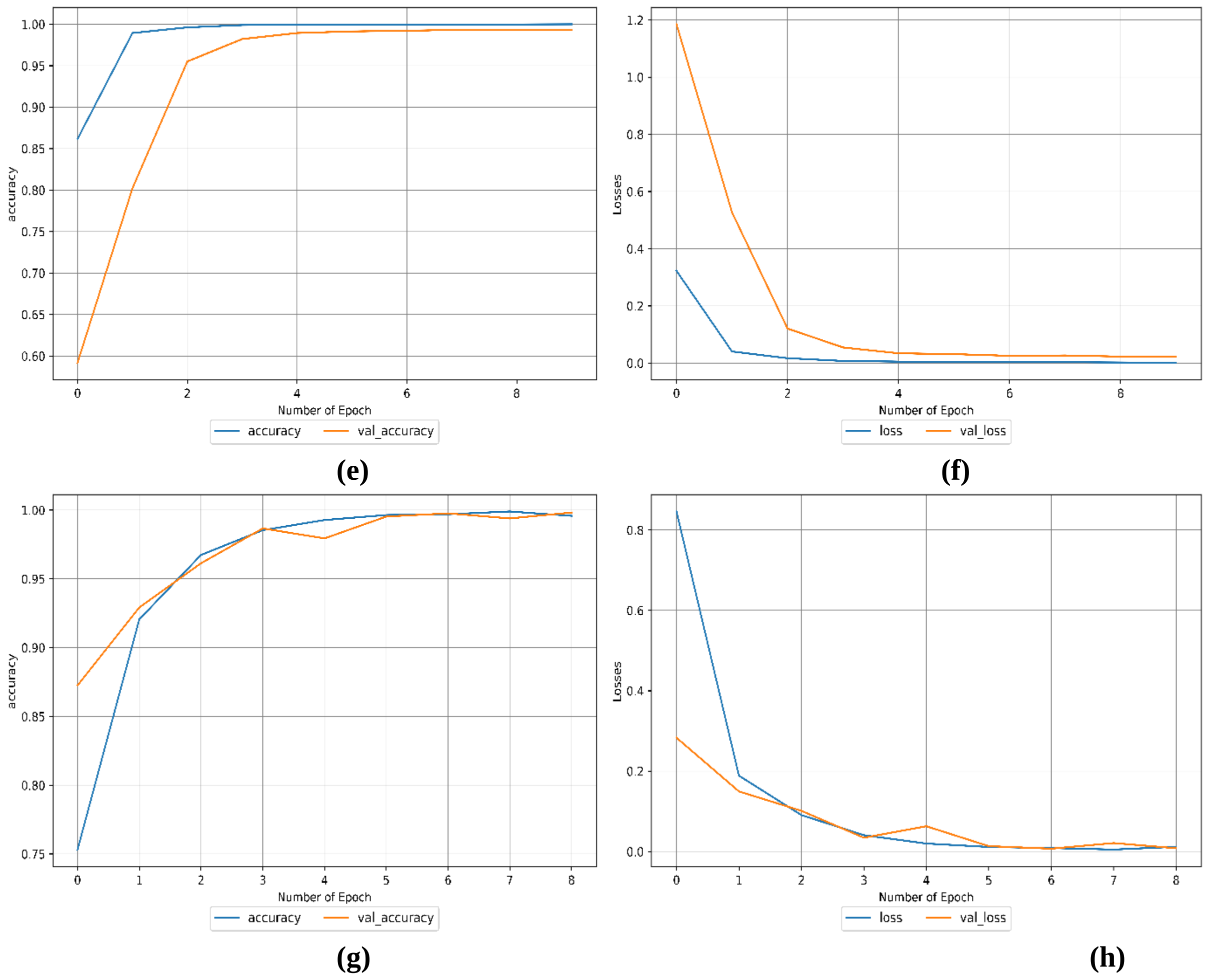

Figure 10. *Accuracy and loss graph of the models (a) CNN1+SVM, (b) CNN2+SVM, (c) ResNet50v2+SVM and (d) VGG16+SVM*

While our study showcases promising results with CNN and hybrid CNN+SVM models, it is crucial to acknowledge the advancements made by previous researchers in the field. The higher accuracy rates reported in the comparative studies may be attributed to various factors such as different datasets, model architectures, hyperparameter optimization techniques, and data preprocessing methods. Understanding these variations and incorporating the relevant advancements into our models can potentially lead to enhanced accuracy and improved performance. Table 10 presents a comparison of similar studies in the literature. Upon examining these studies in relation to our recommended models, it becomes evident that the accuracy rates achieved by the other proposed models are higher. This suggests that there is room for improvement in our proposed models to match or surpass the performance of these comparative studies.

Table 10. *Comparison of similar studies in the literature*

Models	Data Size	Data Type	Performance (%)	Study
CNN	1430	X-ray	97.92	[22]
WCNN	1000	CT	98.19	[23]
CNN	6310	X-ray	95	[24]
MobileNetV3Large	15186	CT	99.74	[25]
SeNet154	22779	CT	98	[25]
CNN	2905	X-ray	98.13	[26]
CNN	15471	X-ray	94.55	[26]
ResNet101	8900	X-ray	98	[27]
VGG19	7455	CT	97	[27]

Table 10(cont). *Comparison of similar studies in the literature*

ResNet50	-	CT	98.78	[28]
CNN	15871	CT	98.36	[29]
CNN+SVM	5360	X-ray	97.41	[30]
CNN+SVM	6000	X-ray	91.1	[31]
ResNet50+SVM	13808	X-ray	97.3	[32]
mAlexNet+SVM	3911	X-ray	99.8	[42]
CNN+SVM	746	CT	91.1	[43]
This Study (Hybid CNN+SVM)	6000	CT	100	-

IV. DISCUSSION

There have been numerous studies in the literature focusing on the detection of COVID-19, including hybrid models that have shown high accuracy [44]. These studies have laid the foundation for exploring innovative approaches to leveraging medical imaging for disease detection. In our proposed study, we observed that both newly developed CNN models and CNN+SVM hybrid models achieved superior accuracy on the original dataset compared to results reported in prior studies. This improvement highlights the potential of our approach to effectively capture and utilize features from medical images for COVID-19 detection. It is worth noting that previous studies often utilized limited datasets with few images per class [45]–[48]. In contrast, our study adopted a comprehensive approach by analyzing a large dataset, which prioritizes studies that incorporate more extensive data. While these studies have contributed valuable insights, their findings may not generalize well due to the constrained size and diversity of the datasets. In contrast, our study adopted a more comprehensive approach by analyzing a significantly larger dataset, which allows for the exploration of a wider range of imaging patterns and patient characteristics. This emphasis on larger datasets not only improves the reliability of the findings but also ensures that the models are trained on data that more closely resemble real-world scenarios.

By prioritizing studies that incorporate extensive data, we aim to address key challenges in medical image classification, including the variability in imaging protocols, patient demographics, and disease presentation. Furthermore, our approach underscores the importance of scalability and adaptability, which are critical for developing models that can be effectively deployed in clinical practice.

V. LIMITATION AND FUTURE WORK

This study emphasizes the importance of dataset size in enhancing the robustness and reliability of our findings. While the system demonstrates good performance on our datasets, it is important to acknowledge several limitations that need to be addressed. Firstly, our research is currently in the theoretical phase, and the models have not yet been validated in real clinical routines. This limits the immediate applicability of our findings to practical medical settings. Additionally, the datasets used in this study, although comprehensive, may not fully represent the diversity of real-world clinical data, such as variations in imaging protocols, patient demographics, and disease presentation. As a result, there is a potential risk that the models may not generalize well across different populations or clinical environments.

Moreover, while our models show promising results in detecting COVID-19 from CT images, their interpretability and the exact mechanisms through which they identify key features remain underexplored. This lack of transparency could hinder clinical acceptance, as clinicians often require an understanding of how diagnostic tools make predictions to trust and effectively use them.

In future research, we plan to address these limitations through several initiatives. First, we aim to validate our models in clinical settings by conducting rigorous tests in collaboration with healthcare professionals. This will not only help evaluate the models' real-world performance but also allow us to understand clinicians' usage patterns and gather valuable feedback on their practicality and reliability. Such insights will guide us in refining and improving the models to better align with clinical needs.

Additionally, we will focus on assessing the severity of COVID-19 and extracting valuable information from CT images to contribute to global efforts against the pandemic. This includes performing detailed descriptive analyses of our models to identify and interpret the key features in CT images that are critical for the detection and severity assessment of COVID-19. By doing so, we aim to enhance the transparency and explainability of the models, thereby facilitating the adoption of these tools in clinical practice.

Finally, we plan to expand the scope of our study by incorporating diverse and larger datasets, ensuring that the models can generalize effectively across various clinical scenarios. This will also involve engaging with a broader range of healthcare professionals across different regions to ensure that the models are both adaptable and widely applicable. Through these efforts, we aim to make meaningful contributions to improving screening processes for clinicians and supporting global healthcare systems in their fight against COVID-19.

VI. CONCLUSION

The objective of this study is to introduce a decision support system that utilizes deep learning algorithms for the accurate diagnosis of COVID-19 by analyzing CT images. Along with two novel CNN models developed in this study, we also conducted a comprehensive modeling study using pre-trained architectures such as ResNet50v2 and VGG16. Furthermore, we propose a hybrid model by combining these CNN models with the SVM algorithm. During the modeling process, we performed parameter selection using the grid search method for hyperparameter optimization. The original dataset used in the modeling consists of two classes, and detailed information about the dataset is provided. To evaluate the performance of our models, we split the original dataset as well as newly created datasets into training and test sets using an 85-15 ratio, and we also employed 5-fold cross-validation. All results were presented in a comparative manner. The accuracy values of the results obtained are 99.93% and 99.86% CNN models, 100% and 99.77% CNN+SVM models, and it is seen that the proposed models can classify the CT images of COVID-19 patients and make the diagnosis of COVID-19 with high accuracy. Additionally, we assessed the effectiveness of our proposed methods on a different dataset, thereby increasing the efficiency of the study. These results provide strong evidence that the proposed deep learning models can be successfully utilized in the healthcare domain.

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DECLARATION OF ETHICAL STANDARDS: Authors declare that all ethical standards have been complied with.

DECLARATION OF COMPETING INTEREST: The authors declare no competing of interest.

DATA AVAILABILITY: The data set used in this study was obtained by obtaining the necessary ethical permissions from Faculty of Medicine, Yozgat Bozok University.

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