CoviDetNet: A new COVID-19 diagnostic system based on deep features of chest x-ray

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Abstract
COVID-19 has emerged as a global pandemic affecting the world, and its adverse effects on society still continue. So far, about 243.57 million people have been diagnosed with COVID-19, of which about 4.94 million have died. In this study, a new model, called COVIDetNet, is proposed for automated COVID-19 detection. A lightweight CNN architecture trained instead of the popular and pretrained convolution neural network (CNN) models such as VGG16, VGG19, AlexNet, ResNet50, ResNet100, and MobileNetV2 from scratch with chest x-ray (CXR) images was designed. A new feature set was created by concatenating the features of all layers of the designed CNN architecture. Then, the most efficient features chosen among the features concatenating with the Relief feature selection algorithm were classified using the support vector machine (SVM) method. The experimental works were carried out on a public COVID-19 CXR database. Experimental results demonstrated 99.24% accuracy, 99.60% specificity, 99.39% sensitivity, 99.04% precision, and an $F_1$ score of 99.21%. Also, in comparison to AlexNet and VGG16 models, the deep feature extraction durations were reduced by approximately 6-fold and 38-fold, respectively. The COVIDetNet model provided a higher accuracy score than state-of-the-art models when compared to multiclass research studies. Overall, the proposed model will be beneficial for specialist medical staff to detect COVID-19 cases, as it provides faster and higher accuracy than existing CXR-based approaches.

KEYWORDS
automatic detection, COVID-19, deep feature extraction with a lightweight CNN, Relief, SVM

1 | INTRODUCTION

Cases of pneumonia of unknown cause were detected in the city of Hubei, Wuhan Province, China, in December 2019. In January 2020, the World Health Organization (WHO) declared these cases to be due to a new type of virus, and in February 2020, they named this virus COVID-19. The virus’s rapid spread among people has become a severe public health problem worldwide. Health systems have come to a standstill, especially in developed countries, due to rapidly rising cases. Many countries have been forced to take social isolation measures to maintain health services and reduce the risk of viral transmission.

Additionally, many countries have banned their citizens from traveling, both home and abroad. Despite all...
these precautions, 251.26 million cases have been detected worldwide, according to WHO data dated November 12, 2021. So far, 5.07 million people have died due to COVID-19 infection. The highest confirmed cases and deaths were found in the Americas during this period, followed by Europe.

COVID-19 has caused health problems in people and caused severe damage to people's economic and social lives. This situation mainly affected developed and developing countries such as the United States, India, the United Kingdom, Brazil, and the Russian Federation, where COVID-19 cases and deaths are very high. Figure 1 indicates that the number of cases and deaths in the countries most affected by COVID-19 in the world, according to WHO statistics.

As can be shown in the graph in Figure 2, until November 12, 2021, in the United States, India, Brazil, United Kingdom, Russian Federation, Turkey, and France, 46.41, 34.40, 21.89, 9.4, 8.95, 8.31, and 7.01 million, respectively, cases have been identified. Also, in Figure 2, the United States, India, Brazil, United Kingdom, Russian Federation, Turkey, and France are 751.60, 462.19, 609.75, 21.89, 9.4, 8.95, 8.31, and 7.01 million, respectively.
142.33, 251.69, 72.71, and 115.61 a thousand, respectively, deaths have been reported. Despite vaccination processes, which started at the beginning of 2021, the epidemic continues to spread rapidly due to the mutational effects of the virus. Some experts indicate that the epidemic's effects may last until 2024.

Some of the widespread symptoms of the early periods of COVID-19 infection are also seen in people affected by colds and other flu virus infections. Therefore, disease diagnostic test kits are needed for the definitive diagnosis of COVID-19. Real-time reverse transcription-polymerase chain reaction (RT-PCR) testing on respiratory or blood samples are some of the effective methods of choice for COVID-19 diagnosis. However, these kits have disadvantages, such as long diagnosis times (1–3 days), costly, and sometimes, failure to detect the virus. Some studies have stated that only 71% of COVID-19 cases can be detected with RT-PCR.

Recently, medical imaging data such as x-rays, computed tomography (CT), and magnetic resonance imaging have been used to detect and diagnose many diseases such as brain tumors and lung. For this reason, lung radiological chest scans are used in COVID-19 case detection. CT and chest x-ray (CXR) are used for breast scanning. Radiologists and physicians can distinguish positive COVID-19 cases with the help of radiological lung imaging; this method is preferred for diagnosis as it gives both faster and more precise results when compared to the RT-PCR method. CT scanning systems are new and expensive. Therefore, they are not available in all medical centers and hospitals.

Meanwhile, CXR systems are found in almost all medical centers and hospitals, and, in addition to being light and portable, these systems provide an excellent convenience in their use. An average of 15–25 s may be sufficient for each patient for the CXR procedure. Therefore, radiologists and physicians prefer CXR images, as they are more economical and faster for case diagnosis. However, radiologists need time to examine CXR images. As a result, developing rapid and highly accurate automatic case detection systems based on artificial intelligence that can reduce radiologists' workload is critical.

1.1 Literature review

Narin et al. proposed the ResNet50, Inception V3, and Inception-ResNetV2 models for diagnosing COVID-19 from CXR images. In their studies, the ResNet50 model was shown to perform better than the other two models, with 98.0% classification accuracy. Ismael and Şengür proposed a combination of pretrained convolutional neural network (CNN) ResNet, VGG models, and an support vector machine (SVM) classifier to diagnose COVID-19. In their study, feature extraction was initially performed using CXR images with ResNet and VGG models; then, the SVM classified suspected COVID-19 cases as either positive or negative, demonstrating 94.7% accuracy.

Hemdan et al. proposed a deep learning (DL) model named COVIDX-Net; the method they proposed achieved 90% success in testing of 50 CXR images. Similarly, Khalifa et al. proposed a generative adversarial network, based on DL, to diagnose COVID-19 cases using limited CXRs. Thus, CNN models, such as ResNet18, AlexNet, GoogLeNet, and SqueezeNet, solved overfitting and achieved higher performance. Chowdhury et al. proposed eight different CNN models, including AlexNet, DenseNet201, ResNet18, SqueezeNet, and MobileNet, pretrained to detect COVID-19 and pneumonia. Their work combined various publicly available datasets to create a dataset containing 423 COVID-19 positive cases, 1485 pneumonia cases, and 1579 normal CXR images; in their experimental studies, they achieved a 97.74% accuracy score in triple classification.

Hussain et al. proposed a 22-layer CNN architecture for COVID-19 detection from CXR images. The proposed CNN model features were classified into 2, 3, and 4 classes. Their study achieved accuracy scores of 99.1%, 94.2%, and 91.2%, respectively.

Ibrahim et al. suggested pretrained CNN models to detect COVID-19 from CXR and CT images. The referenced study used CXR images to detect normal physiology, COVID-19 cases, and pneumonia, while also using CT images to detect normal, COVID-19, pneumonia, and lung cancer cases. For this purpose, they used four different CNN models: ResNet, ResNet + Bidirectional, ResNet + Gated Recurrent Unit (ResNet + GRU), and VGG19; their researcher achieved the highest COVID-19 detection rate using the VGG model, which demonstrated a 98.05% accuracy score in the experimental studies.

Ozturk et al. suggested a CNN architecture with 17 convolution layers to diagnose COVID-19. The researchers obtained an accuracy rate of 87.02% in studies conducted with a three-class dataset. Turkoğlu proposed a model, which they called COVIDetectioNet, in order to diagnose COVID-19 from CXR images. The experimental works used a dataset containing 6092 CXR images labeled as either normal, COVID-19, or pneumonia. The proposed COVIDetectioNet combined attributes from the fully connected, and the convolution layers of the AlexNet. The obtained features were classified with SVM by selecting the Relief feature selection algorithm. Their research achieved an accuracy score of
99.18% in the experimental studies. Reference 25, VGG-16, VGG-19, ResNet50, and Inception V3 CNN models have tried different learning rates to eliminate the effects of the overfitting problem. Also, for a faster classification, the use of the two-layer CNN model in the transfer learning method has been proposed. They achieved an accuracy score of 90.45% in experimental studies.

Apostolopoulos and Mpesiana26 proposed five different CNN models for COVID-19 detection: MobileNet V2, Xception, Inception, ResNetV2, and VGG19. The research team achieved an accuracy rate of 94.72% using the MobileNetV2 architecture. Ucar et al.27 proposed a pretrained SqueezeNet architecture with a Bayes optimization algorithm to detect COVID-19 and achieved a 98.26% accuracy rate in their experimental works. Wang et al.28 proposed a CNN model that includes many convolution layers. Using this method, they detected COVID-19 cases with 92.64% accuracy in the proposed CNN model. Similarly, Nour et al.29 detected COVID-19 with an end-to-end trained CNN model and obtained an accuracy score of 98.97%.

1.2 Motivation and contributions

The literature research shows promising results obtained in CNN-based studies with CXR images.16–29 In these studies, pretrained CNN models that were generally based on transfer learning were used. Additionally, many researchers have focused on accuracy scores and the dual classification of COVID-19 cases as either positive or negative. However, during the pandemic period, in which case numbers are very high, it is essential how long it takes to decide on this diagnosis as well as the correct diagnosis of COVID-19.

This research study, a new CNN architecture, named COVIDetNet, is suggested to diagnose COVID-19 automatically. The structure of the suggested COVIDetNet model is represented in Figure 2. COVIDetNet comprises three stages: deep feature extraction, feature selection, and classification. The proposed CNN model with end-to-end architecture was created and trained using CXR images. In this method, deep features are taken and concatenated from each convolution and the fully connected layer of the constructed CNN model. The Relief feature selection algorithms were used to select the most effective features from a set of combined features. The SVM algorithm was then used to categorize these efficient features. Based on the results of the experiments, it is clear that the method will be useful in detecting COVID-19. The major contributions of the proposed method may be outlined as follows:

- A flexible new CNN architecture was proposed, where all layer structures and dimensions can be changed easily.
- The proposed CNN model requires less training time as it is a lightweight model compared to pretrained CNN models.
- Deep features are mostly extracted from one or some layers of deep learning models. In COVIDetNet, deep features from all convolutional and fully connected layers were obtained, making CX images’ characteristic details more prominent.
- The Relief feature selection algorithm improved the classification performance. Besides, the size of the feature set was reduced with this algorithm. Thus, the prediction time of the classifier was reduced.
- Compared to popular deep learning models, the computational cost of the proposed model is very low. In this regard, the COVIDetNet approach can be used in clinical applications with low-capacity hardware.
- The proposed approach outperformed existing methods in the literature (see Table 6),

The limitations of the proposed method can be explained as follows:

- Preprocessing x-ray images and increasing the input image size in the training phase will increase the computational cost. Therefore, powerful hardware will be required.

1.3 Organization of paper

The research is structured as follows: Section 2 gives the methodology background, consisting of the datasets, CNN architecture, and classification method. The experimental results give in Section 3. Sections 4 and 5 present the discussion and conclusion of the paper, respectively.

2 MATERIALS AND METHODS

In this paper, an effective and new COVIDetNet model is proposed to detect COVID-19 cases in minimum time and with high accuracy. The general architecture of the proposed method is presented in Figure 2. The method consisted of four basic phases: In the first phase, the CXR images were resized according to the COVIDetNet model; in the second phase, deep features were obtained and concatenated from all fully connected and convolutional layers of the CNN architecture, whose layer numbers and sizes are easily changed; following that, the most effective
features from the deep features acquired with the Relief algorithm were chosen; and, finally, the SVM method was used to classify the specified features.

2.1 | Dataset

The dataset was created using a total of 2621 CXR images, which were compiled using various open-source, public data sets. Radiologists labeled CXR images as either normal, COVID-19 positive, or pneumonia. The CXR images belonging to the dataset were organized in three different folders according to their tag classes. The normal, COVID-19, and pneumonia folders contained 1541, 580, and 500 CXR images, respectively. Normal (healthy) and COVID-19 positive CXR images were collected from the Kaggle websites.30,31 The COVID-19 positive CXR images, which radiologists took, comprising data from 200 males and 161 females over 45. Pneumonia CXR images were taken from a dataset generated by Wang et al.32 Figure 3 demonstrates example images of CXRs from the normal, COVID-19, and pneumonia classes, which give in the first, second, and third columns, respectively.


2.2 | Convolution neural network

CNN is a DL algorithm that is very popular in image classification and object detection. CNN structures can be designed as one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D). The 1D CNN is used for serial data processing, while 2D CNN is used for image and text recognition, and 3D CNN structures are often used for video and medical image recognition. CNNs are designed in layers, as in a typical neural network model; neurons, bias, and weights interconnect the layers. However, the CNNs differ from typical neural networks in that they include three types of layers: convolution, pooling, and fully connected layers, in order for the CNNs to form an entire network.

The convolution layer is an important layer for the CNN that uses convolution operation, denoted by “*”, rather than the general matrix multiplication. This layer’s learnable parameters are made up of a series of learnable filters known as kernels. The 2D convolution operation can be defined by Equation (1):

\[(X * K)(a,n) = \sum_i \sum_j K(i,j) X(a-i, n-j),\] (1)

where \(X\) is the CXR input image and \(K\) is the kernel. The \(K\) kernel has \(n \times n\) dimensions. This method provides the ability to obtain lower-dimensional features with the help of movement covering all pixels on the input image with the determined stride size. In brief, the convolution layer creates a feature map of the original images by determining local connections of the properties belonging to the input data that may be similar to the CXR images.

The batch normalization (BN) layer is used to reduce the training process of the CNN and develop network initiating performance. Also, the BN layer is used to minimize gradient vanishing. BN layer variables are calculated as shown in Equations (2)–(5):

\[m_b = \frac{1}{l} \sum_i x_i,\] (2)

\[v_b = \frac{1}{l} \sum_i (x_i - m_b)^2,\] (3)

\[\hat{x}_i = \frac{x_i - m_b}{\sqrt{v_b^2 + \epsilon}},\] (4)

\[y_i = d\hat{x}_i + e,\] (5)

where \(m_b\) is mini-batch mean, \(v_b\) is mini-batch variance, and \(\hat{x}_i\) is the normalized activation. When \(v_b\) is very small, constant \(\epsilon\) is used to improve the numerical operation. Balance factors \(d\) and \(e\) are learnable parameters. BN output is defined by \(y_i\). In DL models, the convolution layer output is transferred to a nonlinear layer to increase the CNN’s fitting capability. This layer, called the activation layer, uses the nonlinear rectified linear unit (ReLU) activation function to reduce gradient explosion and gradient vanishing. In place of sigmoid and tanh activation functions, which are preferred in artificial neural networks, smooth ReLU uses CNNs. The ReLU activation function can be defined as given in Equation (6):

\[f(x) = \begin{cases} x & x > 0 \\ 0 & x < 0 \end{cases},\] (6)

Through the pooling layer, which keeps the kernel size of the obtained feature matrix as a result of the activation process constant, the width and height of the matrix are reduced by the maximum or average value method.

The fully connected layer (fc) attaches to the previous and subsequent layer’s neurons. The first fc comprises flattened matrices carried from the previous layers. Meanwhile, the last fc determines how much a data value matches any class, and passes this information to the softmax layer for classification.

2.3 | The architecture of the proposed CNN model

A simple CNN that can be used on lower-capacity hardware, called COVIDetNet, was designed for deep feature extraction from CXR images. COVIDetNet consists of a 29-layer structure that includes six convolutions, seven ReLUs, six normalizations, four maximum pools, three fully connected layers, and a softmax layer. The COVIDetNet architecture, whose properties such as the number of layers, kernel, stride, and padding sizes were determined experimentally, are shown in Table 1 and its architecture in Figure 4.

In the literature, fc layers of pretrained CNN models have been used for deep feature extraction. However, in the current paper, convolution layer features are also combined with the fc layers. For this, the ensemble average of the features obtained from each of the six convolution layers was taken. Suppose the visual data in a convolution layer output is \(W \times H \times C\); this process can be described by Equations (7)–(9):

\[D = \text{Conv}(\cdot, \cdot, k) \quad k = 1, 2, 3, ..., C,\] (7)
where $W \times H$ and $C$ represent the size of the learned visual features and the number of channels, respectively.

\[ \text{feature}_k = \frac{\sum_{i=1}^{W} \sum_{j=1}^{H} D(i,j)}{W \times H}, \quad (8) \]

\[ \text{feature} = [\text{feature}_1, \text{feature}_2, ..., \text{feature}_c], \quad (9) \]

2.4 | Relief feature selection

The Relief algorithm, was presented by Kira and Rendell.\(^{45}\) It is designed to enable feature selection. Feature selections are depended on the $k$ nearest neighbor algorithm\(^{46}\); this algorithm estimates the quality of the attributes according to the best separation between properties whose values are close to each other.\(^{47}\) For this

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**TABLE 1** COVIDetNet architecture

| Layer                                      | Filter size | Kernel size | Stride size | Output size       |
|--------------------------------------------|-------------|-------------|-------------|-------------------|
| Input image                                | -           | -           | -           | $100 \times 100 \times 3$ |
| Convolution-1                              | $3 \times 3$| 64          | 1           | $100 \times 100 \times 64$ |
| Batch normalization/ReLU/max pooling       | $2 \times 2$| -           | 2           | $50 \times 50 \times 64$ |
| Convolution-2                              | $5 \times 5$| 64          | 2           | $25 \times 25 \times 64$ |
| Batch normalization/ReLU/max pooling       | $2 \times 2$| -           | 2           | $12 \times 12 \times 64$ |
| Convolution-3                              | $3 \times 3$| 32          | 1           | $12 \times 12 \times 32$ |
| Max pooling/batch normalization            | $2 \times 2$| -           | 2           | $6 \times 6 \times 32$ |
| Max pooling                               | $2 \times 2$| -           | 2           | $3 \times 3 \times 32$ |
| Convolution-4                              | $2 \times 2$| 32          | 2           | $2 \times 2 \times 32$ |
| Batch normalization/ReLU                   | -           | -           | -           | $2 \times 2 \times 32$ |
| Convolution-5                              | $3 \times 3$| 16          | 2           | $1 \times 1 \times 16$ |
| Batch normalization/ReLU                   | -           | -           | -           | $1 \times 1 \times 16$ |
| Convolution-6                              | $3 \times 3$| 16          | 2           | $1 \times 1 \times 16$ |
| Batch normalization/ReLU                   | -           | -           | -           | $1 \times 1 \times 16$ |
| Fully connected/ReLU                       | -           | -           | -           | $1 \times 1 \times 500$ |
| Fully connected/ReLU                       | -           | -           | -           | $1 \times 1 \times 350$ |
| Fully connected                            | -           | -           | -           | $1 \times 1 \times 3$ |
goal, the method calculates an index of interest for each feature. Then, according to the calculated index value, it gives a positive weight value (+1 best) to attributes that are close to one another, while a negative weight value (−1 is the worst) is applied to other attributes. Thus, a multivariate Relief filter is created that sorts attributes according to their index interest level. The two-class Relief algorithm and feature selection steps are given below:

Step 1: The initial weight (IW) of each attribute (A) is selected as 0 (IW[A] = 0).

Step 2: The R random sample is taken from the feature set.

Step 3: The distances between Ri and the rest of the features are calculated using Equation (9), while same class examples (hits-Ht) and other class examples (misses-Ms) are found.

\[
\text{diff}(A, I_1, I_2) = \frac{|\text{value}(A, I_1) - \text{value}(A, I_2)|}{\max(A) - \min(A)}. \tag{10}
\]

Step 4: The W[A] value is updated via Equation (10) above:

\[
\text{IW}[A] = \text{IW}(A) - \frac{\text{diff}(A, R_t, Ht)}{r} + \frac{\text{diff}(A, R_t, Ms)}{r}, \tag{11}
\]

where \(I_1\) and \(I_2\) are the selected features, while \(r\) represents the number of random training samples required to update IW. Steps 3 and 4 are repeated for each feature. Thus, using the calculated IW [A] values, the desired number of features are selected from all features.

### 2.5 Support vector machine

SVM is a supervised machine learning model based on statistical learning theory. The SVM method generally finds the separating hyperplane between two or more classes with the maximum margin. Suppose we have a dataset \(\{x_i, y_i\;|\;i = 1, 2, ..., M\}\) with a class label of \{-1, +1\} that consists of \(M\) instances. Accordingly, the optimum hyperplane is shown in Equation (12):

\[
\begin{align*}
\mathbf{w} \cdot x_i + b &\geq 1 \quad \text{for } y_i = +1, \\
\mathbf{w} \cdot x_i + b &\leq -1 \quad \text{for } y_i = -1,
\end{align*} \tag{12}
\]

where \(\mathbf{w}\) and \(b\) symbolize the hyperplane's weight vector and the trend value, respectively. The weight vector, \(\mathbf{w}\), must be at a minimum to maximize the optimum hyperplane boundary. In this case, determining the optimal hyperplane requires the solution of the limited optimization problem via Equation (13) below:

\[
\min \left[ \frac{1}{2} ||\mathbf{w}||^2 \right] \quad \text{for } y_i \cdot (\mathbf{w} \cdot x_i + b) - 1 \geq 0. \tag{13}
\]

When the data to be classified is not linearly separable, a kernel function is used, thus providing a better separation of data. Accordingly, the optimum hyperplane can be shown by Equation (14):

\[
\min_{\mathbf{w}, \zeta_i} \frac{1}{2} ||\mathbf{w}||^2 + C \sum_{i=1}^{M} \zeta_i, \quad y_i \left[ \mathbf{w}^T \varphi(x_i) + b \right] \geq 1 - \zeta_i, \quad \zeta_i \geq 0, \tag{14}
\]

where, \(\varphi(\cdot)\), \(C\), and \(\zeta_i\) represent the mapping function, the regularization parameter, and the slack variable, respectively. Additionally, the lower the value of \(C\), the lower the restriction and the greater the probability of plane fitting. The above Equation (14) is difficult to solve, since it is in a nonconvex form. Therefore, the optimization problem is converted to a dual form with the Lagrange multiplier's equality constraint. The Lagrange function is given by Equation (15):

\[
L(a) = \sum_{i=1}^{M} a_i + \frac{1}{2} \sum_{i,j=1}^{M} a_i a_j y_i y_j (x_i, x_j) \quad \text{for } 0 \leq a_i \leq C, \tag{15}
\]

subject to:

\[
\sum_{i=1}^{M} a_i y_i = 0, \tag{16}
\]

where, \(a_i\) represent the Lagrange multipliers. Thus, the SVM decision function in kernel space is shown by Equation (17):

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{M} a_i y_i \kappa(x_i, x) + b \right), \tag{17}
\]

in which \(\kappa(\cdot)\) represents kernel function.

### 3 EXPERIMENTAL WORKS

The present section includes criteria for evaluating experimental studies, experimental configurations used in learning and optimization, experiments performed, and related results.
3.1 Performance evaluation criteria

The accuracy (Acc), sensitivity (Sen), specificity (Spe), precision (Pre), and F-score metrics are used for the performance analysis of the proposed method. These metrics were computed using Equations (18)–(22).

\[
\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \times 100, \quad (18)
\]

\[
\text{Sen} = \frac{TP}{TP + FN} \times 100, \quad (19)
\]

\[
\text{Spe} = \frac{TN}{TN + FP} \times 100, \quad (20)
\]

\[
\text{Pre} = \frac{TP}{TP + FP} \times 100, \quad (21)
\]

\[
F1 \text{ score} = 2 \times \frac{\text{Pre} \times \text{Sen}}{\text{Pre} + \text{Sen}} \times 100, \quad (22)
\]

by which true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) cases are represented.

3.2 Experimental works and results

The experimental works were implemented with MATLAB 2020b on a workstation with an Intel® Core™ i7-4700HQ processor, 16 GB of memory, and a 4 GB graphics card. For experimental works, the dataset was resized to 100 × 100 in accordance with the COVIDetNet input. Also, the dataset was randomly divided into 80% training and 20% testing.

This study selected the optimization of learnable parameters, momentum stochastic gradient descent algorithm, and a learning rate of 0.0001 for all CNN models used in experimental studies. In addition, the validation frequency was selected as 30, maximum period 10, iteration 262 per period, and mini-batch size 8. The SVM classifier's parameters were computed using the one-versus-all method, and the cubic kernel function. The SVM parameter C was searched in the \((10^{-3}, 10^3)\) range, the kernel scale value was set to automatic, and the box constraint level was set to 1. The 10-fold cross-validation approach was also applied.

In the first experiment, the end-to-end CNN architecture from scratch was trained with x-ray images, and deep features were extracted. The proposed COVIDetNet architecture achieved a validation accuracy score of 98.47% after 2620 iterations in 4 min 19 s as seen in Figure 5.

Then, using the same dataset and same training parameters, feature extraction durations of AlexNet, VGG16, VGG19, ResNet50, ResNet100, and MobileNetV2 CNN models are given in Table 2. In addition, the performance criteria result of all CNN models are detailed in Table 2.

According to the results shown in Table 2, the proposed CNN model performed feature extraction in a short
The best feature extraction times of the other known methods are seen in AlexNet and MobilNetV2 models with 1421 s and 2865 s, respectively. In addition, considering the feature extraction durations in Table 4, the proposed CNN structure is about sixfold faster than the AlexNet structure and obtained the best accuracy of 98.47%. It is also 38 fold faster than the VGG19 model, with the longest feature extraction time of 9970 s.

The confusion matrix of the four models with the quickest feature extraction durations is given in Figure 6.

| CNN model   | Time (s) | Acc   | Sen  | Spe  | Pre  | F1 score |
|-------------|----------|-------|------|------|------|----------|
| AlexNet     | 1421     | 98.08 | 97.31| 98.53| 98.74| 97.98    |
| VGG16       | 8644     | 94.47 | 96.86| 97.63| 93.33| 94.65    |
| VGG19       | 9970     | 92.94 | 89.91| 94.51| 95.48| 91.96    |
| ResNet50    | 5219     | 96.76 | 97.62| 98.39| 95.99| 96.73    |
| ResNet101   | 8325     | 97.52 | 98.59| 98.94| 96.64| 97.51    |
| MobileNetV2 | 2865     | 96.18 | 97.48| 98.22| 95.23| 96.20    |
| Proposed    | 259      | 98.47 | 98.06| 98.91| 98.76| 98.40    |

Note: Bold values shows the performance results where the proposed method is superior to the existing methods.
The confusion matrix and Table 2 results in ResNet50, proposed lightweight CNN for the COVID-19 class, and AlexNet, our model for healthy (normal) class, respectively, have high performance. In these models, MobilNetV2 96.18%, ResNet50 96.76%, AlexNet 98.08%, and the proposed CNN 98.47% accuracy rates were obtained for all three classes.

Convolution and fully connected layers were used for feature extraction with the proposed CNN (see Section 2.4). Thus, 64, 64, 32, 32, 16, 16, 500, and 350 features were extracted from Conv1, Conv2, Conv3, Conv4, Conv5, Conv6, and the fc1 and fc2 layers, respectively. Next, all of the features were concatenated. The deep features obtained were classified using SVM. The experiment’s confusion matrix and receiver operating characteristic (ROC) curve are shown in Figure 7.

As seen in Figure 7, accuracy scores of 97.40%, 99.00%, and 100.00% were obtained for the COVID-19, normal, and pneumonia classes, respectively. The mean accuracy score achieved in all three classes was 98.90%.

Efficient features were selected from 1074 features concatenated with the Relief algorithm. In the experiments with Relief, features in the range of (20, 30) were chosen, according to the one-step-size method; this range and step size were determined experimentally. Next, the performance of each chosen feature vector was calculated with SVM. Performance results of selected features with the Relief algorithm are given in Table 3.

In Table 3, the F scores and precision, specificity, sensitivity, and accuracy scores of the features chosen by the Relief algorithm are detailed. The Relief algorithm’s
The maximum accuracy score was 99.24%, which was attained with 25 and 26 Relief features. Additionally, the second-highest accuracy, 99.05%, was obtained from 23, 24, and 27 Relief features. Using 25 features instead of the 1074 features obtained from the proposed CNN model, the classification performance was increased, and the classification duration was reduced. The confusion matrix and ROC curve of 25 Relief features of the proposed COVIDetNet model are given in Figure 8.

As seen in Figure 8, the normal, COVID-19, and pneumonia samples were identified with 97.5%, 99.7%, and 100% accuracy, respectively. An average score of 99.24% was achieved across the three classes. In addition, with fewer features, such as 25, the classification accuracy was increased by 0.34%. The results in Table 3 and Figure 8 show that the accuracy score is improved with fewer features.

In order to more effectively demonstrate the performance of the proposed method, the Conv1, Conv2, Conv3, Conv4, Conv5, fc7, and fc8 layers of the AlexNet model were combined by taking 96, 256, 384, 384, 256, 4096, and 4096 features, respectively, in feature extraction from popular CNN structures. Then, efficient features were selected among 9568 features combined with the embossing algorithm. Finally, the performance of each selected feature vector was calculated with SVM. The performance results of the features selected by the Relief algorithm are given in Table 4.

### Table 4: Performance results of effective features with prelearned AlexNet deep features Relief algorithm (%)

| Selected feature with Relief | Acc  | Sen  | Spe  | Pre  | F1 score |
|------------------------------|------|------|------|------|----------|
| 1000                         | 97.52| 97.52| 98.50| 97.35| 97.44    |
| 1500                         | 98.28| 98.49| 99.05| 97.99| 98.23    |
| 2000                         | 98.47| 98.60| 99.13| 98.26| 98.43    |
| 2500                         | 98.66| 98.88| 99.23| 98.38| 98.63    |
| 3000                         | 98.66| 98.88| 99.28| 98.38| 98.63    |
| 4000                         | 98.66| 98.88| 99.28| 98.38| 98.63    |
| 5000                         | 98.66| 98.88| 99.28| 98.38| 98.63    |
| 6000                         | 98.66| 98.88| 99.28| 98.38| 98.63    |
| 7000                         | 98.66| 98.88| 99.28| 98.38| 98.63    |
| 7500                         | 98.47| 98.78| 99.20| 98.11| 98.43    |
accuracy score was 98.66%, attained with 2500–7000 Relief features. While the results in Tables 3 and 4 are compared, the highest accuracy is obtained with 25 features in the proposed method, 2500 features are needed in the AlexNet model. In addition to the classification performances, it is seen in Table 5 that the proposed method is faster than the AlexNet model in the feature extraction and effective features selection process.

As seen in Table 5, the proposed CoviDetNet model can detect COVID-19 cases in a total of 287 s (approximately 3 min), 259 s for feature extraction and 28 s for selecting effective features. The same operations can be performed for a total of 1668 s (approximately 28 min) with the widely used AlexNet model. In addition, the proposed COVIDetNet method has a 0.58% higher accuracy rate than the AlexNet model.

### 4 | DISCUSSION

Controlling the rapidly spreading COVID-19 cases can only be possible by rapidly detecting infected people. However, with the PT-PCR tests used for case detection, it results in a minimum of 5 h. For this reason, deep learning-based methods have been developed to obtain fast and highly accurate results under pandemic conditions. Some state-of-the-art methods compared the proposed CoviDetNet model performance results shown in Table 6. Two and three-class studies are included in the comparisons. The COVIDetNet model proposed in Table 4 and Figure 6 achieved a higher accuracy score than the latest model methods. Using DarkCovidNet for COVID-19 detection using CXR, Ozturk et al. achieved 98.08% accuracy in binary classification. However, they reached 87.02% in three classifications. In the three-class studies conducted in 2020, Turkoglu, Ucar et al., Wang et al., and Nour et al. achieved an accuracy score of 98.97%.

In studies conducted in 2021, Hussain et al. achieved 99.10% accuracy in binary classification but reached a 94.20% accuracy rate in three classifications in a similar dataset. Cengil and Çınar detected COVID-19 by combining the features obtained based on transfer learning in AlexNet, Xception, NASNetLarge, and EfficientNet-B0 models. The AlexNet + NASNetLarge and NASNetLarge + Xception approaches achieved 96.0% and 97.60% accuracy rates. In addition, these two methods reached this accuracy score in 3791 and 4485 s, respectively. Barua et al. used a hybrid model called COVID-19FcINet9. The fully connected layer of AlexNet, VGG16, and VGG19 CNN models were used to extract deep features using a combined structure. Effective features received in the iterative feature selection algorithm were classified by SVM. Experimental studies used two different datasets, and they achieved an accuracy of 89.6% and 98.84%, respectively. Our study achieved a higher classification performance than existing studies, as shown in Table 6. This confirms that our proposed model is correct and robust.

As seen in Table 6, there is no standard data set for detecting COVID-19 cases. Researchers combined different datasets for studies. For this reason, it may not be correct to say that the studies carried out are utterly superior to each other. Considering this situation, while comparing the methods in Table 6, the number of classes and dataset sizes are also given.

### 5 | CONCLUSION

COVID-19 seriously affects public health, the global economy, and social life worldwide. Despite the ongoing vaccination programs for the past year, the number of people affected by COVID-19 has increased significantly. Due to this increase in cases, the death toll also increased. Therefore, more effective diagnostic methods are needed to assist clinical studies on COVID-19. For this purpose, a fast and robust model based on the light CNN approach is proposed to detect COVID-19 cases from CXR images. A scratch-trained architecture is used in the proposed CNN instead of pretrained models such as ResNet and AlexNet. Deep features were automatically extracted from fully connected and convolution layers in the proposed CNN architecture. The most efficient features among the deep features were selected and classified by SVM with the Relief approach. For the performance analysis of the model, 2621 CXR images obtained from a publicly available dataset were used. The experimental results of the proposed COVIDetNet model are shown below:
| Research works/year | Method | Type/number of class | Number of cases | Results | Acc (%) | Sen (%) | Spe (%) | Pre (%) | FI | Time duration (s) |
|---------------------|--------|---------------------|----------------|---------|---------|---------|---------|---------|----|------------------|
| Ozturk et al.\(^{23}\)/2020 | DarkCovidNet | CXR 2 | COVID-19: 125  
No findings: 500 | 98.08 | 95.13 | 95.30 | 98.03 | 0.9651 | - | |
| | | CXR 3 | COVID-19: 125  
Pneumonia: 500  
No findings: 500 | 87.02 | 85.35 | 92.18 | 89.96 | 0.8737 | - | |
| Turkoglu\(^{24}\)/2020 | COVIDetectioNet | CXR 3 | COVID-19: 219  
Pneumonia: 4290  
Normal: 1583 | 99.18 | 99.13 | - | 99.48 | 0.9930 | - | |
| Ucar et al.\(^{27}\)/2020 | COVIDiagnosis-Net | CXR 3 | COVID-19: 1536  
Pneumonia: 1536  
Normal: 1536 | 98.26 | 99.13 | - | - | 0.9825 | - | |
| Wang et al.\(^{28}\)/2020 | COVID-Net | CXR 3 | COVID-19: 13870  
Pneumonia: 5538  
Normal: 8066 | 93.3 | - | - | - | - | - | |
| Nour et al.\(^{29}\)/2020 | A novel CNN model + SVM | CXR 3 | COVID-19: 219  
Pneumonia: 1345  
Normal: 1345 | 98.97 | 89.39 | 99.75 | - | 0.9672 | - | |
| Proposed | COVIDetNet | CXR 3 | COVID-19: 500  
Pneumonia: 580  
Normal: 1541 | **99.24** | 99.39 | 99.60 | 99.04 | 0.9921 | 287 | |
| Hussain et al.\(^{31}\)/2021 | CoroDet | CXR 2 | COVID-19: 500  
Normal: 800 | 99.10 | - | - | - | - | - | |
| | | CXR 3 | COVID-19: 500  
Pneumonia: 800  
Normal: 800 | 94.20 | - | - | - | - | - | |
| Cengil and Çınar\(^{11}\)/2021 | AlexNet + NASNetLarge | CXR 3 | COVID-19: 1525  
Pneumonia: 1525  
No Findings: 1525 | 96.00 | 98.10 | 98.50 | 98.10 | - | 3791 | |
| | NASNetLarge + Xception | CXR 3 | COVID-19: 1525  
Pneumonia: 1525  
No Findings: 1525 | 97.60 | 99.00 | 99.20 | 99.00 | - | 4485 | |
| Murugan and Goel\(^{34}\)/2021 | E-DiCoNet | CXR 3 | COVID-19: 900  
Pneumonia: 900  
Normal: 900 | 94.07 | 98.15 | 91.48 | 98.15 | 0.9122 | - | |
| Barua et al.\(^{35}\)/2021 | COVID-19FclNet9 | CXR 3 | COVID-19: 125 | 89.96 | - | - | - | - | - | |
The proposed CNN model is three times faster than the best AlexNet model in feature extraction.
Classification accuracy rates were increased by 0.43% and 0.77%, respectively, with the SVM and SVM + Relief algorithms.
In all evaluation criteria, 99.24% accuracy, 99.60% specificity, 99.39% sensitivity, 99.04% acuity, and 99.21% F1 score were obtained.
Studies on COVID-19 case diagnoses have generally focused on accuracy scores. However, it is also crucial to know how long this diagnosis will take in addition to the accuracy score. The proposed CoviDetNet model can diagnose COVID-19 cases in 287 s.

The proposed model can significantly contribute to radiologists and field experts regarding low-capacity hardware and faster decision-making during intense COVID-19 cases. In future works, more refined models will be constituted with big datasets containing many CXR images.

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CONFLICT OF INTEREST
The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are publicly accessible at https://www.kaggle.com/datasets/bachrr/covid-chest-xray, https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia, and available in Reference 29.

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