POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)

Performance analysis of combination of cnn-based models with adaboost algorithm to diagnose covid-19 disease

Covid-19 hastalığının teşhisi için cnn-tabanlı modeller ile adaboost algoritmasının kombinasyonunun performans analizi

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To cite to this article: Darıcı, M., B., "Performance analysis of combination of cnn-based models with adaboost algorithm to diagnose covid-19 disease", ***Journal of Polytechnic***, 26(1): 179-190, (2023).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Darıcı, M., B., "Performance analysis of combination of cnn-based models with adaboost algorithm to diagnose covid-19 disease", ***Politeknik Dergisi***, 26(1): 179-190, (2023).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.901375

Performance Analysis of Combination of CNN-based Models with Adaboost Algorithm to Diagnose Covid-19 Disease

Highlights

- *CNN-based models combined with Adaboost algorithm to avoid manual feature extraction process.*
- *SMOTE method was applied on just the training set to balance the number of images.*
- *The effect of some hyperparameters on the classification performance of Adaboost was investigated.*

Graphical Abstract

In this study, Chest X-ray images labeled as Covid-19, Normal and Viral Pneumonia were classified using two different proposed models, the effect of some parameters on these models was investigated.

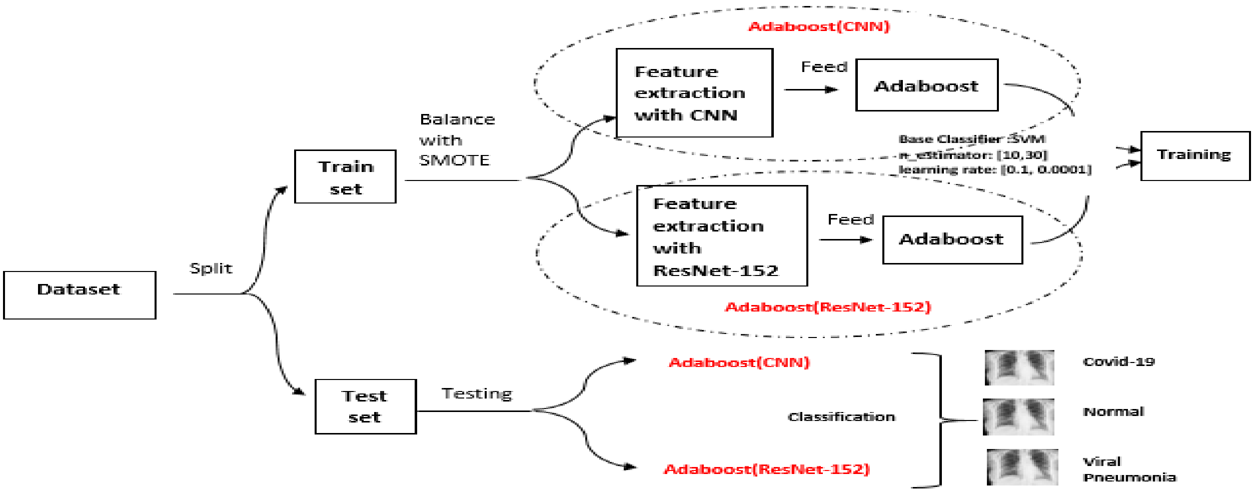

Figure. Steps of the classification process.

Aim

The aim of this study is to propose a different classification model which combines CNN-based models with the Adaboost algorithm.

Design & Methodology

In this study, the effect of some parameters on the classification performance of two different proposed models, named Adaboost(CNN) and Adaboost(ResNet-152), was investigated.

Originality

This paper proposes two different fast and automatic CNN-based feature extraction techniques to use in the Adaboost algorithm for classification. These classification models called as Adaboost(CNN) and Adaboost(ResNet-152). Also, this study explores classification performances of the Adaboost algorithm using different parameters.

Findings

Experimental results show that when the number of estimators is 25 and the learning rate is 0.1, both proposed models give the best average accuracy results, which are 0.945 for Adaboost(CNN) and 0.89 for Adaboost(ResNet-152). Our proposed CNN as an automatic feature extraction technique for chest X-ray images is better than ResNet-152.

Conclusion

Automatically extracted features using the proposed CNN give better results for the Adaboost algorithm. The Adaboost algorithm can provide very high accuracy results in diagnosing the diseases, including Covid-19 from the chest X-ray images with the automatically extracted features. Results show that the combination of different types of CNN-based models with the Adaboost algorithm can be used to classify medical images.

Declaration of Ethical Standards

The author(s) of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Performance Analysis of Combination of CNN-based Models with Adaboost Algorithm to Diagnose Covid-19 Disease

Araştırma Makalesi / Research Article

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(Geliş/Received : 02.04.2021 ; Kabul/Accepted : 23.09.2021 ; Erken Görünüm/Early View : 23.10.021)

ABSTRACT

At the end of 2019, Covid-19, which is a new form of Coronavirus, has spread widely all over the world. With the increasing daily cases of this disease, fast, reliable, and automatic detection systems have been more crucial. Therefore, this study proposes a new technique that combines the machine learning algorithm of Adaboost with Convolutional Neural Networks (CNN) to classify Chest X-Ray images. Basic CNN algorithm and pretrained ResNet-152 have been used separately to obtain features of the Adaboost algorithm from Chest X-Ray images. Several learning rates and the number of estimators have been used to compare these two different feature extraction methods on the Adaboost algorithm. These techniques have been applied to the dataset, which contains Chest X-Ray images labeled as Normal, Viral Pneumonia, and Covid-19. Since the used dataset is unbalanced between classes SMOTE method has been used to make the number of images of classes balance. This study shows that proposed CNN as a feature extractor on the Adaboost algorithm(learning rate of 0.1 and 25 estimators) provides higher classification performance with 94.5% accuracy, 93% precision, 94% recall, and 93% F1-score.

Keywords: Adaboost, automatic feature extraction, cnn, resnet-152, smote.

Covid-19 Hastalığının Teşhisi için CNN Tabanlı Modeller ile Adaboost Algoritmasının Kombinasyonunun Performans Analizi

ÖZ

2019 yılı sonunda yeni bir Coronavirüs formu olan Covid-19 tüm dünyada hızlı bir şekilde yayıldı. Bu hastalığın artan günlük vakaları ile hızlı, güvenilir ve otomatik tespit sistemlerine olan ihtiyaç arttı. Bu nedenle, bu çalışma, göğüs kafesi röntgen görüntülerini sınıflandırmak için makine öğrenmesi algoritmalarından biri olan Adaboost algoritması ile Evrişimsel Sinir Ağları'nı (CNN) birleştiren yeni bir teknik önermektedir. Adaboost algoritmasının eğitim için ihtiyaç duyduğu özellikler temel CNN algoritması ve önceden eğitilmiş ResNet-152 ile göğüs kafesi röntgen görüntülerinden ayrı ayrı elde edilmiştir. Adaboost algoritmasında bu iki farklı özellik çıkarma yöntemini karşılaştırmak için farklı öğrenme oranı değerleri ve tahmin sayısı kullanılmıştır. Bu teknikler, Normal, Viral Zatürre ve Covid-19 olarak etiketlenmiş göğüs röntgeni görüntülerini içeren veri setinde uygulanmıştır. Kullanılan veri seti sınıflar arasında dengesiz olduğundan, sınıfların görüntü sayısını dengelemek için SMOTE yöntemi kullanılmıştır. Bu çalışma, Adaboost algoritmasında otomatik özellik çıkarıcı olarak kullanılan, önerilen CNN modelin (öğrenme oranı 0.1 ve tahminci sayısı 25) % 94.5 doğruluk,% 93 kesinlik,% 94 duyarlılık ve % 93 F1 skoru değerleri ile daha yüksek sınıflandırma performansı sağladığını göstermektedir.

Anahtar Kelimeler: Adaboost, otomatik özellik çıkarma, cnn, resnet-152, smote.

1. INTRODUCTION

The new disease, which was first seen in Wuhan, China, in December 2019, started to threaten the whole world over time [1]. This disease which is caused by the SARS-CoV-2 virus has been named coronavirus disease (Covid-19). For confirmed COVID - 19 cases, common complaints reported include fever, cough, muscle pain, or fatigue. However, these symptoms are not unique features of COVID - 19 because they are like the flu symptoms of other viral diseases is similar [2]. According to the statistics of the European Centre for Disease Prevention and Control, coronavirus disease affected 71,554,018 people and caused 1,613,671 deaths since 31 December 2019 and as of week 2020-50. While in some cases, this disease can progress with mild symptoms. It can also cause severe pneumonia—inflammation of the air sacs in the lungs. Pneumonia is usually caused by bacteria or viruses [3]. Patients with Covid-19 symptoms are tested for the diagnosis of the disease. However, it may take a few days to get results from these tests (RT-PCR). This can lead to fatal consequences, especially for patients with severe symptoms.

The other way of diagnosis this disease is to use some imaging techniques such as Chest radiography (X-ray),

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magnetic resonance imaging (MRI), and computed tomography (CT). Since Chest X-Ray, a cheap and fast technique, makes the patients receive less radiation dose than the other imaging techniques, it is a more preferred method used for diagnosis the viral diseases [5]. Chest X-Rays are also used in the diagnosis of pneumonia. Finding the source of this disease in patients with symptoms of pneumonia can help diagnose Covid-19 disease. However, the diagnosis of this disease from the chest is a difficult task even for expert radiologists. It can take time. Moreover, expert knowledge and experiences are required to understand the cause of pneumonia and to diagnose Covid-19 disease from Chest X-ray [4]. Generally, it is not quite easy to reach experts to understand whether pneumonia is caused by corona or bacteria because of the increasing number of cases per day and the insufficient number of experts. Therefore, it is immediately needed an approved and safe treatment that can affect SARS-CoV-2, which is the cause of the Covid-19 disease, to decrease the number of cases and death rate also to end the pandemic [3]. For this reason, an automatic and fast system is needed for the early diagnosis of this disease.

In unusual situations such as the Covid-19 pandemic, the need for hospitals and doctors is increasing. Hospital capacity, number of doctors, etc., may be insufficient because of the increasing number of cases.

In recent years, terms such as Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are so popular. With developing technologies, imaging techniques, and the increasing number of open-access datasets, these methods are being used a lot in many fields. Since the need for fast and reliable automated systems that provide early diagnosis, these methods are also widely used in the field of health. And a lot of work is done on this, tried to obtain intelligent systems with high accuracy.

In [6], Gang W. et al. proposed some machine learning algorithms to diagnose prostate cancer in a Chinese population. They have used four different machine learning models such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Least Squares Support Vector Machine (LS-SVM), and Random Forest (RF). They evaluated their all models on the dataset which consists of 1625 Chinese men with prostate biopsies from Hong Kong hospital.

Akalin et al. determined the absence of heart disease in their study using some popular algorithms such as Gaussian Bayes, K-Nearest Neighbor, and Random Forest with and without feature scaling. They obtained 80.52% accuracy with the K-Nearest Neighbor algorithm, 80.52% with Gaussian Bayes, and 82.50% with Random Forest using the dataset provided by the University of Cleveland [7].

There are also some studies about the classification of images obtained using several imaging techniques such as CT, X-ray to diagnose pneumonia or Covid-19. These studies are generally based on binary classification (Pneumonia/Healthy, Covid-19/Healthy). For example, in [4], Narin et al. used five different pre-trained CNN models to make three different binary classifications on Chest X-ray images. They created three different datasets from their all data, and their binary classes are Covid-19/Normal, Covid-19/Viral Pneumonia, and Covid-19/Bacterial Pneumonia, respectively. They proposed ResNet-50 among all pre-trained models since it gave the highest accuracies for all binary classes.

Similarly, there are some studies [8, 9, 10] in the literature with the same purpose of classification of radiographic images using machine learning and deep learning models. It is possible to increase these samples. There are also some studies conducted to make multi-class classification [11, 12, 13, 14]. These studies use different types of CNN models and transfer learning approaches to classify their X-Ray images as Covid-19, normal, pneumonia. For example, in [11], Sevi et al. used four different deep learning models such as CNN, VGG16, VGG19, Inception-V3, and they compared their results obtained from these different models. Similarly, Ioannis et al. [12] trained their VGG19 model to classify their Chest X-Ray dataset.

These studies show that machine learning and deep learning techniques can be very useful in medicine. These proposed methods can decrease diagnostic time and provide fast and accurate systems for diagnosing diseases.

This study provides some models which classify Chest X-Ray images into three different classes (Bacterial Pneumonia, Covid-19, Normal). It was aimed to obtain highly accurate results with CNN-based feature extractors on Adaboost algorithm to diagnose Covid-19.

2. BAGGING and BOOSTING ALGORITHMS

Ensemble learning is an effective and adopted technique that combines different learning algorithms to achieve improved performance of the overall model [16]. There are some different Ensemble Learning methods such as Bagging, Boosting, etc.

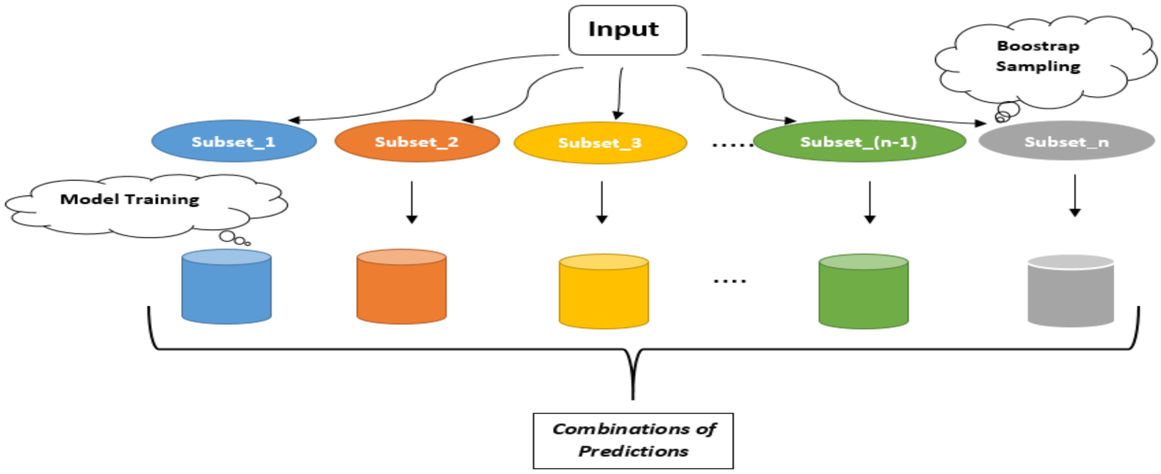

Figure 1. Bagging Algorithm

2.1. Bagging Algorithm

Bagging, which has been proposed by Breiman [17], stands for bootstrap aggregating. Bagging aims to increase accuracy and regression estimation by combining predictive results of models trained on randomly distributed training sets. In the Bagging method, samples of each subset of the original dataset are selected with replacement. That means after selecting samples of the first subset randomly, these samples are placed into the original set, then samples of the second subset are randomly chosen again from this original set. In short, each sample has an equal chance to be included in chosen training subset [18]. Then, each subset is trained with the designated classifiers. Predictions of each model, which work independently, are combined at the end to obtain better results. The main working principle of the Bagging method is shown in Figure 1.

2.2. Boosting Algorithm (Adaboost)

Boosting, which is another Ensemble Learning technique, combines weak classifiers, predictors to obtain a stronger classifier [19]. Adaboost, which is the short form of "adaptive boosting", was presented first by Freund ve Schapire [15] in 1997. Adaboost is the most used boosting method. The main concept of the Adaboost algorithm is to add more weights to misclassified samples. So, the incorrectly classified sample is intended to be classified correctly in the next step [20]. The working principle of Adaboost is listed below:

- In the beginning, equal weights are given to each sample of original data.
  Number of training instances: N
  Weights of each sample : $\frac{1}{N}$ (1)
- Training samples are trained on classifiers, and the total error of the model is calculated as:

$\sum$(weights of incorrectly classified samples) (2)

- Performance of base classifier is calculated:

Performance = $\frac{1}{2}\,ln\,\frac{(1-Total\ Error)}{Total\ Error}$ (3)

- New weights for misclassified samples:
  Sample weight$\times e^{Performance}$ (4)
- New weights for correctly classified samples:
  Sample weight$\times e^{-Performance}$ (5)

Updating the weights using the above formulas allows reducing the weight of correctly classified samples while increasing the weight of incorrectly classified samples.

- Then using these updated weights, the new dataset is created dependent on the value of weights. When selecting new samples, weights with higher values have more chance to be included in the new dataset. Also, the same sample could be included in the new data more than once.
- After all, the same steps are repeated for the new dataset [21].

In the end, it is obtained a model which is sensitive to the misclassified samples of the previous model. It is possible to use some different base estimators/weak classifiers in Adaboost. Also, the steps above are repeated until the algorithm reaches the determined number of estimators. So it is important to determine the appropriate number of estimators to achieve higher results.

After the algorithm reaches the determined number of estimator, the voting method is generally used to obtain final predictions of samples. Main concept of Adaboost algorithm can be seen in Figure 2.

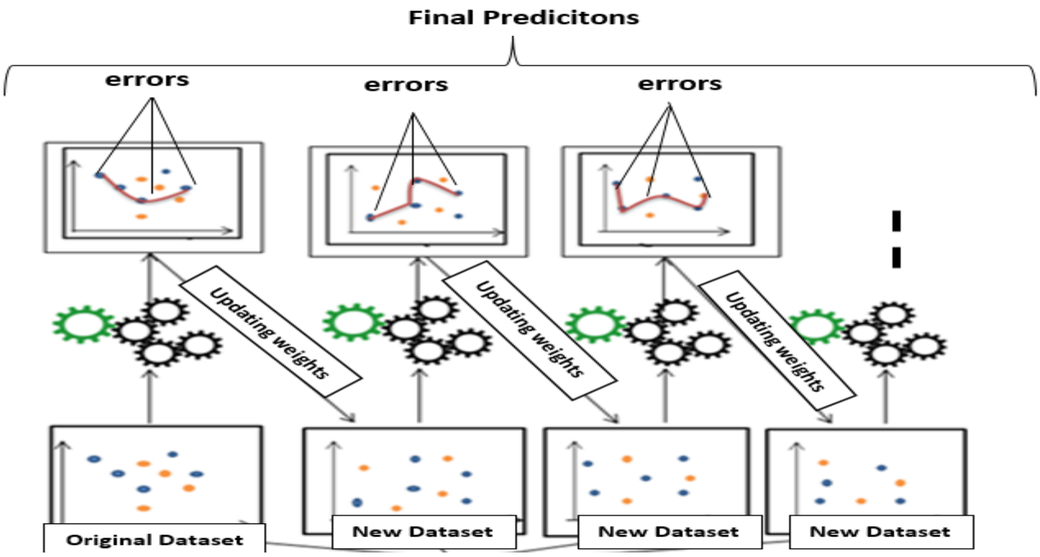

Figure 2. Adaboost Algorithm

3. MATERIALS and METHODS

The main purpose of this study is to make a multi-class classification of Chest X-Ray images using the Adaboost algorithm. Since it is needed to feed the Adaboost algorithm with features of these images, automatic feature extraction methods with CNN and ResNet-152 have been used. The effects of these CNN-based automatic feature extractors on the Adaboost algorithm have been investigated using several hyperparameters such as learning rate and the number of iterations.

3.1. The Dataset

In this study, the dataset [22], which consists of Chest X-Ray images, has been used. This dataset is a collection of the different datasets from different studies [23, 24]. In the dataset[1] , there are 1341 normal/healthy X-Rays, 1345 virus pneumonia X-Rays, and 219 Covid-19 X-Rays. Since collaborators still continue to update the dataset, it is possible to have the different number of images for each label at different times.

There are 2905 images in total, each of which is different in size. Normally the dataset has an unbalance distribution over classes. The number of images in each class was balanced with the Synthetic Minority Over-sampling Technique (SMOTE) to prevent the inclination towards the class that has majority during the training. SMOTE method is an over-sampling approach in which the minority class is oversampled by creating "synthetic" examples to make the image distribution in classes balanced. The algorithm developed by Chawla et al. in 2002 [25] has been applied to a lot of unbalanced dataset problems. It differs from the other sampling techniques since it creates synthetic samples instead of copying minority class data. It is listed the steps of how the algorithm creates synthetic samples [25]:

- Step 1: k-nearest neighbors (kNN) of each sample in the minority class are calculated.
- Step 2: It is taken the difference between the sample and its kNN.
- Step 3: This difference is multiplied by a random number which is chosen between [0,1].
- Step 4: Obtained result from Step 3 is added to the original sample, and the new sample is obtained.
- Step 5: Step 1, 2, 3, 4 are repeated until reach the balanced dataset.

Before applying SMOTE method, the original dataset is splitted into training and testing. 80% of the original dataset has been used in training and 20% of them in testing. After splitting the data as training and testing, SMOTE method is just applied to samples in the training set. The result of usage SMOTE method after splitting instead of before splitting is to have a reliable model. Since some similar samples have been obtained with SMOTE method, it was aimed to prevent that similar samples are in both training and the testing set. Because if one of the similar samples exists in training and the other one is in testing, the model could easily classify this sample since it saw that sample in training

[1] https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

The distributions of the number of samples for each class before and after SMOTE method can be seen in Table 1 and 2, respectively.

Table 1. The number of images in classes before SMOTE method.

	Classes		
Subset	*Covid-19*	*Viral Pneumonia*	*Normal*
Train	173	1076	1075
Test	46	269	266

Table 2. The number of images in classes after SMOTE method.

	Classes		
Subset	*Covid-19*	*Viral Pneumonia*	*Normal*
Train	1076	1076	1076
Test	46	269	266

As seen in Table 2, the number of images in all classes in the training set became equal after the SMOTE method. In this study, since images in the dataset are in different sizes, all RGB images in train and test sets were resized to 112× 112 pixel size. In Figure 3, one sample for each class (Covid-19, Normal, Viral Pneumonia) in the used dataset is given.

(a) (b) (c)

Figure 3. Chest X-Ray samples; (a) Covid-19, (b) Normal, (c) Viral Pneumonia.

3.2. Classification with Adaboost(CNN)

In this part of the study, the first proposed method is considered to classify Chest X-Ray images. Adaboost method, which is one of the Ensemble Learning techniques, has been used as a classifier. This Adaboost algorithm needs some features to be able to make a classification. Feature extraction is a difficult and time-consuming process in machine learning applications. For successful feature extraction, the properties of the images and labels must be well known. However, when we look at Figure 3, it can be said that the features that distinguish between the classes of X-Ray images even visually are absent. Visual disease diagnosis in medical images is a difficult task even for those who are experts in the field. Therefore, for the first part, convolutional neural network (CNN) has been used as a feature extractor. This first proposed method has been called Adaboost(CNN) in this study. Before the Adaboost algorithm as a classifier, in Figure 4, the steps of CNN as a feature extractor are presented. As seen in Figure 4 below, the inputs of the model are Chest X-Ray images that were resized to 112x112x3 pixel size. In this model, there are five convolution layers. The convolution layer is also known as the feature extraction layer because the property of the given image in the network is extracted in this layer.

In this model, each convolution layers consist of a convolution process, an activation function of ReLU and a max-pooling layer. The different number of filters has been used for each convolution layer. For example, for the first convolution layer, the convolution process is applied with 16 filters of 3x3 size to the input. The number of steps for sliding filters on input is set to 1. This number of steps is called stride. Also, zero padding has been used to control the size of output at the end of the convolution process. By zero padding, the border of the inputs is filled by zeros. After convolution, ReLU has been used as an activation function and max-pooling to create new features by selecting maximum values in filters. For each convolution process, the stride is 1, the filter size is 3x3, the numbers of filters are 16, 32, 64, 128, 256, respectively. Also, zero-padding has been used for these convolution processes. After using ReLU activation function for each convolution layer, max-pooling layer has been used with 2x2 filters, and 2 in the stride to decrease the size of feature maps without affecting the depth size. These parameters for each layer affect the size of output at the end of the processes. The size of each feature map can be seen in Figure 4.

After the last convolution layer, flattening has been applied to the output. Flattening converts the multi-dimensional feature map to one-dimensional feature vector. Finally, Fully Connected Layer (FC) has been used to fully connect each neuron of the one-dimensional feature vector with 1024 neurons.

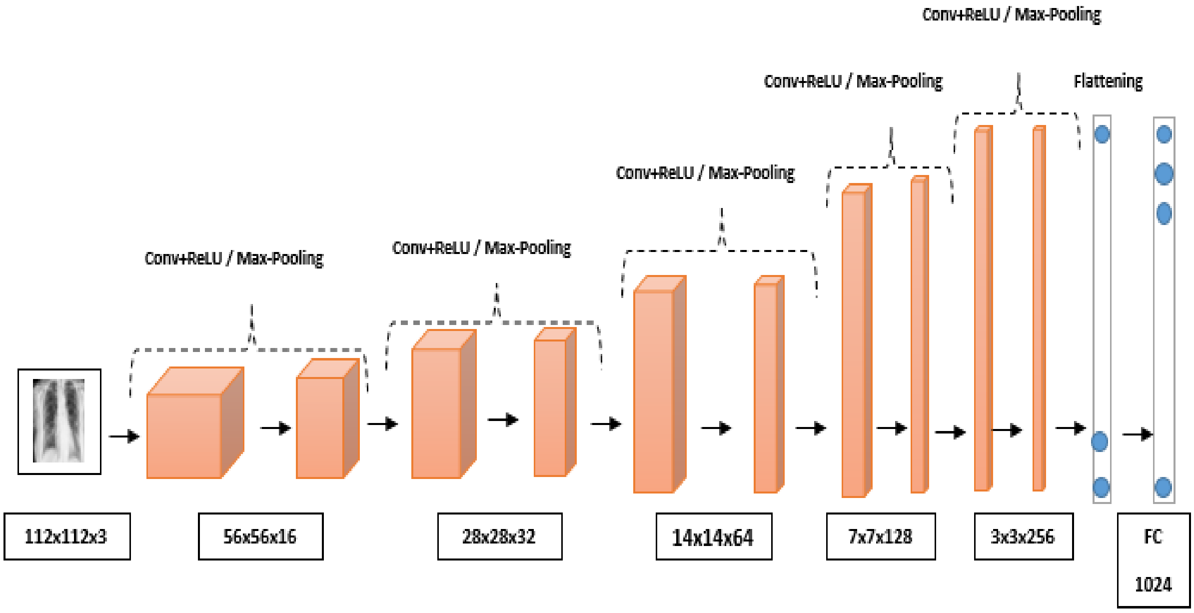

Figure 4. Feature extraction using CNN.

In the end, 1024 features have been obtained from the given input to be able to feed Adaboost algorithm. After obtaining features using CNN without classification part, Adaboost algorithm has been used for classification. As said earlier, Adaboost algorithm needs a weak/base classifier.

In this study, Support Vector Machine (SVM) is selected as a base classifier. SVM is a supervised learning method proposed by Cortes and Vapnik (1995) [26]. The main purpose of SVM is to define the hyperplane that can make the most appropriate distinction between classes. SVM tries to learn the class labels of a data set whose properties are specified, and then the classification performance of this model is tested with the unseen test data [27].

In Adaboost(CNN) model, which is the first proposed method of this study, the features of X-Ray images have been extracted using CNN, and the effect of the number of estimators and value of learning rate have been investigated. As mentioned earlier, Adaboost algorithm continues to make predictions iteratively until the number of iterations is reached. And learning rate, used in Adaboost algorithm, controls the contribution of each model to the ensemble prediction. So both parameters, which are the number of iterations and learning rate, are important in Adaboost to have better classification results.

In order to see the effect of these parameters on the classification, the number of estimators of the algorithm was changed between 10 and 30, while the learning rate value took values between 0.1 and 0.0001. For each iteration number and learning rate, the performance of the model whose features come from CNN is noted

The main concept of Adaboost(CNN) is summarized in Figure 5.

Figure 5. Classification steps of Adaboost(CNN)

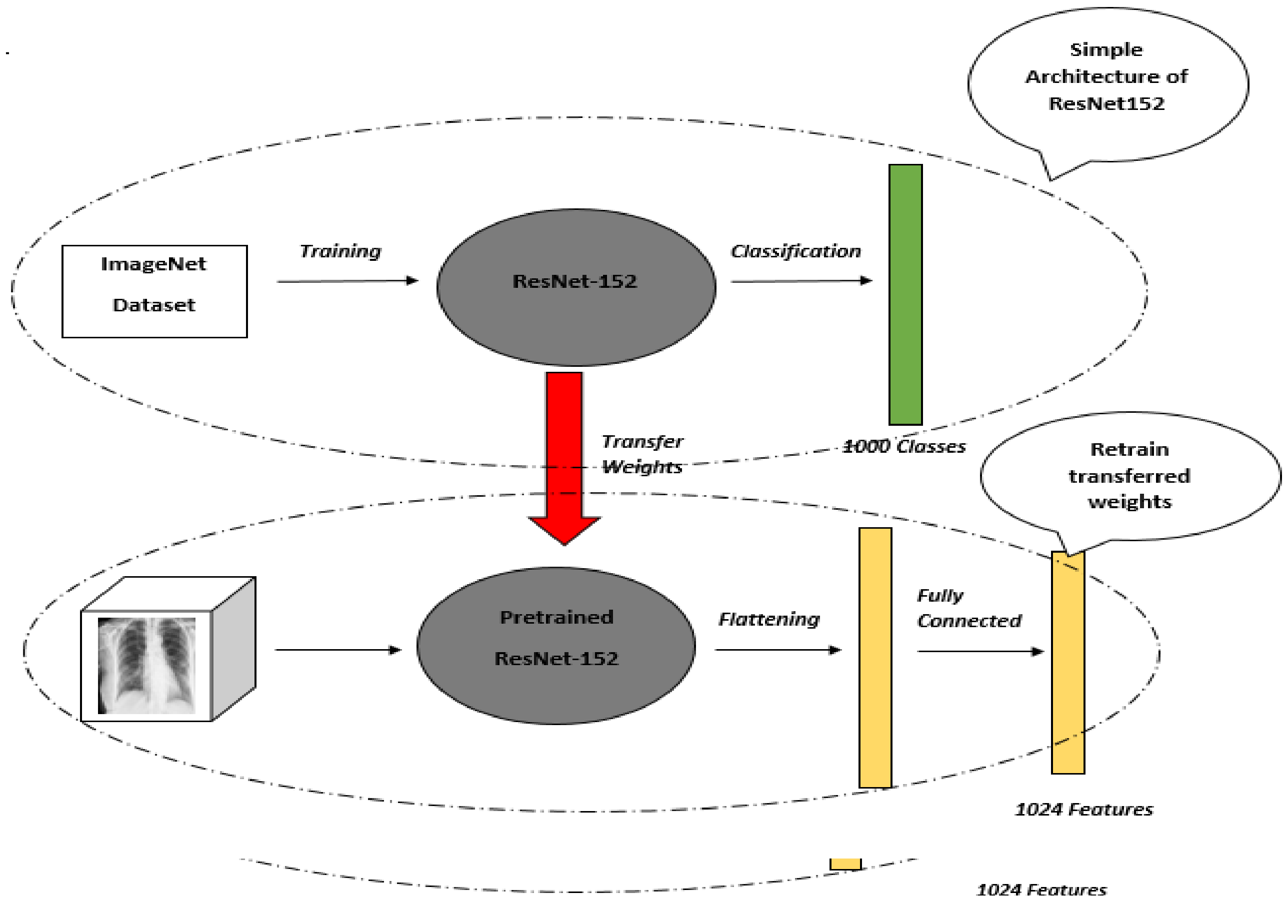

Figure 6. Feature extraction using pretrained ResNet-152.

3.3. Classification with Adaboost(ResNet-152)

In the second proposed method, the feature extraction step has been done by ResNet-152 model using transfer learning, differently from Adaboost(CNN) method in Section 3.2. Since feature extraction is done by ResNet-152 and classification by Adaboost algorithm, this proposed method is named Adaboost(ResNet-152).

In short, transfer learning is a situation in which machine learning methods reuse information obtained previously to solve a new task. Previously obtained weights, features are reused thanks to this transfer learning methodology which allows the shorten training time. Usually, the weights of a pre-trained model with a 1000-class ILSVRC 2012 ImageNet [28] dataset, which can take weeks to train on a normal computer, are transferred. The new model is retrained with the new dataset, and the last layer is changed to suit the problem [29]. ResNet architecture [30] is the best architecture of ILSVRC 2015 in image classification, localization, and detection. ResNet draws attention with its deep network structure and achievements. ResNet-152 is one of the ResNet architectures that is 152 layers deep. Using this architecture without transfer learning will take a long time because of its very deep structure. Therefore, in this study ResNet-152 has been used as a feature extractor using the transfer learning method. In this part, the last fully connected layers of the pretrained ResNet-152 model on ImageNet [28] dataset are extracted. The last feature map before the fully connected layer is flattened.

Instead of extracted fully connected layer, a fully connected layer with 1024 neurons has been used as a last layer to be able to have 1024 features like in Adaboost(CNN) model.

Using the weights of the pre-trained model and changing the last layer, the model has been retrained with the Chest X-Ray images we have. Steps of obtaining 1024 features from ResNet-152 architecture using transfer learning can be seen in Figure 6.

After obtaining 1024 features from Chest X-Ray images,

Adaboost algorithm has been fed with these features. As in Adaboost(CNN) method, the Adaboost algorithm has been used as a classifier in Adaboost(ResNet-152) method. SVM has been selected as a weak classifier in the Adaboost algorithm. Similar to Adaboost(CNN), the effect of the number of estimators and the value of learning rate have been investigated in Adaboost(ResNet-152), and the performance of the model whose features come from pretrained ResNet-152 is noted. In Figure 7, the main concept of Adaboost(ResNet-152) has been presented.

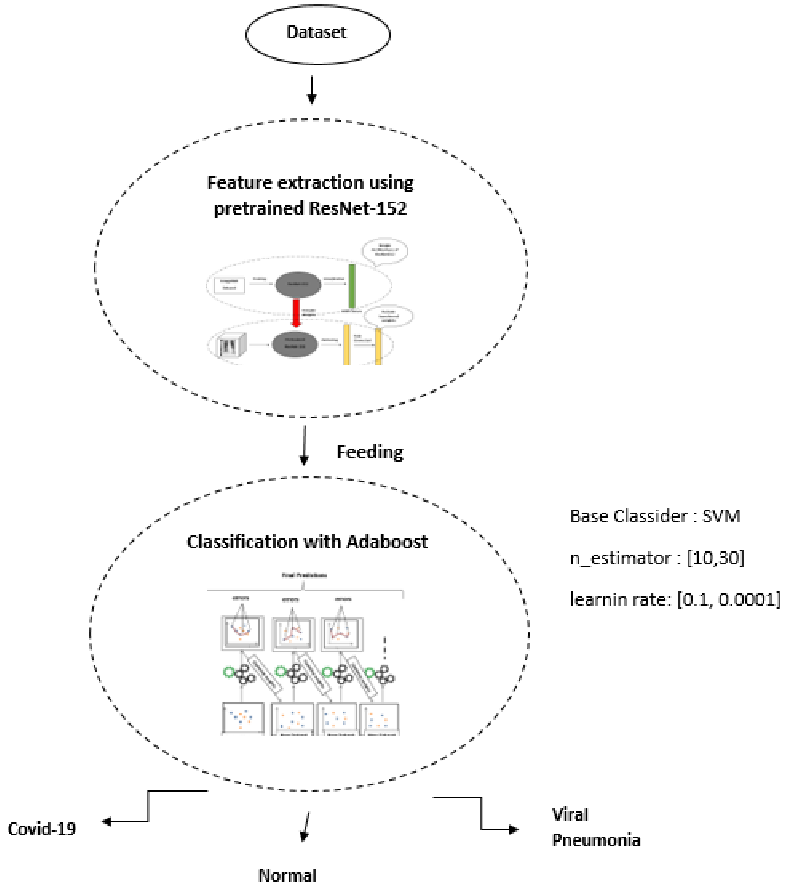

Figure 7 . Classification steps of Adaboost(ResNet-152)

4. RESULTS

4.1 Experimental Results

The classification performance of each proposed model in this study is evaluated by accuracy metric. Then precision, recall, and F1-score are calculated for the model which gives the best average accuracy result.

$$Accuracyclass_{\_x} = \frac{TP_{class\_x} + TN_{class\_x}}{TP_{class\_x} + TN_{class\_x} + FP_{class\_x} + FN_{class\_x}} \quad (6)$$

$$Precisionclass_{\_x} = \frac{TP_{class\_x}}{TP_{class\_x} + FP_{class\_x}} \quad (7)$$

$$Recallclass_{\_x} = \frac{TP_{class\_x}}{TP_{class\_x} + FN_{class\_x}} \quad (8)$$

$$F1\_scoreclass_{\_x} = \frac{Precision_{class\_x} \times Recall_{class\_x}}{Precision_{class\_x} + Recall_{class\_x}} \quad (9)$$

These metrics are calculated for each class in this study. In the formulas (6), (7), (8), and (9), $class_{\_x}$ stands for classes which are Covid-19, Normal and Viral Pneumonia. Accuracy is calculated by the ratio of the values we correctly estimate in the model to the total number of data. Precision shows how many of the values we predicted as Positive are actually Positive. Recall is a metric that shows how many of the values which we should predict as Positive predicted as Positive. And F1-score is the harmonic mean of precision and recall values. After calculating each metric for each class, each obtained result is divided by the number of classes, which is 3 in this study, to have average results. The detailed results can be seen in Table 3, Figure 8, Table 4, and Figure 9.

Table 3. Average accuracy results of Adaboost(CNN) for each learning rate and the number of estimator.

	Learning Rates			
Number of Estimators	0.1	0.01	0.001	0.0001
10	0.936	0.926	0.92	0.927
15	0.94	0.924	0.928	0.93
20	0.943	0.921	0.925	0.928
25	0.945	0.924	0.927	0.93
30	0.943	0.925	0.926	0.927

Covid-19	42	0	4
Normal	2	258	9
Viral Pneumonia	3	14	249
	Covid-19	Normal	Viral Pneumonia

Model / Metric	Precision	Recall	F1_score
Adaboost(CNN)	0.93	0.94	0.93

Figure 8. Confusion matrix of Adaboost(CNN); precision, recall, and F1_score values for the model has the best average accuracy

Table 4. Average accuracy results of Adaboost(ResNet-152) for each learning rate and the number of estimators.

	Learning Rates			
Number of Estimators	0.1	0.01	0.001	0.0001
10	0.80	0.602	0.592	0.588
15	0.867	0.612	0.58	0.575
20	0.871	0.592	0.58	0.58
25	0.89	0.597	0.581	0.60
30	0.884	0.61	0.59	0.58

Covid-19	37	4	5
Normal	10	251	8
Viral Pneumonia	9	31	226
	Covid-19	Normal	Viral Pneumonia

Model / Metric	Precision	Recall	F1_score
Adaboost(ResNet)	0.83	0.86	0.84

Figure 9. Confusion matrix of Adaboost(ResNet-152); precision, recall, and F1_score values for the model has the best average accuracy

In Table 3, the average accuracy results of Adaboost(CNN) model for each number of estimators and each learning rate value have been shown. Since Adaboost(CNN) gives the best average accuracy when the number of estimators is 25, and the learning rate is 0.1, confusion matrix and average precision, recall, and F1_score values for these parameters have been presented in Figure 8. As seen in Table 3 and Figure 8, the best average accuracy result of Adaboost(CNN) model is 0.945, and precision, recall, F1_score results are 0.93, 0.94, 0.93, respectively.

Similarly, in Table 4, the average accuracy results of Adaboost(ResNet-152) model for each number of estimators and each learning rate value have been shown. Since Adaboost(ResNet-152) gives the best average accuracy when the number of estimators is 25, and the learning rate is 0.1 similarly in Adaboost(CNN), confusion matrix and average precision, recall, and F1_score values for these parameters have been presented in Figure 9. As seen in Table 4 and Figure 9, the best average accuracy result of Adaboost(ResNet-152) model is 0.89, and precision, recall, F1_score results are 0.83, 0.86, 0.84, respectively.

As a summary in this study, the performance of the Adaboost algorithm, one of the Ensemble Learning models, has been investigated for classifying Chest X-Ray images.

The features of these images for each class, which are Covid-19, Normal and Viral Pneumonia, have been obtained using two different CNN-based algorithms. First of all, using CNN model, 1024 features were obtained to feed the Adaboost algorithm. This proposed model is named Adaboost(CNN). For the second model, ResNet-152 architecture used using transfer learning method to obtain 1024 features. Adaboost algorithm was fed with these features to classify images. This proposed model is called Adaboost(ResNet-152). To see the effect of parameters such as number of estimators and learning rate values on Adaboost, these values were exchanged at specified intervals for both proposed models, and average accuracy results were noted for each parameter. Precision, recall, and F1_score values were given based on parameters that gave the best accuracy results after obtaining average accuracies. Based on observations, at the specified interval, when the number of estimators is 25, and the learning rate is 0.1, both proposed models gave the best average accuracy results, which are 0.945 for Adaboost(CNN) and 0.89 for Adaboost(ResNet-152). If we compare these two proposed models, it is easily seen that Adaboost(CNN) is better than Adaboost(ResNet-152) model. Since parameters are the same for the best accuracies, we can also say that our proposed CNN is better at extracting features than ResNet-152 model used in this study.

4.2. Comparison

In this study, some additional experiments were conducted to see the effectiveness of the Adaboost classifier with CNN features. In this case, CNN and ResNet-152 models, used as feature extractors, were used as classifiers. To be able to make these models a classifier, a classification layer (softmax) has been added to the end of each model. For both new models, RMSProp optimizer (learning rate: 0.01) has been used. Additionally, for the training process of each model, the batch size and epoch were set to 32 and 20, respectively. In Table 5 below, obtained accuracy results can be seen

Table 5. Results of CNN models as feature extractors and classifiers.

Method	Result (Accuracy)
Adaboost(ResNet-152)	89%
Adaboost(CNN)	94.5%
CNN	83%
ResNet-152	70%

As seen in Table 5 above, it can be easily said that using CNN models as feature extractors with the Adaboost classification algorithm gives better classification results for the Covid-19 dataset.

Finally, to see the effectiveness of our proposed model, some comparisons were made with similar studies. The comparison table can be seen in Table 6 below.

Table 6. The comparison of the results of the proposed method with similar studies.

Study	Method	Result(Accuracy)
[11]	CNN/VGG16/VGG19/ Inception V3	85%, 93%, 95%, 48%
[14]	ResNet+Location Attention	86.7%
[13]	COVID-Net	92.4%
[12]	VGG-19	93.48%
This study	Adaboost(ResNet-152)	89%
This study	Adaboost(CNN)	94.5%

As seen in Table 6, the approach of using CNN as a feature extractor with the Adaboost classification algorithm can outperform the studies in the literature for Covid-19 diagnosis.

5. CONCLUSION

Diagnosis of diseases such as Covid-19 and pneumonia is crucial for human life. Diagnosis of these diseases can take a long time, and sometimes the wrong diagnosis can be made. For this, a machine learning algorithm is proposed in this study to classify these diseases in a short time with high accuracy. In this proposed algorithm, instead of manually extracting features, features are extracted automatically from Chest X-Ray images using two different CNN-based methods, which are the proposed CNN and pre-trained ResNet-152.

Since the used dataset has an unbalanced distribution over classes, which are Normal, Covid-19, and Viral Pneumonia, SMOTE method has been applied on the just training set to have a balanced set. Adaboost algorithm, one of the Ensemble Learning algorithms, was trained with automatically extracted features. This algorithm, whose results are examined with different parameters, gives outstanding results with an average accuracy rate of 0.945 for classifying Covid-19 and pneumonia, which are very difficult to diagnose even by experts from Chest X-Ray images. Results show that the Adaboost algorithm can give very high accuracy rates in diagnosing the disease from the Chest X-Ray images with the features that are automatically extracted from the proposed CNN. The combination of different types of CNN-based models with the Adaboost algorithm can be used to classify medical images.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Muazzez Buket Darıcı: Performed the experiments and analyse the results. Wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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