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CLASSIFICATION OF X-RAY AND CT IMAGES IN DIFFERENT COLOR SPACES USING ROBUST CNN

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Keywords
Convolutional Neural Network, Covid-19 Detection, CT and X-ray Chest Image, Pneumonia.

Abstract
Since deep learning models have been successfully used in many fields, they have been used to identify sick and healthy people in X-ray or Computed Tomography (CT) chest radiology images. In this study, Covid-19 and pneumonia classification is performed on both X-ray and CT images using the robust Convolutional Neural Network (CNN). BGR, HSV, and CIE LAB color space transformations are applied to X-ray and CT images to show that the model performs a successful classification independent of dataset characteristics. The binary classification accuracy rates of Covid-19 and pneumonia for X-ray images and CT images are 98.7% and 98.4%, 97.6% and 99.4%, respectively. Precision, Recall, Specificity, F1 score, and Mean Squared Error metrics are calculated for each X-ray and CT dataset. In addition, 5-fold cross-validation proved accuracy of the model. Although X-ray and CT chest radiology images are transformed into different color spaces, the proposed model performed a successful classification. Thus, even if the image characteristics of the radiology device brands change, the computer-based system will be able to make successful disease diagnoses at low cost where expert personnel are insufficient.

FARKLI RENK UZAYLARINDAKİ X-RAY VE BT GÖRÜNTÜLERİNİN GÜÇLÜ ESA İLE SINIFLANDIRILMASI

Anahtar Kelimeler
Evrişimli Sinir Ağı, Covid-19 Tespiti, BT and Röntgen Göğüs Görüntüsü, Zatürre.

Öz
Derin öğrenme modelleri birçok alanda başarıyla kullanıldığından beri, X-ray veya Bilgisayarlı Tomografi göğüs radyolojisi görüntülerinde hasta ve sağlıklı kişileri tanılamak için kullanılmaktadır. Bu çalışmada, güçlü Evrişimsel Sinir Ağı (ESA) kullanılarak hem X-ray hem de BT görüntüleri üzerinde Covid-19 ve zatürre hastalığı sınıflandırması gerçekleştirilmektedir. BGR, HSV ve CIE LAB renk uzayı dönüşümleri; modelin veri kümesi özelliklerinden bağımsız olarak başarılı bir sınıflandırma gerçekleştirdiğini göstermek için X-ray ve BT görüntülerine uygulanmıştır. Röntgen ve BT görüntülerinin için Covid-19 ve zatürre olmak üzere ikili sınıflandırma doğruluk oranları sırasıyla %98,7 ve %98,4, %97,6 ve %99,4'tür. Her X-ray ve BT veri seti için Kesinlik, Geri Çağırma, Özgüllük, F1 puanı ve Ortalama Karesel Hata metrikleri hesaplanmıştır. Ayrıca, 5 kat çapraz doğrulama modelin doğruluğunu kanıtlamıştır. X-ray ve BT göğüs radyolojisi görüntüleri farklı renk uzaylarına dönüştürülmesine rağmen, önerilen model başarılı bir sınıflandırma gerçekleştirmiştir. Böylece radyoloji cihazı markalarının görüntü özellikleri değişse bile bilgisayar tabanlı sistem, uzman personelin yetersiz olduğu yerlerde düşük maliyetle başarılı hastalık teşhisleri yapabilecektir.

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CLASSIFICATION OF X-RAY AND CT IMAGES IN DIFFERENT COLOR SPACES USING ROBUST CNN

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Highlights

- The robust CNN model classifies both X-ray and CT chest radiology images in different color spaces as Covid-19 or pneumonia disease.
- It can be used as an auxiliary expert system for diagnosis in regions where the number of patients is high, and the number of physicians is low.
- This model is suitable for different medical imaging devices in any hospital.

Graphical Abstract

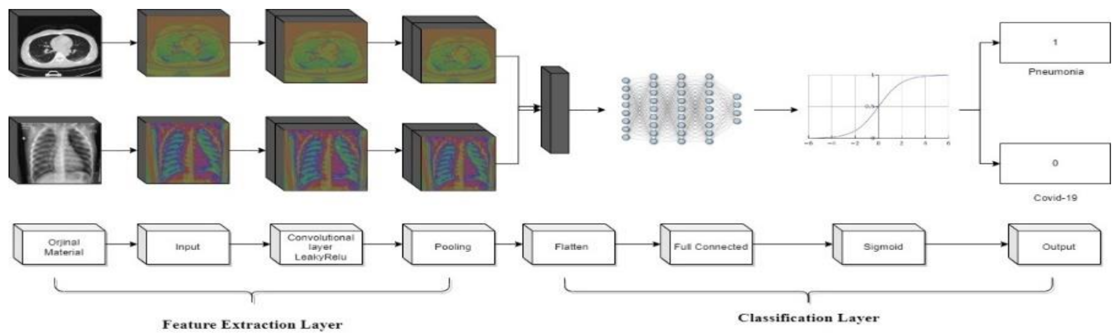

Figure. Architecture design of the proposed model.

Purpose and Scope

The motivation of this study is the rapid diagnosis of chest diseases with X-ray and CT images, the differences in features between X-ray and CT images, and different brands of imaging devices produce images with different image properties.

Design/methodology/approach

In this study, we aim to accurately classify four separate chest radiology image datasets created with different imaging techniques and color spaces with a single deep learning model CNN which has shown successful results in image-based applications. The success of this robust model is demonstrated by classifying both X-ray and CT chest radiology images as Covid-19 and pneumonia disease with a high success rate in BGR, HSV, and CIE LAB color spaces.

Findings

A low-cost computer-aided expert system is proposed according to the cost of RT-PCR testing. X-ray and CT image features can vary depending on the device model. In this study, original images, device-dependent BGR and HSV color space and device-independent CIE LAB color space transformations are performed, and it is shown that a model can perform successful classification using CNN even if the device feature and color space change.

Originality

The robust model with well-chosen learning rate, batch size, and epoch number produces better results than a combined model. Moreover, the model proposed in this study outperforms other works in the literature as it can achieve good results for both X-ray and CT images in different color spaces. The success of the study motivates the following study. It is aimed to realize a mobile application with a CNN-based transfer learning algorithm. Thus, a user-friendly system will be created with successful classification.

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1. Introduction

Covid-19 virus emerged in 2019 as a new strain of severe acute respiratory syndrome (SARS). The highly contagious Covid-19 virus has spread rapidly among humans, causing many deaths (COVID Live, 2023). Diagnosis of the Covid-19 virus is often confused with pneumonia because of symptoms such as chest pain, shortness of breath, cough, and inflammation of the lung lobes (Toğaçar et al., 2009). Although medical images are used in the diagnosis of Covid-19 virus, the Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) test is accepted as the first (Yan et al., 2020). Reasons such as the lack of a high success rate of the RT-PCR test method, the time required for the test result, the supply of test kits, and the inability to evaluate the test kits in every hospital have led researchers to different diagnosis studies. Scientists propose various deep learning models to support doctors in the diagnosis and treatment of Covid-19 and pneumonia (Bozkurt, F. 2022; Mishra et al., 2020; Islam et al., 2020; Serener and Serte, 2020; Foysal et al., 2020; Polsinelli et al., 2020; Nayak et al., 2021). As seen in these studies, imaging techniques such as X-ray and Computer Tomography (CT), which are currently used in hospitals, have a complementary role in the diagnosis of lung diseases. X-ray imaging uses tiny doses of ionizing radiation to create a black-and-white image. CT is an imaging method that uses special x-ray beams to create detailed pictures or scans of areas inside the body. It scans the relevant parts of the body in more detail than the X-ray imaging technique, creating a detailed and layered picture.

In this study, we aim to accurately classify four separate chest radiology image datasets created with different imaging techniques and color spaces with a single deep learning model Convolutional Neural Network (CNN) which has shown successful results in image-based applications (Taşdelen and Sen, 2021; Somuncu and Aydın Atasoy, 2021; Banerjee et al., 2022; Gilanie et al., 2021). The success of this robust model is demonstrated by classifying both X-ray and CT chest radiology images as Covid-19 and pneumonia disease with a high success rate in BGR, HSV, and CIE LAB color spaces. Thus, a low-cost expert system is proposed with a robust model independent of dataset differences, which saves the time needed to finalize the RT-PCR test for patients, reduces the cost spent on testing, and is independent of dataset differences. The contributions of this paper are as follows:

- With the proposed approach, a powerful model suitable for different medical imaging devices in hospitals is proposed.
- It can be used as an auxiliary expert system for diagnosis in areas with many patients and few doctors, as it successfully classifies Covid-19 and pneumonia disease using CNN despite different image features.
- Unlike similar works using the strengths of CNN architecture, classification is performed with a single network architecture on both X-ray and CT chest radiology images in different color spaces.

The following parts of the study are as follows: In Chapter 2, current literature studies on Covid-19 and pneumonia disease are examined. In Chapter 3, information about dataset properties, color spaces, and the CNN is given. In Chapter 4, the evaluation of the proposed model on the dataset and the success criteria of the model are examined. In Chapter 5, the results of the study are compared with other studies and future works are discussed.

2. Related Works

Deep learning algorithms are used in many fields, such as face recognition systems, the health sector (Kaya et al., 2019; Oğuz and Yağanoğlu, 2021; Aydin Atasoy, N., Faris Abdulla Al Rahhawi, A., 2024), voice recognition studies (Atasoy and Eltanashi, 2020), autonomous systems, image processing (Yıldız, 2019), prediction applications (Elhagaggagi, 2021), natural language processing, text, and character recognition studies (Somuncu and Aydın Atasoy, 2021), defense and security, object recognition, classification (Metin and Karasulu, 2021) and they produce successful results.

Polsinelli et al. (Polsinelli et al., 2020) propose a modified SqueezeNet model for detecting Covid-19 disease using a dataset (Yang et al., 2023) and Italian (COVID-19 DATABASE, 2023). They performed a study with Matlab Tools with nearly 2000 images in two different datasets. The modified model outperforms the plain SqueezeNet as it creates features better in the training phase. Hyperparameters are determined using a Bayesian approach. With the CNN-based modified model, an accuracy of 85.03% is achieved, and the classification time is sufficiently low. This study shows that CNN can analyze images even with limited hardware resources.

Nayak et al. (Nayak et al., 2021) propose a deep learning-based approach using X-ray chest images for early diagnosis of Covid-19 disease. They varied the parameters of batch size, learning rate, number of epochs, and type of optimizers to find the best model among AlexNet, VGG-16, GoogleNet, MobileNet-V2, SqueezeNet, ResNet-34, ResNet-50 and Inception-V3 deep learning models based on CNN architecture. Thus, they aim to realize an automatic system that classifies as Covid-19 or healthy. 286 images were used for training, and 120 images were used for testing. Among these models, ResNet-34 showed the best performance with a 98.33% accuracy rate.

However, according to the classification success of deep learning models, the dataset of this study needs to be bigger. Therefore, the success rates of the selected models are very close to each other.

Karim et al. (Karim et al., 2022) propose a computer-aided diagnosis system for Covid-19 disease detection. They combine CNN with Ant Lion Optimization Algorithm and Softmax, Support Vector Machines, K-Nearest Neighbours and Decision Tree, and Multiclass Naïve Bayes Classifier to classify lung X-ray images as sick and healthy. The study aims to determine the best classification algorithm compatible with CNN. They have used well-known datasets (COVID-19 Radiography Database, 2023; Cohen et al. 2020) for evaluating the performance of the proposed model. They have used AlexNet for data resize and feature extraction, Ant Lion Optimization Algorithm for feature selection, and Bayes Naïve classifier, which is the best model for classification. The accuracy, precision, and F1-score of the proposed model are respectively 98.31%, 100%, and 98.25%. Thus, they achieved very good classification performance. Similarly, Oğuz and Yağanoğlu (Oğuz Ç., Yağanoğlu M., 2022) propose a decision support system for Covid-19 disease diagnosis with Support Vector Machine (SVM), k Nearest Neighbor (kNN), Random Forest (RF), Decision Trees (DT), Naive Bayes (NB) classification methods after extracting features from 1345 CT images with different models such as ResNet-50, ResNet-101, AlexNet, Vgg-16, Vgg-19, GoogLeNet, SqueezeNet, Xception. While this system shortens the decision-making time of doctors, the best diagnosis model can be determined according to the success performances of different network models. Thus, unnecessary tests are prevented, and diagnosis is accelerated.

Thakur and Kumar (Thakur and Kumar,2021) performed binary classification (BC) and multi-classification (MC) with different CNN models using X-ray and CT images. They classified Covid-19 and healthy for BC and Covid-19, healthy and pneumonia for multi classification. BC accuracy rate was 99,64%, and multi-classification accuracy rate was 98.28%. For both models, they used Stochastic Gradient Descent (SGD) as the optimizer method and a fixed learning rate of 0.02. The authors stated that they converted the original input dataset to the grayscale image in the first pre-processing step. However, X-ray and CT images are grayscale according to the way they are generated (CT scan, 2023; X-Ray, 2023). The original dataset characteristics and the reason for this conversion are not specified in the study. Another study that cares about feature selection, Rahimzadeh et al. (Rahimzadeh et al., 2021) propose a computer-based diagnostic system to detect Covid-19 disease from CT images. They used 15589 Covid-19 images and 48260 healthy images of 282 healthy persons and 95 Covid-19 patients. To reduce the time and false detection process, they first detected the infected regions in CT images using the Grad-Cam algorithm. They performed BC for Covid-19 disease detection with ResNet50V2, Xception, and their proposed model. Their proposed model performed the best classification with a 98.49% accuracy rate. The study yields successful results Grad-Cam is a technique used in deep learning, especially with CNN, to understand which regions of an input image are important for the network's prediction of a particular class.

Unlike studies that emphasize feature extraction such as SGD and Grad-Cam algorithm, Islam et al. (Islam et al.,2020) preferred a model that can learn long-term dependencies within the network propose a model for detecting Covid-19 disease by combining CNN and Long Short-Term Memory (LSTM) models using X-ray images. They used 1525 X-ray datasets balanced as Covid-19, healthy, and pneumonia. In this study, CNN is used for deep feature extraction, and LSTM is used for classification using the extracted feature. The proposed model classifies lung X-ray images as Covid-19, pneumonia, and healthy. Accuracy, AUC, specificity, sensitivity, and F1-Score values of the proposed model are 99.4%, 99.9%, 99.2%, 99.3%, and 98.9%, respectively. In this study, it is seen that the success of LSTM and CNN has increased compared to studies that attach importance to feature extraction.

Serener et al. (Serener and Serte, 2020) aim to reduce the diagnostic difficulty of Covid-19, mycoplasma pneumonia and typical viral pneumonia diseases. They performed BC with seven different architectures: ResNet-50, ResNet-18, MobileNet-V2, VGG, SqueezeNet, AlexNet, and DenseNet-121. ResNet-18 and MobileNet-v2 showed the best performance results. The dataset consists of 325 original and 1005 enhanced 224x224 CT chest images. The classification success of these deep learning models is 89% for Mycoplasma Pneumonia and Covid-19 detection and 76% for Mycoplasma Pneumonia and Typical Viral Pneumonia detection. The study needed to achieve more success compared to other studies in the literature. Increasing the dataset too much and inadequate model training significantly affect the success of the model. Unlike Serener et al. (Serener and Serte, 2020), Bozkurt (Bozkurt,2021) obtained high accuracy as 97.17% using DenseNet121 model. This is because he implemented the DenseNet121 model architecture with the regularization effect of dense connectivity, considering its ability to reduce overlearning in training on not very large data.

As seen in the literature, many studies based on CNN have been successfully performed with small and large datasets using X-ray and CT chest images, and the success of the classification models is increased by combining several models. In this study, both X-ray and CT chest radiology images in different color spaces are classified as Covid-19 or pneumonia using single CNN architecture.

3. Material and Method

In this study, Covid-19 and pneumonia disease classification is performed with X-ray and CT chest radiology images indifferent color spaces using four different datasets. The procedures performed for a successful classification are shown in Figure 1, which shows the application steps for the successful classification of different chest radiology datasets from various imaging devices.

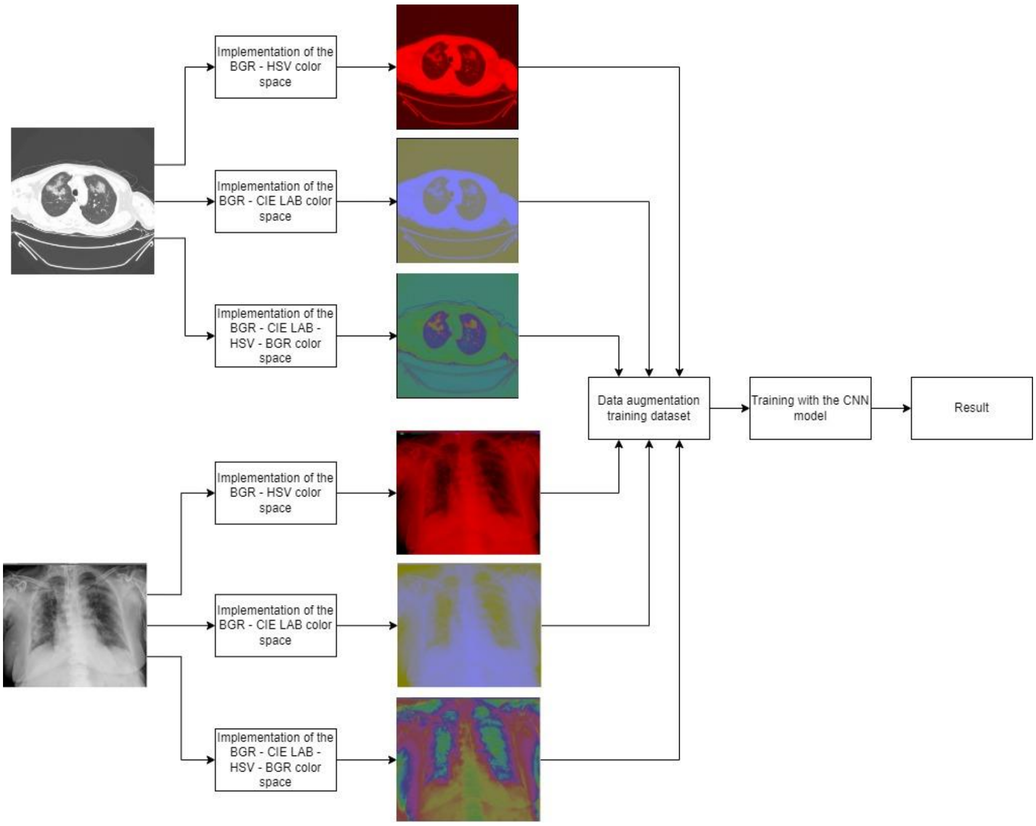


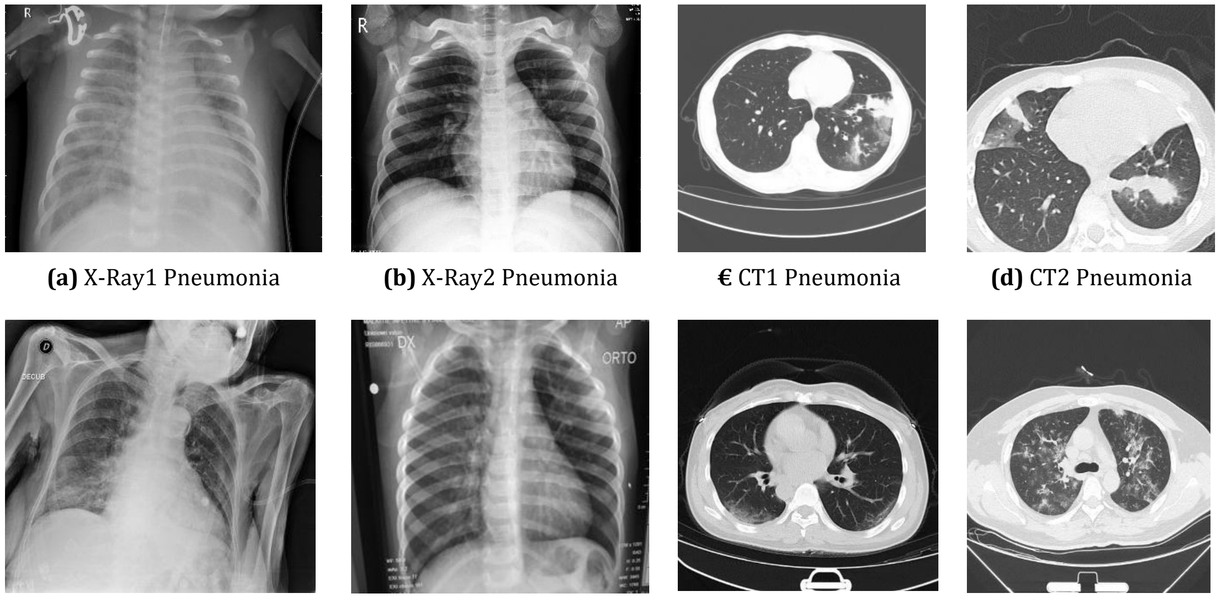
Figure 1. General scheme of the study

3.1. Dataset

This study is carried out with four different chest radiology datasets containing X-ray and CT images, as shown in Table 1. Due to the different image sizes in the datasets, all grayscale images are resized to 150 x 150 as the first pre-processing step. In Figure 2, sample images from the dataset are created by applying reflection, rotation, and scaling data augmentation operations.

Table 1. Dataset attributes

Dataset name	Covid-19 image count	Pneumonia image count	Original image dimensions
X-Ray1 (Chest X-ray, 2022)	576	4273	1982 x 1482, 2000 x 2000, 2563 x 1148, 951 x 727, 907 x 689
X-Ray2 (Pneumonia & COVID-19 Image Dataset, 2022)	980	4239	256 x 256, 331 x 331, 1980 x 2004, 1024 x 1024, 416 x 341
CT1 (COVID-19&Normal&Pneumonia_CT_Images, 2022)	2035	3390	512 x 512
CT2 (Yan, 2020; Yan, 2020)	41841	2700	512 x 512, 380 x 380



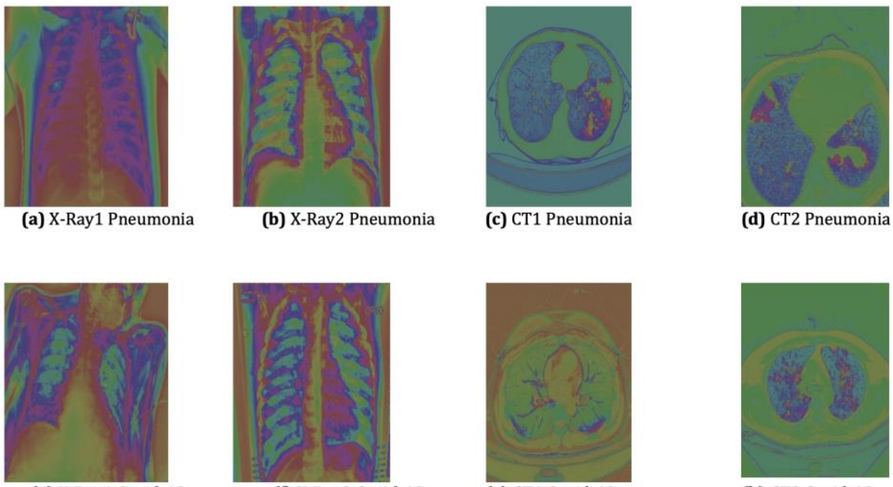
(a) X-Ray1 Pneumonia **(b)** X-Ray2 Pneumonia € CT1 Pneumonia **(d)** CT2 Pneumonia

(e) X-Ray1 Covid-19 **(f)** X-Ray2 Covid-19 **(g)** CT1 Covid-19 **(h)** CT2 Covid-19

Figure 2. Original chest radiology images from each dataset

X-ray images are created by coloring them according to the retention of X-rays by tissue as they pass through air and gas, soft tissue, adipose tissue, and bone in the body. In air-containing formations such as the lung, the lung tissue appears black due to the low intensity of the beam, while bone and soft tissues of the same thickness appear whiter. In CT images, tissues are colored white, black, and gray according to the Hounsfield scale. Grayscale is the intensity information of each pixel value representing some amount of light. Therefore, the input data are grayscale images. Although X-ray and CT images are widely used in the diagnosis of chest diseases, the level of lesion detection in X-ray images is lower than in CT images (Gürsoy et al.,2022). In CT images, the body is visualized in thin slices, and the x-ray uptake rates of the tissues are directly measured. However, since not all healthcare facilities have CT imaging devices, the same model is used in this study to classify both X-ray and CT radiology images. However, since not all healthcare facilities have CT imaging devices, the same model is used in this study to classify both X-ray and CT radiology images.

The original grayscale images of each dataset are first converted to BGR color space (OpenCV reads images as BGR image format by default) and then to BGR-HSV, BGR-CIE LAB, and BGR-CIE LAB- HSV-BGR, color spaces. The input dataset created by completing the color space transformations after the dimensioning pre-processing is shown in Figure 3.



(a) X-Ray1 Pneumonia **(b)** X-Ray2 Pneumonia **(c)** CT1 Pneumonia **(d)** CT2 Pneumonia

(e) X-Ray1 Covid-19 **(f)** X-Ray2 Covid-19 **(g)** CT1 Covid-19 **(h)** CT2 Covid-19

Figure 3. Sample input images with BGR-CIE LAB- HSV-BGR color space transformations for each dataset

The concept of color space emerged because of the need to group colors in a standard way due to the high color diversity in images. Color spaces are classified as device-dependent and device-independent (Bello-Cerezo et al., 2016). X-ray and CT image features may vary depending on the device model. In this study, original images, device-dependent BGR and HSV color space, and device-independent CIE LAB color space transformations are performed to show that a model performs successful classification even if the device feature and color space change.

3.2. Robust CNN Model

CNN, which is one of the most popular deep learning models used successfully in different problems (Liu et al., 2022; Steiniger et al., 2022), consists of three parts: convolution, pooling, and fully connected layers (Lecun et al.,2015). Since CNN produces successful results by detecting basic features with its layered structure, CNN is preferred in this study for classifying diseased chest radiology images.

An input layer, multiple hidden layers, and an output CNN, which is a multilayer artificial neural network consisting of two layers, basically includes two basic operations: convolution and pooling. CNN include hidden layers, convolutional layers, activation function layers, pooling layers, fully connected layers, and normalization layers. The convolution process using multiple filters can extract features (feature map) from the data set from which relevant spatial information can be preserved. The pooling, also called subsampling, is used to reduce the dimensionality of feature maps from the convolution process. Maximum pooling and average pooling are the most common pooling operations used in CNN.

Our proposed architecture is shown in the Table 2. The convolution layer size of our proposed model is set as 32, 64, 128, 128 and a kernel with a small size of 3x3 is used to avoid information loss. The activation function comes after the convolution layers and is also known as the activation layer. In this study, it is aimed to prevent the dead neuron problem by using the LeaklyRelu activation function. Pooling is usually placed after the activation layer. Its main purpose is to reduce the input size for the next convolution layer. The decrease in size because of this layer leads to information loss. Such loss is beneficial to the network for two reasons. First, it creates less computational overhead for subsequent network layers. Secondly, it prevents the system from memorizing. Just like the convolution process performed in the first step, certain filters are defined in the pooling layer. These filters are moved over the image according to a certain stepping value to achieve maximum pooling of the pixels in the image. The pooling process is performed for all images as many as the filters formed because of the convolution layer, and the pooling layer is optional in CNN. and the optimization function Adaptive Moment Estimation (Adam) are preferred to prevent the derivative from being zero for negative values. Because adaptive algorithms learn the learning rate by themselves and are dynamic. Since the learning rate affects the learning performance of the model, the choice of this hyperparameter is critical. Also, EarlyStopping is used to stop the model at the right time. In the fully connected layers, the dropout value in the connection layer of the proposed model is chosen as 0.4 since the dilution of nodes below a particular threshold value increases the performance. Sigmoid activation function is preferred in the output layer of the network because it is preferred both in binary classification (Covid-19 and pneumonia) and because it can easily update the threshold value. Sigmoid activation function was preferred in the output layer of the network because it is preferred both in binary classification (Covid-19 and pneumonia) and because it can easily update the threshold value.

Table 2. Architecture layer of proposed model

Layer Type	Filter Size	Number of Filter	Output Shape	Number of parameters to train
Input	-	64	150x150x3	0
Convolution	3x3	32	148x148x32	896
Leaky ReLU	-	-	148x148x32	0
Max Pooling	2x2	-	74x74x32	0
Dropout	-	-	74x74x32	0
Convolution	3x3	64	72x72x64	18496
Leaky ReLU	-	-	72x72x64	0
Max Pooling	2x2	-	36x36x64	0
Convolution	3x3	64	34x34x128	73856
Leaky ReLU	-	-	34x34x128	0
Max Pooling	2x2	-	17x17x128	0
Convolution	3x3	128	15x15x128	147584
Leaky ReLU	-	-	15x15x128	0
Max Pooling	2x2	-	7x7x128	0
Flatten			6272	0
Dense	-	-	256	1605888
ReLU	-	-	256	0
Dropout	-	-	256	0
Dense	-	-	2	514
Sigmoid	-	-	2	0
Total Parameters: 1847314				

4. Experimental Results

The computer and library information for which the model is designed are as follows: Intel Core i5-11600K 3.90 GHz CPU and Nvidia Geforce Gtx 1060 6GB Graphics Card, Spyder, TensorFlow, Keras, Numpy, Pandas, Matplotlib and OpenCV library is used for the conversion between color spaces.

X-Ray1, X-Ray2, CT1, and CT2 datasets are determined as 80% training and 20% as validation datasets. Figure 4 shows the graphs of the model accuracy and loss values for the best 35 epoch.

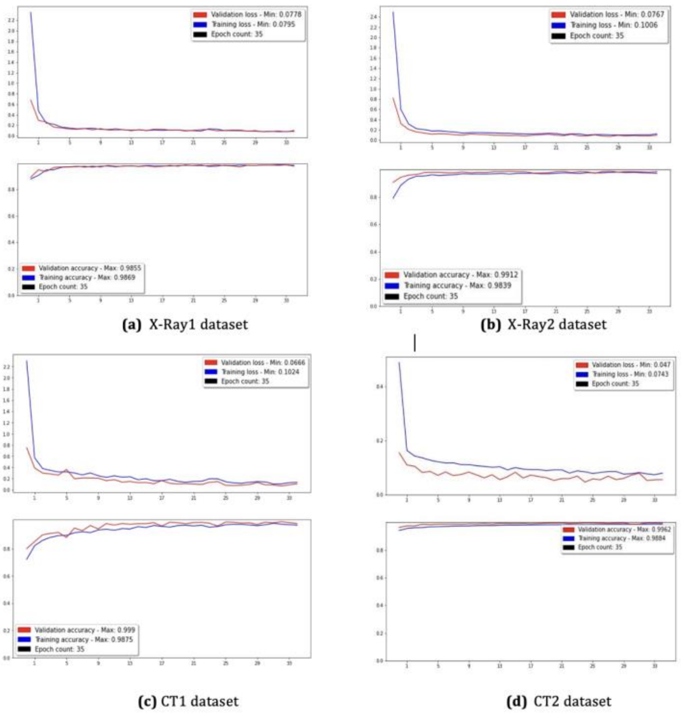


Figure 4. Model accuracy and loss graphics for every dataset

Accuracy value (Acc) is calculated using the formula in Equation 1. In the equation, the "True Positive (TP)" prediction is correct, and the feature is correct; The "True Negative (TN)" prediction is incorrect, but the feature is in the right place; "False Positive (FP)" means the prediction is correct but the feature is wrong, and "False Negative (FN)" is the prediction and feature are wrong.

$$Acc = \frac{TP+TF}{TP+\mathrm{TF}+\mathrm{FP}+FN} \qquad (1)$$

The performance of the proposed model in this study is measured using Recall (R), Precision (P), Specificity (S), and F1score metrics. The formulas for these metrics are given for class n in Equation 2 - 5.

$$P(n) = \frac{TP}{TP+FP} \qquad (2)$$

$$R(n) = \frac{TP}{TP+FN} \qquad (3)$$

$$S(n) = \frac{TN}{FP+TN} \qquad (4)$$

$$F1_{Score(n)} = 2 * \frac{P(n)*R(n)}{P(n)+R(n)} \qquad (5)$$

K-fold cross-validation allows us to see if the high performance of the model is random. This method shows both whether we are facing an overfitting problem and the quality of the model. A 5-fold cross-validation method is used to increase the validity of the created model, and the confusion matrices shown in Figure 5 are created for each dataset. As seen in Figure 6, the number of misclassified Covid-19 samples in the proposed model CT1 dataset is higher than that of pneumonia. The reason for this is that the only weakness of the CT image compared to the X-ray is the lack of anatomical integrity, as the images are cross-sectional.

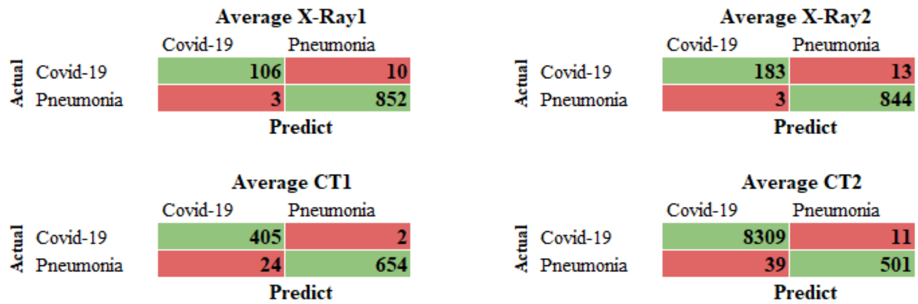


Figure 5. Confusion matrix for every dataset for 5-fold cross-validation

In addition, to observe the robustness of the model when subjected to noisy or exaggerated inputs, the Mean Squared Error (MSE) loss function value is calculated using Equation 6. MSE gives a loss value between 0 and infinity and allows the depreciation of the significant errors of the trained model by quadratic calculation. This is because smaller values indicate better accuracy. Model performance metrics for all datasets and MSE value calculated for all N samples are shown in Table 3.

$$MSE = \frac{1}{N}\sum_{i}^{N}(y_i^{real} - y_i^{predict})^2 \qquad (6)$$

Table 3. Average performance results of the 5-fold cross-validation for each dataset

	Acc	F1score(n)	P(n)	R(n)	S(n)	MSE
X-Ray1	0.987	0.993	0.972	0.914	0.996	0.013
X-Ray2	0.984	0.99	0.984	0.934	0.996	0.016
CT1	0.976	0.98	0,944	0.995	0.965	0.024
CT2	0.994	0.953	0.995	0.999	0.928	0.006

When Table 3 is analysed, the highest loss value is observed in the CT1 dataset. If the image in Figure 3 (g) is examined, it is seen that there is significant distortion in the image after the color space transformation. This is due to both the anatomy distortion due to the slice-by-slice rendering of the original CT image and the conversion of the grayscale image to another color space. However, when we look at the whole of Table 3, we see that successful results are obtained.

5. Result and Discussion

The comparison of the proposed model with other studies in the literature is shown in Table 4. Different architectures of the CNN network were used for the detection of Covid-19 and pneumonia diseases in X-ray and CT images. They proposed CNN-based ResNet-50, MobileNet-v2, VGG, AlexNet, and LSTM architectures for image feature extraction and classification, and the results were successful in many models using X-ray or CT images. Thakur and Kumar achieved a 98.28% success rate for multi-classification with both X-ray and CT data. The proposed model and Thakur and Kumar's model and dataset type selection were similar. However, Thakur and Kumar performed median filtering, normalization, and shuffling pre-processing steps to improve the dataset image quality. The authors used SGD as the optimization function and a constant learning rate of 0.02. In the model proposed in this study, the Adam function, whose optimization function is better than SGD, and adaptive determination of the learning rate are preferred. In addition, the model shows successful results even though X-ray and CT images are converted to other color spaces.

Table 4. Performance comparison with other studies in the literature

References	Method	Dataset	Acc
Toğacar et al. (Toğaçar et al., 2009)	AlexNet	X-ray	BC (Pneumonia and healthy): 94%
Nayak et al. (Nayak et al.,2009)	ResNet-50, ResNet-34, MobileNet-v2, VGG-16, SqueezeNet, AlexNet, Inception-V3, GoogleNet	X-ray	BC (Covid-19 and healthy): 98%
Foysal Haque et al.(Foysal Haque et al.,2020)	ResNet-50, InceptionV3, Inception-ResNetV2	X-ray	BC (Covid-19 and healthy): 97%
Islam et al.(Islam et al.,2020)	CNN-LSTM	X-ray	MC (Covid-19, pneumonia and healthy): 99.4%
Rahimzadeh et al. (Rahimzadeh et al.,2021)	Xception ResNet50V2	CT	BC (Covid-19 and healthy): 98.49%
Özturk et al. (Özturk et al., 2020)	DarkNet	X-ray	BC (Covid-19 and healthy): 98.08% BC (Covid-19, pneumonia and healthy): 87.02%
Thakur and Kumar (Thakur and Kumar, 2021)	CNN	X-ray CT	BC (Covid-19 and healthy): 99.64% MC (Covid-19, pneumonia and healthy): 98.28%
Bozkurt (Bozkurt,2021)	Shallow-CNN	X-ray	Multi-classification (Covid-19, pneumonia and healthy): 94.73%
Proposed model	**CNN**	**X-Ray1 X-Ray2 CT1 CT2**	**BC X-ray (Covid-19 and pneumonia): 98.7%, 98.4% BC CT (Covid-19 and pneumonia): 97.6%, 99.4%**

Uçar et al. (2021) is the closest work in the literature as it performs color space transformation on the input dataset. Therefore, the performance of these two studies is evaluated in Table 5. Uçar et al. propose a model that classifies Covid-19 and pneumonia disease with X-ray images in RGB, CIE Lab, and RGB CIE color spaces. The study aims to examine the effect of different color spaces on feature extraction and model performance. DenseNet121 and EfficientNet B0 pre-trained models are used to detect the images of sick individuals. Then, using the Bi-LSTM network and Gradient Boosting, Random Forest, and Extreme Gradient Boosting, Covid-19 and pneumonia disease detection was performed with an accuracy of 92.489%.

Table 5. Performance comparison with the closest study in the literature

Dataset Name	Acc	F1score(n)	P(n)	R(n)	S(n)
X-Ray1	0.987	0.993	0.972	0.914	0.996
X-Ray2	0.984	0.99	0.984	0.934	0.996
CT1	0.976	0.98	0.944	0.995	0.965
CT2	0.994	0.953	0.995	0.999	0.928
X-Ray (Uçar et al.2021)	0.924	0.8879	0.888	0.889	0.943

As seen in Table 5, a robust model with well-chosen hyperparameters, optimization algorithm, learning rate, batch size, and epoch number produces better results than a combined model. Moreover, the model proposed in this study outperforms other works in the literature as it can achieve good results for both X-ray and CT images in different color spaces.

Low-cost and rapid detection of Covid-19, which causes much damage to the body, is essential for the health of patients, but PCR test results can be obtained within a few hours to a day. Contact of the sick individual with different individuals until the test result is available also increases the spread. Therefore, to reduce the spread rate with fast detection, chest imaging methods are preferred as a treatment method in hospitals. Covid-19 and pneumonia are successfully detected with input data transformed into color spaces. Thus, it can be preferred as a computer-based expert system in health institutions where radiology specialists are missing or insufficient. The success of the study motivates the following study. It is aimed to realize a mobile application with a CNN-based transfer learning algorithm. Thus, a user-friendly system will be created with successful classification. Additionally, hybrid solutions with different deep learning techniques studies on these methods are planned.

Conflict of interest

No conflict of interest was declared by the authors.

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