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APPROACH TO DETECTION OF FACE OCCLUSION IN ACCESS CONTROL SYSTEMS

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A B S T R A C T	K E Y W O R D S
The article analyzes methods for detecting face masks in access control and management systems, and also presents a method of convolution neural networks for detecting face masks using deep machine learning technology. Face mask images in the form of a neural network model were trained on the generated database, and performance metrics were determined using metrics such as model accuracy, F1-score, precision and recall.	access control system, biometric system, machine learning, deep learning, neural networks, evaluation metrics.

INTRODUCTION

A biometric access control system allows you to recognize people based on their individual physical characteristics (fingerprints or palm prints, eye color, voice, facial features, hand shape, DNA, etc.). Thus, the quality and security of system control will be significantly improved, and the risk of unauthorized access to the system and bypassing the system will be reduced.

Currently, much attention is paid to biometric access control systems. Modern technologies allow integration into almost any existing access control system.

Biometric access control systems are convenient for users because data carriers are always with them, they cannot be lost or stolen.

This article is devoted to the detection of face masks in access control systems. The following are methods for detecting face masks in access control and management systems.

The authors of the article [1] tried to identify and distinguish medical masks from real images. The proposed model consists of the YOLO-V2 and ResNet-50 neural network architectures. At the training stage, the authors used two optimizers: Adam and SGDM. During this training process, SGDM outperformed Adam in validation mean squared error, time, and validation error. However, Adam is found to outperform SGDM in terms of error and RMS for mini-batch. The average accuracy of the Adam optimizer was 0.81, which is better than the SGDM average accuracy of 0.61. In addition, the Adam optimizer has an average log-gap of 0.4, which is better than the average log-gap of the SGDM optimizer (0.6). The system combines two detectors, one for faces and one for masks. During the testing phase, over 95% true positives and less than 5% false positives were obtained using images from the BAO dataset and the individuals image dataset.

The authors of [2] proposed a hybrid model using classical machine learning and deep learning for face mask detection. The proposed model consists of two components: ResNet-50 consists of a feature extraction and classification process using a network architecture. Three classifiers are used: decision trees, support vector machine (SVM) and ensemble algorithm. The RMFD real face and mask dataset, the SMFD simulated masked face dataset, and the naturally generated LFW face dataset are the three face datasets selected for training. The SVM classifier is used more widely than other classifiers. It achieved test accuracy of 99.64%, 99.46%, and 100% for the RMFD, SMFD, and LFW datasets, respectively.

- Deep learning is an important breakthrough in the field of artificial intelligence. This opened up great opportunities for extracting small characters in image analysis. Due to the COVID-19 epidemic, some deep learning approaches have been proposed to identify patients with viral pneumonia.

RESEARCH METHODOLOGY

Radiography is a technique used to determine the functional and structural effects of chest diseases in order to obtain high-resolution images of disease progression. In this regard, a number of works have been carried out [3], in which a new method for determining the severity of the course of diseases based on CNN by analyzing X-ray images of the patient's lungs has been proposed. The purpose of this method is to help medical professionals and researchers make clinical decisions. The results of the experiments, as well as the approximate value of 91.34% of efficiency, accuracy and other indicators according to the F1 criterion, showed the effectiveness of the method. In a similar context to this work [4] presented a new model for automatic disease detection using X-ray images called DarkCovidNet. It has been used to make the correct diagnosis for both binary classification (meaning viral and asymptomatic) and multiclass classification (viral, pneumonia and asymptomatic). For binary classes, the classification accuracy obtained with this model was about 98.08%, but for cases with multiple classes, the accuracy was 87.02%.

An important advantage of this method is that such models can be used to diagnose diseases associated with the chest, such as tuberculosis and pneumonia. However, the proposed work can be adapted to the stage of COVID-19 case detection, and the authors can increase the data set and retrain the proposed model to ensure its efficiency and model robustness. A similar approach [5] was proposed by the authors of the deep CNN model. Their neural network model called COVID-Net is considered open source and available to the general public. The accuracy achieved by this model is 93.3%. Thus, this model will help medical professionals in screening, predicting outcomes.

ANALYSIS AND DISCUSSION

Computed tomography is a medical imaging technique used in radiology to obtain detailed images of the body for diagnostic purposes. Accurate and rapid screening for the detection of the COVID-19 virus can be achieved using computed tomography images. In this regard, various experimental works have been carried out [6], in which various deep learning methods have been proposed to distinguish between virus-containing and non-virus-containing CT images to aid in diagnosis. The data set contains 349 images corresponding to patients with COVID-19 and 463 images corresponding to patients without the disease. These images are divided into three sets: 80% of them for training, 10% for testing and 10% for verification. The CTnet-10 model presented in this article achieved an accuracy of 82.1%. In addition, the neural network models VGG-16, ResNet-50, InceptionV3, VGG-19 and DenseNet-169 for determining cadence based on computed tomography images achieved an accuracy of 89%, 60%, 53.4%, 94.52% and 93.15% respectively. The VGG-19 model showed a high accuracy result compared to other models.

Combining two types of images into one data set is an effective way to diagnose a disease. In this regard, the authors of [7] presented two deep learning models CNN and ConvLSTM. Two sets of data were generated to build the models. The first data set included computed tomography and the second included x-rays. Each dataset contains a category of images with and without COVID-19 disease. Image categories of COVID-19 and pneumonia are classified for certification of proposed models.

The first model includes five CNN-based convolutional layers and five pooling layers. Two layers (a fully connected layer) and a classification layer make up a classification network. The second model is a hybrid model. It combines ConvLSTM and CNN at the same time.

There are many types of neural networks such as CNNs that have proven to be effective in areas such as face classification and recognition. The CNN structure mainly includes Convolutional Layers, Fully Connected Layers, ReLU Layers, and Fully Connected Layers. A number of other structures include normalization layers, softmax, and a classification layer [9].

The classification network is also available in the first model. In order to reduce the complexity of the planned deep learning system, training, validation, and testing consists of three steps that form two modalities. Optimization methodology is essential in training. The authors of [7] used the Adam optimizer to minimize errors between actual and assumed targets. Such a model should be treated with caution. The proposed models are evaluated according to the accuracy index, the Matthews correlation coefficient (MCC) and the F1-criterion. The evaluation process also considered specificity, negative predictive value, sensitivity, and positive predictive value.

The models were tested four times: initially on a dataset containing 288 images of COVID-19 cases and 288 infected images, this dataset was supplemented with various rotation and scaling operations, and the number of infected and uninfected images was 2880 and 2880, respectively; secondly, in the case of a dataset containing x-ray images, the dataset consists of two separate augmented subsets, namely "Augmented dataset A" and named "Linked dataset", these subsets contain 304 images of sick and 304 healthy people; third, a database called "COVID-19 X-Ray Dataset" containing X-rays of COVID-19 and viral pneumonia; fourth, it was trained on a dataset combining two conditions, normal and diseased X-rays and CT scans.

When testing models on CT images, the data set was divided into a training set (70%) and a test set (30%). The data was trained in 40 epochs. The accuracy of the test for the CNN and ConvLSTM models was the same and amounted to 99%. This is due to their stylistic design and similarity of images. When they were tested on augmented data set A, the accuracy of the test was 99% for the first model and 100% for the second. However, when they were tested on augmented dataset B, the accuracy of the test was 100% for the first model and 99% for the second model. Regarding the test performed on the combined dataset containing X-rays and CT images, the accuracy of the test was 99% for the first model and 98% for the second model. Finally, when they were tested on the radiographic dataset, the first model was tested with 95% accuracy and the second model with 88% accuracy.

We can consider this method challenging as it aims to distinguish between two diseases (COVID-19 and pneumonia) with a high degree of similarity. The proposed models showed the same accuracy of 99% when tested on X-ray and CT images, while in preliminary work they achieved an accuracy of

95-98% and 83-90.1% for X-ray and CT images, respectively. within %. Thus, the proposed two models can be considered as an effective system for detecting COVID-19.

PROPOSED MASK DETECTION SYSTEM BASED ON DEEP LEARNING MODELS

The following steps were taken to train the MobileNet classifier mentioned above on the basis of the face mask image that we formed. A set of masked and unmasked faces was used as the dataset for training the convolutional neural network, with a total of 1460 images used. The database was divided into two classes: a class of face images with a mask (700) and a class of face images without a mask (760). 80% of the images in the dataset make up the training set, 10% of the data is for validation, and 10% for model testing. For each epoch (25 in total), the model is retrained on the training set. The training results of the model, as well as the training accuracy and training error, are displayed as fractions of the accuracy period and the error period, respectively. After each training period, each model was tested on a validation dataset. Like training outcomes, validation results report validation accuracy and error. Both results are then compared with the error function. An error function value tending to zero means that the model is well trained. Otherwise, the hyperparameters are retuned during the next model training period. The process of calculating errors and updating network parameters is called backpropagation, which is the second most important process developed after forward propagation during the training phase of any neural network.

To build the optimal model, hyperparameters were tuned, as well as learning rate, subset size, number of cycles, optimizer, and error function. However, the learning rate is called the training phase during which the model updates its fitted weights. It contains the input to the algorithm as well as the output to calculate the errors. The subset size determines the number of tests that must be run before updating the internal model parameters. In other words, it means the number of tests going through the network at the same time.

The study sample data can be divided into only one or a few parts. The number of epochs is a hyperparameter that indicates how many times the learning algorithm is run on the full training dataset. Optimizers help to minimize the error function. They update the model with respect to the output of the error function. It is worth noting that various machine learning algorithms are based on error functions. The error function can be used to estimate the error of the model. Thus, the weights can be updated to minimize the error on the next estimate. During the model testing phase, model performance indicators were determined using metrics such as accuracy, F1-criterion, precision, and recall. Here, a pre-trained ResNet-10 architectural model was used to detect faces in a video stream.

After doing the initial work of collecting and preparing data for training the face mask model, the convolutional neural network model was trained.

From the above graphs, it can be seen that the neural network model is well trained, the training error is gradually decreasing, and the recognition accuracy has reached 98%. The table below summarizes the performance metrics of the trained neural network model.

Table 1. Performance indicators of the neural network model

Class type	**Evaluation metrics**			
	precision	**recall**	**f1-score**	**Accuracy**
positive images	0.97	0.99	0.98	0.97
negative facial images	0.99	0.97	0.98	

CONCLUSION

In the biometric access control and management system, the existing methods for solving the problem of detecting face masks were analyzed and considered, which is considered relevant for monitoring the COVID-19 pandemic. The shortcomings of the face mask detection data set were studied and experiments were carried out.

The developed system can find practical application in solving various problems of video analytics and in access control and personal identification systems, as well as in identifying persons who have violated sanitary and epidemiological requirements.

By expanding the training set with high-quality images and increasing the training time of the convolutional neural network, high accuracy of the algorithm can be achieved.

Using a neural network approach to deep learning also requires a large amount of data to achieve high model accuracy. For this reason, images of normal faces and masked faces have been created using public face images available on the Internet as well as private face images.

Experimental results show a high accuracy in determining the presence of a face mask. The deeply trained neural network model showed an accuracy of 97.3%, which is a significant result.

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