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Thermal Images Detection Of Covid-19 Using Convolutional Neural Network

Hanaa Mohsin Ahmed[1] , Basma Wael Abdullah[2]

[1,2] Computer science department , University of Technology, Iraq.

Abstract—COVID-19 plays a central role through exceptional circumstances that have led to the disruption and suspension of many joints of life, the use of artificial intelligence to analyze thermal images helps the diagnosis of COVID-19 detection. This research hypothesized that by using the radiographic changes of COVID19 in thermal images using FLIR (Forward Looking Infrared) technology with Thermal Camera to detect peoples' infection of Covid-19 by the use of intelligence systems can extract certain graphical elements related to COVID19 and offer a clinical diagnosis before pathogenic testing; therefore, vital time is saved for disease prevention. Using real dataset which collected by the author for the period 1st August to 15th September which contains 50 images for healthy peoples besides 50 patients whom infected with Covid-19. CNN (convolutional neural network) model inspired by the Xception architecture was presented for the diagnosis of patients infected with coronavirus pneumonia. The suggested technique achieved 0.92 as an average training precision. Ultimately, these findings revealed that Deep Learning (DL) model can enhance early diagnosis, treatment and isolation; therefore, it might help to manage the crisis.

Keywords—, Convolutional Neural Network, COVID-19, Deep Learning, Detection. Thermal images.

1. Introduction

Heat is produced through physiological processes. A change in the temperature of the body is a natural sign of disease due to the fact that it is a sign of abnormal or normal function. According to some researches, a temperature increase of more than 2.2°C might necessitate additional research. The human body's core temperature is usually kept at 37 degrees Celsius. This raises serious concerns regarding the potential privacy consequences of such data massive data use and collecting. Whereas multimodal biometric surveillance tools like these could be effective in limiting the SARS–CoV-2 spread, we caution that the corporations and governments capability to exploit such technologies will possibly continue beyond the present public health crisis [1].

Fever (a body temperature more than 38°C) is considered as one of the indexed symptoms of infection within a growing list of COVID-19 symptoms. As the pandemic spreads, businesses and government agencies are increasingly using fever checks to assess the risk of COVID-19 infection among travelers, citizens, and employees. This involves the use of regular thermometers and infrared cameras, which measure the energy emitted from the eye's inner corner and pass the data through a machine learning (ML) algorithm to determine internal temperature that have had mixed results in earlier pandemics [2].

State law enforcement agents in China, which had the first wave of infection, have carried out temperature checks at highway checkpoints and, in a few instances, forcibly entered private residences for conducting such checks. Officials in South Korea have started carrying out fever tests and issuing travel certificates to the United States just to people who have a body temperature of less than 37.5 degrees Celsius. Fever-detecting cameras were lately integrated into Thailand's biometric border screening system to assess travelers' temperatures and alert border authorities to febrile persons. Fever check technology, especially remote fever detection, is becoming more common in the post-COVID-19 world [1].

Various commercial businesses, on the other hand, have combined facial recognition and thermal imaging. In spite of the recognized shortcomings of facial recognition and limitations related to thermal detection, multimodal biometric technologies are being marketed as efficient instruments for combatting the pandemic by companies all over the world. The claims made by these firms, which have yet to be comprehensively examined in the empirical literature, show that integrating thermal detection with the capabilities of face recognition for detecting and monitoring possibly infected individuals has clear advantages. For instance, police in China are now deploying Hanwang Technology gadgets that claim to be able to recognize a person's name in less than a second when a temperature exceeds 37.5◦C [1].

Thermal Imaging-Based Recognition. Recently, as miniaturized thermal sensors have grown more commonly available, they have gotten more attention. Despite the fact that their monetary cost per pixel remain significantly higher than that of vision-based cameras, they have various benefits, including enhanced weather conditions and better privacy. They can also recognize individuals depending on their thermal signature. The difficulty of tracking and recognizing persons from aerial views is investigated by Portmann et al. [3.] Thermal images with a resolution of 324×256 are used in their framework, which yields a real-time performance of 16 Hz. By merging visible-light and thermal images as a single input, JIN KYU et al [4] introduced a unique person n re-identification (ReID) approach for simplifying the convolutional neural network (CNN) structure. A total of two open databases were utilized to test the suggested approach's performance. The approach provided in this work performed exceptionally well. Jisoo Park et al. [5] described an approach used to detect persons in infrared CCTV images taken at night that was both effective and precise. A total of three separate infrared image datasets were created for such purpose. A pixel-wise classifier depending on CNN was also constructed for fine-grained individual detection. For all datasets, the suggested technique achieved F1 scores of over 80% in object-level detection.

2. Thermography in Medicine

Thermal cameras are highly accurate devices that can accurately measure the temperature of skin surface and image all areas of the human body in great detail. Medical thermography has a wide range of uses. In addition, medical thermal imaging camera produces a thermal image which shows the various amounts of heat emitted by the human body. In the case when the temperature elevated or normal, this image acts as a signal to operators, thermographers, or doctors. Furthermore, a medical thermal imaging camera can also be utilized for measuring a part of the body for detecting high temperatures resulting by circulation problems, inflammation, infection, or injury [6].

Thermal imaging is a powerful and effective tool in human medicine [7].

- Infrared camera systems efficiently offer a thorough image of the distribution of body temperature.
- Thermography is a patient-friendly method because it is non-invasive and non-contact.
- High-resolution imaging of the smallest temperature variations.
- Thermography can detect a variety of disease patterns.

3. Literature review

Many research done related to Covid-19 detection in different territory and vary of dataset [8], most of dataset where CT scan images or x-ray images, the accuracy here between 75% - 98% whom used datasets as shown in Table1[9,10,11,12,13,14]. While this research depends on real time dataset with thermal camera (FLI Rone).

Table 1. A review on covid-19 Techniques and tools.

Title	Techniques	Performance	Advantages	Limitation	Database	Result
[11]	DL neural network-based technique nCOVnet	Identifying Covid-19 from CT scan and X-ray images using fast screening process	The training process helps to detect the Covid with faster speed and resolving the unavailability of RT-PCR kits issues.	High costs of importing chemicals as well as other elements, results are unbiased.	ImageNet dataset	97.62% true positive rate is achieved within 5 seconds of analysis
[12]	New machine learning model, fractional multichannel exponent moments	Patients X-ray images are analyzed and optimized features are selected to	The orthogonal moments are robust to noise, inexpensive and fast computatio	High CPU-running time	Joseph Paul Cohen and Paul Morrison and Lan Dao in GitHub dataset and talian Society of Medical and	98.09% on second dataset and 96.09% on first dataset.

	for feature extraction and modified manta-ray foraging optimization	classifies the Covid-19 and non-Covid-19 patients	n on real-time applications		Interventional Radiology (SIRM) COVID-19 DATABASE	
[13]	Transfer learning with CNNs	Diagnosing Covid-19 medical conditions from X-ray images using multiple layers of networks	Reducing the exposure of medical staff and nursing outbreaks maximizes the detection performance	data availability limitations	Github Repository- Radiological Society of North America (RSNA), (b) Radiopaedia, and (c) Italian Society of Medical and Interventional Radiology (SIRM)	Sensitivity, accuracy, and specificity obtained are 98.66%, 96.78%, and 96.46% respectively.
[14]	linear regression, Multilayer perceptron and Vector auto-regression method	Forecasting the potential Covid-19 patterns, which help to, determines the future anticipating rate.	Predicting the confirmed, recovered and data status in future over the time	Need to improving the prediction rate	COVID-19 Kaggle data	95% of confidence Interval
[15]	Deep transfer learning approach with convolution models like ResNet50, ResNet18, DenseNet-121, and	Preparing the publicly available Covid-19 chest X-ray images and the images are trained to predict the Covid-19 patients	Time sensitive relevance while creating database and maximum recognition accuracy	Requiring large set of Covid-19 images for improving the automatic detection process	Joseph Paul Cohen for collecting the COVID-Chestxray-dataset	98% of sensitivity rate, 90% of specificity,

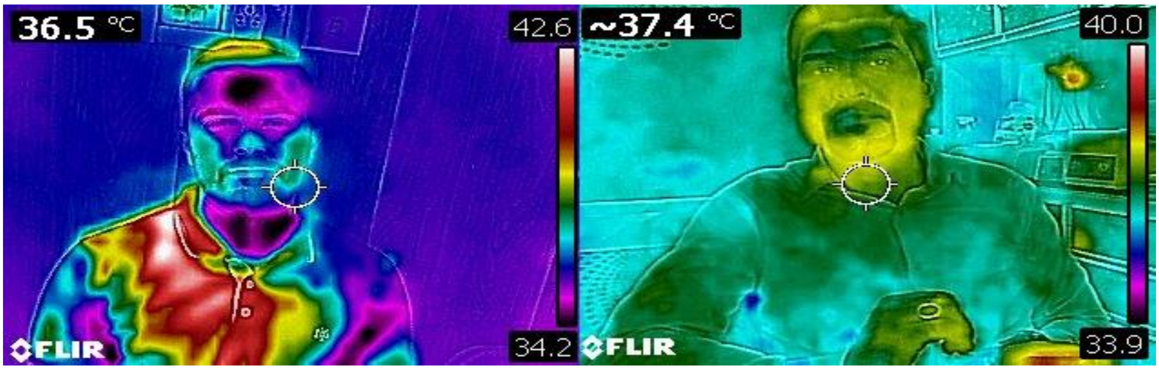
	Squeeze Net.					
[16]	Machine learning algorithm with READY multicenter clinical trial	Predicting the requirement for ventilation in Covid-19 patients to assisting the resource allocation, triage patients and emergency intubations	Create accurate advance warning system, minimize the risk factors, enhance patient care, reduce clinician burden, and reduce mortality and morbidity	Need to improve the model to detect the Covid in earlier stage.	Respir Atory Decompensati on and model for the triage of covid-19 patients	90% sensitivity, 78% specificity and higher diagnostic odds ratio 12.58

4. MATERIAL AND METHODS

Most researchers currently use machine learning technologies for diagnosis [15-19]. Most of them use conventional methods to detect, classify, and classify various anomalies, such as selecting, reducing, extracting, and classifying features based on those features. The biggest drawback of these solutions is the time required for function engineering. Furthermore, conventional approaches have poor performance measures. DL architectures are designed to meet these challenges. The possibility of deep functionality prompted us to investigate CNN architectures.

A. Dataset

This study involved the training and testing of a covid19 recognition model from thermal images. To train the model, a suitable image dataset is needed. For this purpose, thermal image dataset of people expected to have covid-19 infection was captured using an infrared (FLI Rone) camera. real time dataset used as the source of a recent dataset. The dataset contains 100



images, where 50 images include a healthy (normal) face condition and the remaining 50 images have confirmed Covid19 cases. The proposed data set can be seen in fig. 1, is healthy "Negative" and figure 2. is "Positive”. The positive image data exhibits an inflammation spread in the face area which can be diagnosed by radiologists.

Figure 1. healthy image

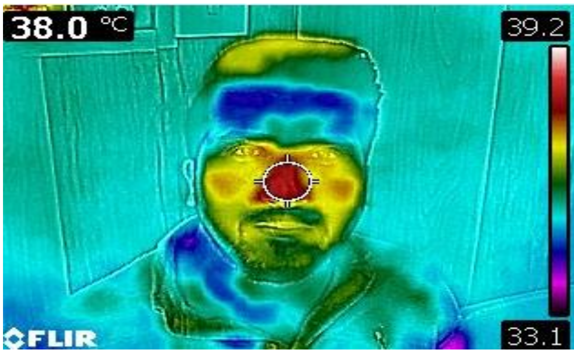


Figure 2. Infected image

B. Preprocessing

This step is necessary to ensure that all images are valid for training. Since the image data is downloaded from online sources, an additional image corruption check is included to filter out damaged or corrupted images. Moreover, the images are rescaled to (180,180) pixels in order to be consistent with the model's input size.

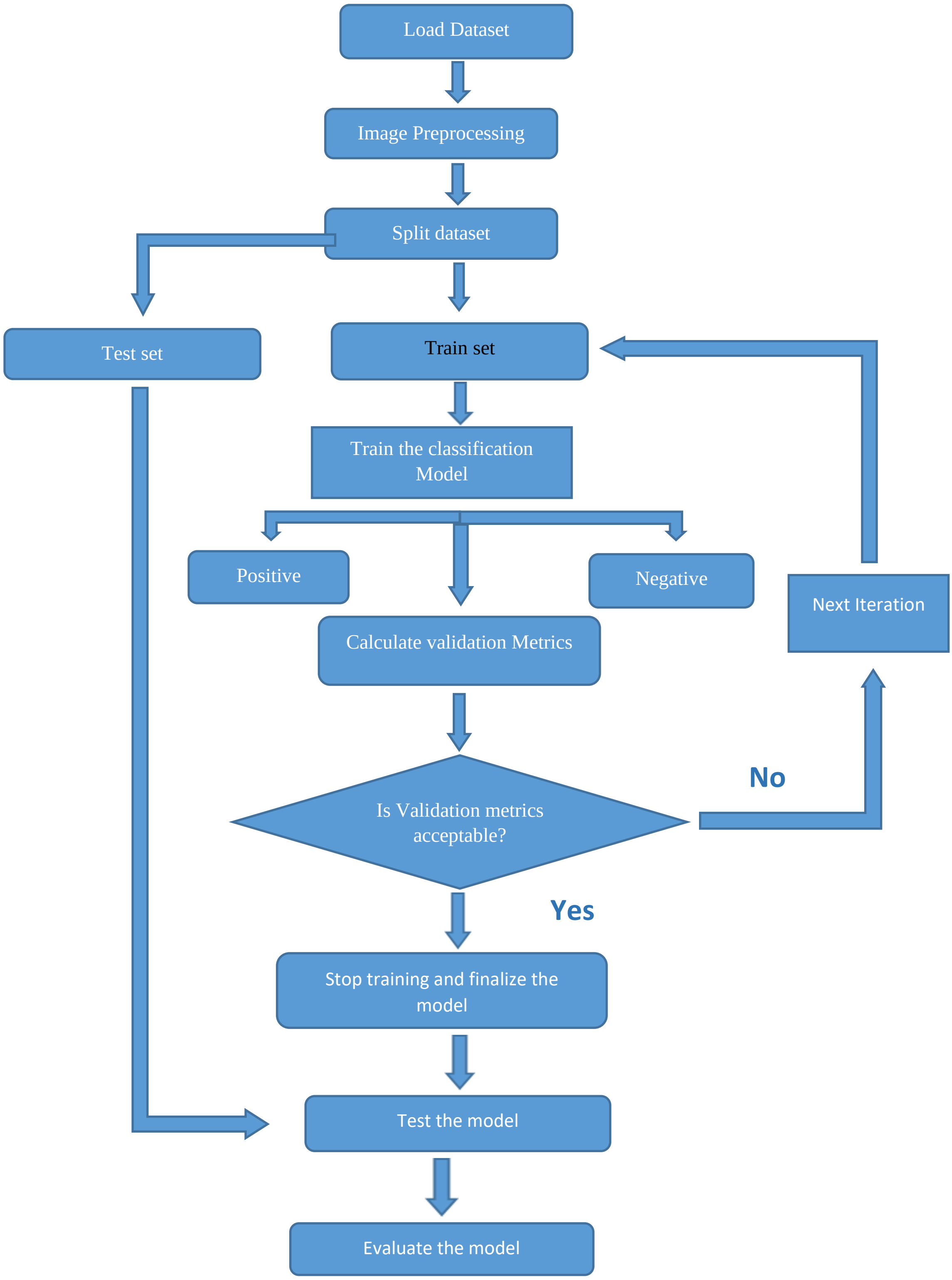
C. Using image data augmentation

Data augmentation enhances the performance of CNN, slows overfitting, and is simple to implement before training a model. Overfitting usually occurs, in the case of limited data and features where the model, limits its capacity for generalizing results to new data. This is usually seen when the testing accuracy of unseen data is much lower than the training accuracy. To overcome this issue, using random, however, realistic modifications to training images, like random horizontal flipping or minor random rotations, is helpful for the exposure of the model to new features of training data, a sample of the proposed augmentation methods (rotation, flipping, scaling).

D. The proposed CNN architecture

CNN was selected in this study for classifying images into normal, and COVID19. Since it is a multistage trainable neural network architecture, it is sophisticated for classification problems and is advanced technique to ML inspired by the human brain. CNN works similarly to the human visual system and has been built on the concept that raw data is made up of 2D images, allowing specific characteristics to be encoded. Generally, CNN generates feature maps through convolving images with kernels. In addition, kernel weights connect units to tweaked layers in a feature map, and such weights are modified throughout training via a backpropagation process. Since the same kernels were utilized by all units, the convolutional layer had to learn less weights. Fig. 3, shows the steps needed with CNN for achieving the goal of chest image classification.

Fig.3. Flow diagram of the proposed system.



The proposed neural network architecture is shown in Table 2, where 20 layers is implemented including the activation, convolutional, and pooling layers succeeded by fully connected layer at the end to classify between two classes, in which Conv indicates convolutional layers, SConv indicates separable convolution layer, BN indicates Batch Normalization layer, ReLU indicates Rectified Linear Unit as an activation function, FC indicates fully connected layer. Each of the layers is explained in the following section.

TABLE 2. THE PROPOSED MODEL'S ARCHITECTURE

Layer #	Type of Layer	Kernel Size and Stride	Output Size
1	Input layer	-	180×180×3
2	Conv2D, BN, Rel U	Kernel size=3×3, stride=2	90x90x32
3	Conv1, BN1, RelU1	Kernel size=3×3, stride=2	90x90x64
4	SConv1/Conv2, BN2, RelU2, Max Pooling	Kernel size=3×3, stride=2	90x90x128/ 45x45x128
5	Add1	Addition of two inputs	45x45x128
6	Activation: RelU2	Activation Function	45x45x128
7	SConv2/Conv3, BN3, RelU3, Max Pooling	Kernel size=3×3, stride=2	45x45x256/23x23x256
8	Add2	Addition of two inputs	23x23x256
9	Activation: RelU3	Activation Function	23x23x256
10	SConv3/Conv4, BN4, RelU4, Max Pooling	Kernel size=3×3, stride=2	23x23x512/12x12x512
11	Add3	Addition of two inputs	12x12x512
12	Activation: RelU4	Activation Function	12x12x256
13	SConv4/Conv5, BN5, RelU5, Max Pooling	Kernel size=3×3, stride=2	12x12x728/6x6x728
14	Add4	Addition of two inputs	6x6x728
15	Activation: RelU5	Activation Function	6x6x728
16	SConv5 BN6, RelU6, Max Pooling	Kernel size=3×3, stride=2	6x6x1024
17	Activation: Relu7	Activation Function	6x6x1024
18	Average Pool	Gloabal Average Pooling	1x1x1024
19	Dropout	Drop with 0.5 learning rate	1x1x1024
20	FC	Fully Connected	1

1. Convolutional layer

A convolutional layer has been made up of a set of filters, each of them has its group of parameters which should be learned. The filters' height and weight are not more than that of input volume. Every one of the filters is convolved with input volume for the production of a neuron-based activation map. To put it another way, the filter has been slid across the input's height and width, while the dot products between filter and input are evaluated at each one of the spatial positions. Also, stacking the activation maps of all filters along depth dimension yields the convolutional layer's output volume. Because each filter's height and width are small compared to input, each one of the neurons in activation map has been just connected to a small local input volume region, and because the activation map is created by doing convolution between input and filter, while filter parameters have been shared across all of the local positions. Weight sharing minimizes the number of the parameters that are required for effective expression, generalization and learning [20], [21].

2. Activation Function

The data was transformed into non-linear form using this function. The rectifier linear unit (Re LU) is the activation function used in the proposed framework, and it has been represented by Eq (1) [22].

$$f(x) = \begin{cases} 0, \text{if } x < 0 \\ x, \text{if } x \geq 0 \end{cases} \quad (1)$$

where x = an input value

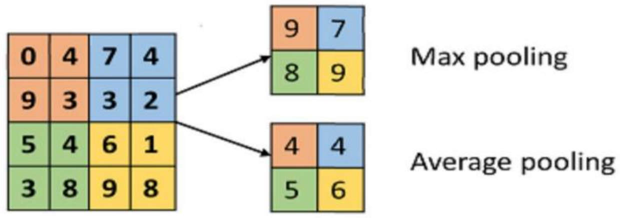
Softmax and Sigmoid are the two activation functions' types which are commonly utilized. Another activation function type utilized in neural computing is Softmax function. It is utilized to make a probability distribution out of a set of real numbers. The output of the Softmax function is a range of the values in the range from 0 to 1, with summation of probabilities being equal to 1.

Sigmoid function is widely used in classification problems, particularly in output layer regarding a binary classification, in which the results are either 1 or 0. Due to the fact that the value of the sigmoid function is only in the range from 0 to 1, the result might be simply predicted to be 1 in the case where the value is higher than 0.50 and 0 otherwise.

Softmax and Sigmoid functions vary primarily in that the Sigmoid is utilized for binary classification, whereas the Softmax is utilized for multivariate classification [21].

3. Pooling Layer

This layer was created to merge spatially neighbor features in feature maps. To join features, max-pooling or average-pooling is utilized. Pooling can be implemented using a variety of non-linear functions, the major one is max pooling. It divides input image to a collection of non-overlapping rectangles and produces the maximum for every one of these sub-regions; the precise placement of a feature is less significant compared to its approximate location relative to other features. Pooling in CNN has been based on this concept. The pooling layer results in the reductio of spatial size of representation as well as the number of the parameters, amount of computation in a network, and memory footprint allowing for better fitting control. Also, a pooling layer is frequently inserted between subsequent convolutional layers in the architecture of CNN. Another translation invariance type is provided by the pooling procedure. The pooling layer resizes each depth slice regarding the input spatially and functions independently on each one [23]. Fig.4 shows a simple example of average and



maximum pooling.

FIG.4. EXAMPLE OF MAX AND AVERAGE POOLING. [23]

4. Dropout Layer

Then, a dropout layer is used with a likelihood of 0.5 and finally, features have been passed on to fully connected layer, which has a 3-output size for the classification of input thermal image as one of 2 classes, which are: normal, or COVID-19.

5. Fully-connected layer

A multilayer perceptron on top of last convolutional layer will be used for eventually classifying the image into a category. The previous convolution and pooling techniques drastically decreased the size of input image while preserving the classification's distinctive qualities. The output feature map must be flattened since feeding an MLP needs input vectors (1D arrays). As a result, MLP receives small-sized feature maps as a 1-D array and selects the appropriate class for the feature maps [24], [25]. The specifics of the suggested architecture for normal and Covid19 classifications are provided in Table 1, which includes layer type and filter size is "Kernel" or "feature detector" achieving the greatest results in testing and training process in the case when utilizing 3x3 filter size. Stride: Moves the filter matrix over the input matrix by a certain number of pixels. Stride equal to 2 is chosen, which means moving the filters 2 pixels at a time, while the value 2 rather than 1 since it creates smaller, more significant feature maps.

After all the layers has been defined and prepare, the data is fetched, and the training process is executed followed by a validation and testing step.

6. Model Training and Validation

After the development of the suggested CNN model, we trained it for 30 epochs while employing data augmentation for preventing overfitting. Then, we used evaluation metrics to indicate the performance which was recorded on the validation set, and reaching high system accuracy comes from the system's high efficiency with few errors. The accuracy, precision, recall, and f-score metric scales that we employed are listed below [26-28].

- **Accuracy:**

Accuracy = (TP + TN) / (TP + FP +TN + FN) (2)

Accuracy indicates the number of the correct classifications that have been made out of all classifications, i.e., the number of the TNs and TPs that have been performed out of FP + FNs + TP + TN. It indicates the ratio of the “True” cases to summation of “True” cases and “False” cases [29], [30].

- **Precision:**

Precision = TP / (TP + FP) (3)

Out of all that have been marked to be positive, the number of them that have been in fact truly positive.

- **Recall:**
  Recall = TP/ (TN + FN) (4)

Out of all actual real positives, how many have been positive.

- **F1-Score:**

F1 score = 2 x (Precision x Recall) / (Recall + Precision) (5)

Often, the weightage is given to FN and other times to FP. F1 score is the weighted average related to Recall and Precision, implying that FN and FP are given equal weight. In comparison to "Accuracy," this is an extremely significant metric.

The issue with employing accuracy is that in the case where we have a very imbalanced training data-set (for instance, a training data-set with 5% negative class and 95% positive class), the model will learn the way of correctly predicting the positive class but not the way of identifying the negative class. However, the model is going to have a high accuracy level in test dataset since it will have a good understanding of how to recognize positives.

Where [31], [32]:

- True positive (TP) represents the number of the positive samples which were classified correctly.
- False Negative (FN) represents the number of positive samples which were classified incorrectly.
- False Positive (FP) represents the number of negative instances samples which were classified incorrectly.
- True negative (TN) represents the number of negative instances samples which were classified correctly.

5. RESULTS AND DISCUSSION

Thermal imaging was used in this study to detect the existence of a COVID19 infection. Python and the Google collaboration environment were used to perform the experiment. All images were pre-processed using intensity normalization to ensure proper detection. The CNN architecture mentioned above was utilized for extracting the image features, then all the extracted features were passed to the SoftMax classifier for detection.

The data set was divided into 2 parts throughout the experiment, with 20% used for testing and 80% for training. The table (2) show the training results based on an average value of 30 epochsa. This work achieved 92% accuracy throughout the training process. It is evident that after 30 epochs our model has outperformed and experimental results have shown that the suggested approach to extract radiological parameters for a rapid and accurate diagnosis of COVID19 is effective.

Table 2. Analyses of a variety of the performance measures for training of the suggested model utilizing deep learning

CNN Model	Number of Epochs	Accuracy	Recall	precision	F1-score
Xception	30	92%	93.3%	93%	93.1%

CONCLUSION

To assist in preventing the COVID-19 spread, this research use infrared camera for detecting individuals with a high body temperature who are likely to get COVID-19. Thermal imaging datasets were produced for testing and training COVID-19 disease recognition model to handle such problem. There are 100 images in the dataset, 50 images have proven cases of COVID-19, the remaining 50 show a healthy (normal) facial condition. The above-mentioned CNN architecture, which was influenced via Xception design, was utilized for extracting features from images for diagnosing coronavirus pneumonia patients. The performance of the model was evaluated using a total of 4 metrics. The proposed categorization model had an accuracy rate of 92%. Based on the results, we anticipate that this work will help to prevent the spread of COVID-19.

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