Journal of Theoretical and Applied Information Technology
31st January 2023. Vol.101. No 2


ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# KNN-WT BASED COVID-19 DETECTION USING CHEST X-RAY BINARY CLASSIFICATION

**MADHU JAIN[1], RENU SHARMA[2*]**

[1, 2]Jaypee Institute of Information Technology, Department of Electronics and Communication, Noida, India

E-mail: [1]ermadhu2003@gmail.com, [2*]renu.sharma28par@gmail.com

**ABSTRACT**

A novel virus commences in Wuhan China in December 2019. It was named as novel coronavirus (nCovid-19) or severe acute respiratory syndrome corona virus-2 (SARS-CoV-2). Due to its zoonotic nature, it had affected animals as well as human beings. The stated virus is spreading at such a rapid rate that it has razed human lives and the global economy. To aid in such pandemic situation, we have proposed a novel neural network-based model for diagnosing coronavirus from a raw chest X-Ray image. The proposed model uses K-Nearest Neighbor (KNN) for classifying the input image. It will support binary classification i.e., COVID effected X-Ray and normal X-Ray. Several collected input images are initially pre-processed using dual-tree complex wavelet transform (DTCWT). Then, feature extraction is executed using mobilenet architecture. Further, image classification is performed using the KNN based model. Lastly, the output is predicted whether it belongs to the Covid-19 class or normal class. For visualizing the effectiveness of the proposed KNN based classifier, parameters such as accuracy, recall, precision, and F1 score are calculated. A comparison is made by calculating the average of all the parameters with existing techniques. Experimental results showed that the proposed KNN-WT model achieves an accuracy of 99%. It outperformed all the existing algorithms.

**Keywords:** — *KNN classifier, DTCWT, chest X-Ray, Image Classification, COVID-19*

## 1. INTRODUCTION

COVID-19 was first coined in December 2019 in Wuhan, China. Earlier, in February 2003, severe acute respiratory syndrome (SARS) [1], a respiratory viral disease emerged from China. SARS is an airborne disease and had devastated almost four countries. Another respiratory disease middle eastern respiratory syndrome (MERS-CoV) [2] was first emerged in Saudi Arabia, 2012. Symptoms of all stated viruses include fever, cough, chest infection, and respiratory issues. Apart from these symptoms, the novel virus may enormously affect the digestive system. This comprises liver disorder, diarrhea, etc. By the virtue of Covid-19, there are 196,002,128 [3] active cases as of 28/07/2021, out of which 177,687,802 [3] are recovered cases and 4,193,297 [3] death cases. This created a pandemic scenario since February 2020. Fig. 1 shows the bar graph for the active COVID cases across the globe [3]. It covers areas such as Europe, America, south-east Asia, etc. A lot of people get affected whether it's economic loss, health issues, or way more. Several lockdowns happened in every part of the globe which controlled the pandemic well. Early detection of COVID-19 helped the patients to recover at a high pace. There are limited ventilation beds for admission in hospitals, limited supply of personal protective equipment (PPE) available. Many hospitals came under problems when demand for intensive care units (ICU) had increased. Only those patients are treated in ICU who have severe breathing issues or other health-related ailments. Due to such reasons, early detection of the novel virus is necessary. Earlier few methods are available for diagnosing the patient includes nasopharyngeal swabs for ensuring the presence of RNA fragments. Another method involves analysis of radiographic images such as chest X-Ray (CXR) and computed tomography (CT) scan. The former method is discontinued initially due to unhygienic contamination of the virus. But now due to scarcity of machines and to minimize visits to hospitals, testing through swabs again started. Although there are various advantages of diagnosing the patient with chest X-Ray images. Some includes: 1. X-Ray

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

imaging is assuredly available in every hospital and is very cost-effective. 2. Digital X-Ray imaging provides a rapid diagnosis of the virus compared to earlier X-Ray machines. 3. The after-effects of X-Ray imaging are less as compared to other radiographic methods. Since this pandemic situation appeared, a lot of researchers are working consistently for developing different approaches. Many research articles are already available for detecting COVID-19 symptoms [3-10]. There are several ways for testing symptoms of corona virus. One of the methods is real-time polymerase chain reaction (RT-PCR) [8]. The diagnosis result of this test will be provided within 2-3 days. But there are some critical cases when a diagnosis report is required instantly. So, in these cases chest radiographic imaging plays a major role. It includes a CT scan and CXR. As far as economical imaging is concerned, because this pandemic affected the economy of the people, CXR is more suitable. Earlier researchers developed algorithms based on deep neural networks [9-12]. These methods are based on extracting the features from a large dataset of CXR images. Feature extraction along with a deep neural network-based image classifier is a part of transfer learning. So, when a neural network model is designed it undergoes training and testing phase as a part of the initial step. Afterward, the knowledge which is extracted from the initial step is transferred to train a new model. This new model may have a different dataset. This process is known as transfer learning.

In this paper, KNN-WT based method is proposed for binary classification. The input image is a chest X-Ray image and the proposed model will classify it into one of the class i.e., normal class or COVID-19 affected.

## 2. EXISTING RESEARCH WORK

Apostolopoulos and Bessiana [5], proposed a transfer learning-based algorithm for multi-class CXR classification. In this article, three types of CXRs have been collected namely pneumonia, COVID, and normal person. In this paper, author has used transfer learning concept for multi-class classification. They have collected chest CXRs from two different public repositories. These CXRs belongs to three categories namely normal, covid-19 and pneumonia affected patients. They have achieved accuracy of 96.78%, sensitivity as 98.66% and specificity as 96.46%. Another article based on transfer learning for classifying the CXR and CT scan images was presented by Afshar Shamsi et al [6]. They concluded that the lack of access to available repositories of CXR and CT scan images restricted them to design a new CNN model. So, the author had tested pre-trained models namely DenseNet121, visual geometry group (VGG16), ResNet50 [7], and InceptionResNetV2 [7]. In the next phase, required features were extracted from CT and CXR images. Afterward, multiple classifications techniques were tested and comparison showed that linear support vector machine (SVM) proved promising results. R. G. Babukarthik et. al., [8] stated a method for predicting COVID positivity cases. The prediction is based on a genetic deep convolution neural network (GDCNN). They have worked on more than 5000 CRX images for classifying them among COVID, pneumonia, and other pneumonia symptoms. The parameters calculated are the accuracy having a value of 98.84%, the precision value is 93%, the sensitivity value is 100% and the specificity value is 97%. They proved that prediction based on GDCNN is better than methods such as ResNet18, ResNet50, DenseNet121, and VGG16. These are feature extraction models. Densely connected convolution network (DenseNet) model was designed by Huang et. al., [9]. This model is an extended version of ResNet. It consists of summation operation which improves generalization ability and other drawbacks in ResNet are also overcome. Features extracted at each layer are forwarded as an input for the next layer. Szegedy et. al., [10] proposed InceptionV3 model. It consistes of 159 layers and it belongs to third generation of inception model. Basically, they have used several filter sizes i.e. 1 x 1, 3 x 3, and 5 x 5. The idea behind this involves, extraction of multi-level features from the input dataset. Another combination of inception module and residual module is presented as InceptionResNetV2 [7]. This improved the performance with relatively low cost. Karen Simonyan et.al., [11] proposed visual geometry group (VGG-Net) model for feature extraction. There are two different versions of VGG namely VGG16 and VGG19. In the same context, Google research team had designed MobileNet architecture for feature extraction. Its accuracy is equivalent to VGG16 with less parameters computation. It has reduced the dimensionality of feature maps. So, after exploring these feature extraction methods we have considered MobileNet architecture for feature extraction. Here, a novel algorithm is based on K-nearest neighbor (KNN) is proposed. It is based on a supervised learning technique. It works on visualizing the similarity between the input image and the set of images on which it is trained. This can be used for regression as well as for classification also. The proposed classification model is a combination of wavelet transform and KNN. In the initial phase of the algorithm, an input image is pre-processed using wavelet transform. This will improve the resolution and contrast of the image. The accuracy rate achieved for multiclass classification is 99%. This paper is divided into several sections. Introduction of the research along with related research is demonstrated in section I. The existing research work is explained in section II. Problem statement and proposed work is explained in section III and IV respectively. In section V dataset description is presented whereas section VI covers the parameter calculation formulas. Section VII and VIII explains the discussion about the proposed method and performance metrics respectively. At last, the work is concluded in the section IX.

## 3. PROBLEM STATEMENT

This paper focuses on binary classification of the chest X-Ray images. The classes which are considered here are COVID and normal. This will ease the process of diagnosing patient suffering with COVID.

## 4. PROPOSED WORK

In this paper, a KNN-WT model for binary image classification is proposed. A block diagram of the proposed model is shown in Fig.2. The steps include the image pre-processing based on dual-tree complex wavelet transform (DTCWT), Mobile-Net architecture, KNN classifiers followed by prediction of the specific class. Description of the blocks are as follows:

### 4.1 Input Image

The dataset consisting of CXR images is collected from open-source i.e., Kaggle [12] and GitHub [13]. Types of images collected are normal and COVID affected. The size of the input image is 224 x 224. A total of 626 images were collected, among these images 130 images are used for training the model and 496 images are used for testing the proposed model.

### 4.2 Image-Preprocessing

In this stage, pre-processing is performed for improving the resolution and contrast of the input image [30][31][32]. This is accomplished using DTCWT [14]. The advantages of using DTCWT include shift-invariance property and directional sensitivity. These properties improved the visual quality of the resulting images globally. Also, lesser artifacts are generated as compared to another wavelet transforms such as discrete wavelet transform (DWT) [15], stationary wavelet transform (SWT) [16].

### 4.3 Mobile-Net Architecture

It consists of series of layers used to develop a less complex deep learning model. There are two types of convolution performed namely depth-wise separable convolution and standard convolution. This architecture is suitable for mobile devices, computers without graphic processing units (GPU), etc.

### 4.4 KNN Classifier

The principle of KNN is based on determining the K-nearest neighbor distance. It relies on the training dataset. KNN will predict the output depending on the training dataset. Initially, when a new point or an image is applied to the KNN classifier, then the minimum distance is calculated between the new point and the training point.

For the analysis of the proposed algorithm, input CXR images of variable sizes are applied to the model. A detailed descriptive diagram is shown in Fig. 3. All the input images are pre-processed using DTCWT and converted to 224 X 224 size. The resulting images are applied to the feature extraction block. In this phase, operations like depth-wise and point-wise convolution are performed. After convolution operation batch normalization, the pooling operation is executed in several stages. So, after extracting the features from multiple operations, the KNN classifier is used to classify the desired output. This will classify whether the input image belongs to the normal or COVID [17-19] class. The feature extraction is a part of Mobile-Net architecture.

The Mobile-Net architecture is designed to create small, low-latency models for mobile and computer vision applications. Many researchers focused on the small network but do not consider the speed of the network. The Mobile-Net architecture foremost focused on optimizing the latency and yet additionally yield small network. Further, the images are passed through the feature extraction block followed by the KNN classifier. As we know that KNN is a supervised machine learning algorithm used for classification purposes. The strength of the KNN lies in the fact that it performs very well when

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the dataset is less. Also, one of the advantages of using the KNN is that it uses distance metric to find the nearest neighbor. Then it classifies whether it is a positive or negative class that gives more accurate results. Another fact regarding the KNN is that it is a non-linear classifier and does not require the classes to be linearly separable. It does not require any prior assumptions about the distribution of the data. So, these facts about the KNN encourages us to design KNN-WT based model.

## 5. DATASET

In this work classification of the CXR images among normal and COVID is proposed, so availability of the dataset is a big challenge. Although real-time images are difficult to find, an open-source database is quite beneficial. For the quantitative and qualitative representation of the proposed KNN-WT based classifier, the dataset is collected from the public GitHub repository, managed by Dr. Joseph Cohen [13] and Kaggle [12]. This dataset is updated on daily basis and it consists of CXR as well as computed tomography (CT) [20] scan images. In this repository, images are managed for patients who are suffering from SARS, MERS, pneumonia, COVID [21-23], or other respiratory-related disease. The proposed KNN-WT model is trained on over 608 images, out of which 304 images belongs to a normal class and 304 images belongs to the COVID class. In the testing phase of the proposed model, 783 images are used; out of which 234 images belongs to normal class and 549 images belongs to COVID-19 class. The size of input image after pre-processing is 224 x 224.

## 6. PARAMETER CALCULATION

For quantitative analysis of the binary classification of resulting images, results are recorded for 5 folds. The performance in the form of the confusion matrix (CM) for the training dataset is shown in Fig. 4 and for the testing phase shown in Fig. 5. The parameters calculated for the qualitative analysis are accuracy, precision, recall and F1 score. These parameters are calculated for each fold and the average value is also calculated. Formula for such parameters are summarized in Table I. In the next section, experimental results are shown along-with the comparison with existing models.

## 7. DISCUSSION

As a part of quantitative analysis of the proposed work, we have calculated several parameters. These values are included in Table II. Also, the comparison with the existing methods are done and mentioned in Table III. The results clearly showed the outperformance the proposed method over existing methods which is the greatest achievement of the proposed algorithm. There are certain limitations which are mentioned below:

1. These findings are based on limited dataset available on open repositories [12, 13]. It can produce different result when we consider real-time images.
2. The KNN will provide low accuracy for noisy datasets. So, pre-processing is required for lowering the noisy effect [30].

## 8. PERFORMANCE & EXPERIMENTAL RESULTS

In this section, performance of the proposed KNN-WT model is discussed. We have used Python 3.6.9 for designing the model. Also, Google Colab is used as developing environment. For designing the model, open source libraries are used such as tensor flow and Keras. Fig. 6 shows the graphical representation of the proposed model accuracy and loss. This graph is drawn between the number of epochs versus logarithmic value of training data accuracy and loss. It can be seen from the graph that with increasing number of epochs, accrurary is increased and losses are reduced. Table II shows the comparison of proposed model calculated parameters with existing methods [24]. The parameters calculated are accuracy, recall, precision, and F1 score as stated in Table I. It can be seen from the table that the achieved value for accuracy is 99%. The chest X-Ray image which are produced are shown in Fig. 7. Fig. 7(a) shows the CXR image of a normal patient. Fig. 7(b) & 7(c) shows some of the CXR images for normal and COVID-affected patients respectively. To show the comparison of the proposed algorithm with the current state-of-the-art, an analysis is presented in Table III. It showed various classification groups that are being tested and compared with the proposed algorithm.

## 9. CONCLUSION

This article brings out a distinctive approach for binary classification of the CXR images. These images are collected from open sources [12] [13]. The proposed algorithm is based on the KNN-WT model. The proposed model is vigorous and designed to efficiently classify the COVID affected chest x-ray from normal x-ray image. The performance of the proposed model acquired an accuracy of 99% by testing almost 608 images and training 783 images. It provides much better results as compared to other methods [24-30]. So, it is concluded from the Table III that the proposed model outperforms the existing methods. DTCWT has improved the resolution and contrast of the image globally which in turn contributes in improving the accuracy of the algorithm. Also, KNN has performed the binary classification well. This research will help the rapid identification of the novel corona virus.

**REFERENCES**

[1] Bashar I. Ahmad, "A SARS method for reliable spectrum sensing in multiband communication systems", *IEEE Trans. Signal Processing,* Vol. 59, No. 12, 2011, pp. 6008-6020.

[2] Insung Ahn and Jin-Hwa Jang, "Comparative study of middle east respiratory syndrome coronavirus using bioinformatics techniques", *IEEE International Conference on Bioinformatics and Biomedicine*, November 9-12, 2015.

[3] https://www.worldometers.info/coronavirus/

[4] Y. Fang, Huangqi Zhang, Jicheng Xie, Minjie Lin, Lingjun Ying, Peipei Pang, and Wenbin Ji, "Sensitivity of chest CT for COVID-19: Comparison to RT-PCR", *Radiology*, Vol. 296, No. 2, 2020, pp. 115-117.

[5] Ioannis D. Apostolopoulos and Tzani A. Mpesiana, "Covid-19: Automatic detection from X-Ray images utilizing transfer learning with convolutional neural networks", P*hysical and Engineering Sciences in Medicine, SpringerLink,* 43, 2020, pp. 635-640.

[6] Afshar Shamsi, Hamzeh Asgharnezhad, Shirin Shamsi Jokandan, Abbas Khosravi, Parham M Kebria, Darius Nahavandi, Saeid Nahavandi and Dipti Srinivasan, "An uncertainty- Aware transfer learning-based framework for COVID-19 diagnosis", *IEEE Transactions on neural networks and learning systems*, Vol. 32, No. 4, 2021, pp. 1408-1417.

[7] K.E. Asnaoui, and Y. Chawki, "Using x-ray images and deep learning for automated detection of coronavirus disease", Journal of Biomolecular structure and dynamics, Vol. 39, No. 10,2021, pp. 1–12.

[8] R. G. Babukarthik, V. Ananth Krishna Adiga, G. Sambasivam, D. Chandramohan and J. Amudhavel, "Prediction of COVID-19 using genetic deep learning convolutional neural network (GDCNN)" *IEEE Access,* Vol. 8, 2020, pp. 177647 – 177666.

[9] Yu-Huan Wu, Shang-Hua Gao, Jei Mei, Jun Xu, Deng-Ping Fan, Rong-Guo Zhang, and Ming Ming Cheng, "JCS: An explainable COVID-19 diagnosis system by joint classification and segmentation. *IEEE Transactions on image processing*, Vol. 30, 2021, pp. 3113-3126.

[10] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich, "Going Deeper with Convoutions", *IEEE Conference on computer vision and pattern recognition*, June 07-12, 2015.

[11] Karen Simonyan, and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", *CoRR, abs/1409*, 1556, 2014.

[12] Chest X-Ray images (Pneumonia) https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[13] Open database of COVID-19 cases with chest X-ray or CT images https://github.com/ieee8023/covid-chestxray-dataset

[14] Muhammad Zafar Iqbal, Abdul Ghafoor and Adil Masood Siddiqui, "Satellite image resolution enhancement using dual-tree complex wavelet transform and nonlocal means", *IEEE Geoscience and Remote Sensing Letters*, Vol. 10, No. 3, 2013, pp. 451-455.

[15] Hasan Demirel and Gholamreza Anbarjafari, "Image resolution enhancement by using discrete and stationary wavelet decomposition", *IEEE Transactions on Image Processing*, Vol. 20, No. 5, 2011, pp. 1458-1460.

[16] Hasan Demirel and Gholamreza Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform", *IEEE Geoscience and remote sensing letters*, Vol. 7, No. 1, 2010, pp. 123-126.

[17] Xinggang Wang, Xianbo Deng, Qing Fu, Qiang Zhou, Jiapei Feng, Hui Ma, Wenyu Liu, and Chuansheng Zheng, "A weakly-supervised framework for COVID-19 classification and lesion localization from chest CT", *IEEE Transaction Transction Medical Imaging,* Vol. 39, No. 8, 2020, pp. 2615-2625.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195


[18] S. Tabik, A. Gomez-Rios, J. L. Martin Rodriguez, I. Sevillano Garcia, M. Rey Area, D. Charte, E. Guirado, J. L. Suarez, J Luengo, M. A. Valero Gonzalez, P. Garcia Villanova, E. Olmedo Sanchez, and F. Herrera, "COVIDGR dataset and COVID SDNet methodology for predicting COVID-19 based on chest X-Ray images", *IEEE Journal of biomedical and health informatics, Vol.* 24, No. 12, 2020, pp. 3595-3605.

[19] Dawit Kiros Redie, Abdulhakim Edao Sirko, Tensaie Melkamu DEmissie, Semagn Sisay Teferi, Vimal Kumar Shrivastava, Om Prakash Verma, and Tarun Kumar Sharma, "Diagnosis of COVID-19 using chest X-Ray images based on modified DarkCovidNet model", *Evolutionary Intelligence*, 2022.

[20] Shanjiang Tang, Chunjiang Wang, Jiangtian Nie, Neeraj Kumar, Yang Zhang, Zehui Xiong, and Ahmed Barnawi, " EDL-COVID: Ensemble Deep Learning for COVID-19 case detection from chest X-Ray images", *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 9, 2021, pp. 6539-6549.

[21] Zehra Karhan . and Fuat Akal, "Covid-19 Classification Using Deep Learning in chest x-Ray images", *Medical technologies congress (TIPTEKNO),* November 19-20, 2020.

[22] Ali Narin, Ceren Kaya and Ziynet Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-Ray images and deep convolutional neural networks", *Pattern Analysis and Applications,* Vo. 24, 2021, pp. 1207-1220.

[23] L. Wang, A. Wong, and Zhong Qiu Lin, "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images, Scientific reports, Vol. 10, No. 1, 2020.

[24] P.K. Sethy, S.K. Behera, P. K. Ratha, and Preesat Biswas, "Detection of Coronavirus Disease (COVID-19) Based on Deep Features and Support Vector Machines", *International Journal of Mathematical, Engineering and Management Science*, Vol. 5, No. 4, 2020, pp. 643-651.

[25] E.E.D. Hemdan, M.A. Shouman, and M.E. Karar, "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Image", *Biomedical Image Analysis*, 2020.

[26] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, Ruixuan Wang, H. Zhao, Y. Chong, Jun Shen, Yunfei Zha, and Y. Yang, "Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images", *IEEE/ ACM Transaction Comput. Biol. Bioinform*., Vol. 18, No. 6, 2021, pp. 2775-2780.

[27] X. Wang, Y. Peng, Le Lu, Z. Lu, M. Bagheri, and Ronald M. summers, "Chest X-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases", *Proc. IEEE Conf. Comput. Vis. Pattern Recognition*, 2019, pp. 2097–2106.

[28] D. Wang, Bo hu, and Chang Hu, "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus-infected pneumonia in Wuhan, China", *J. Amer. Med. Assoc.,* Vol. 323, No. 11, 2020, pp. 1061–1069.

[29] S. Uddin, I. Haque, H. Lu, M A. Moni, and E. Gide, "Comparative performance analysis of K-nearest neighbour (KNN) algorithm and its different variants for disease prediction", *Scientific Reports*, No. 12, 2022.

[30] Renu Sharma, and Madhu Jain, 2021, "A versatile medical image enhancement algorithm based on wavelet transform", *Journal of Information Processing Systems*, Vol. 17, No. 6, 2021, pp. 1170-1178.

[31] Renu Sharma, and Madhu Jain, "Wavelet transform based enhancement of medical images" in book "*Recent trends in communication and electronics*", 30th June 2021.

[32] Renu Sharma, and Madhu Jain, "Novel algorithms for resolution enhancement of images", *Journal of Theoretical and applied information technology (JATIT)*, Vol. 97, No. 5, 2019, pp. 1512-1522.

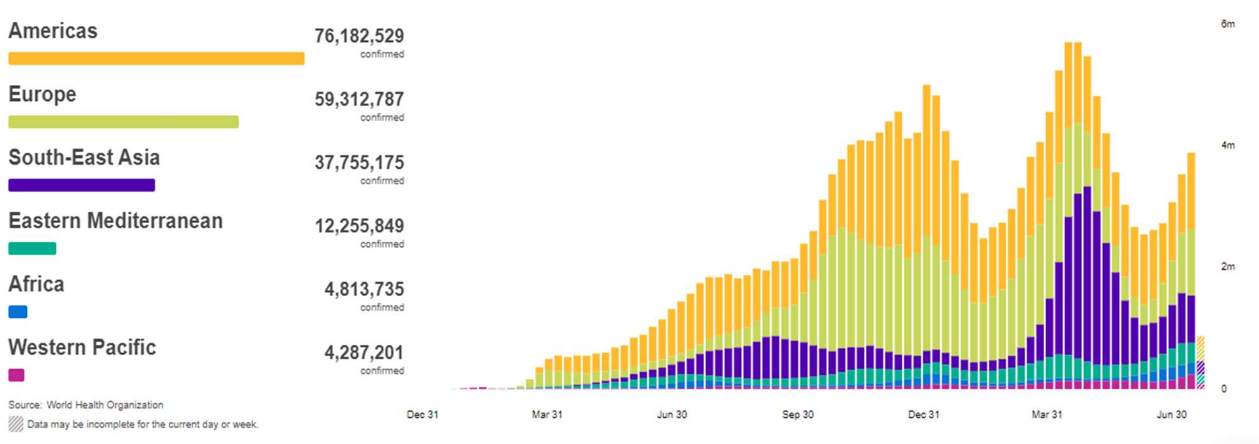


*Figure 1 Current active cases of COVID across the Globe [3]*

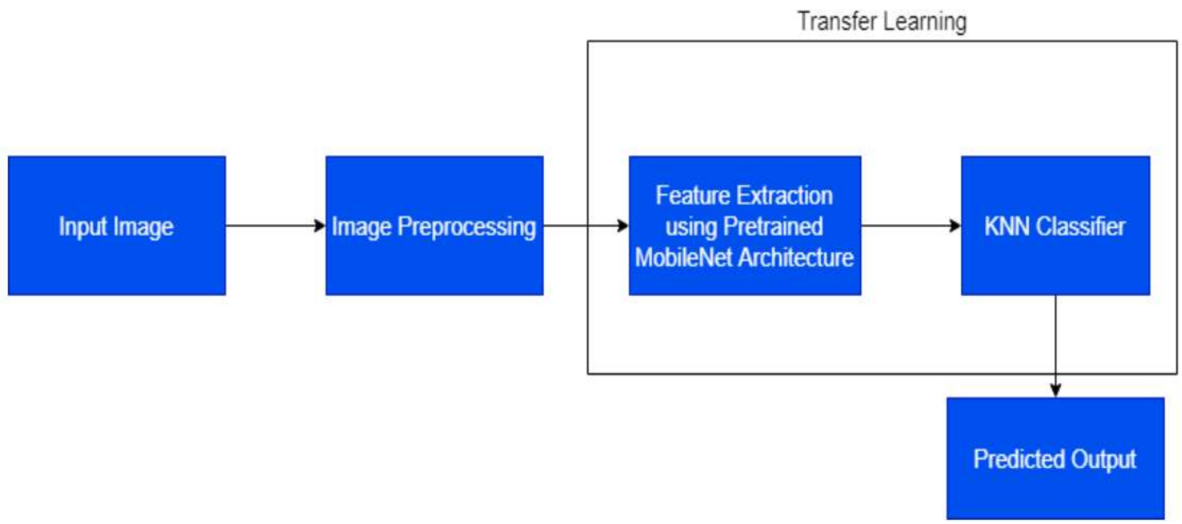


*Figure 2. Block diagram of the proposed system*

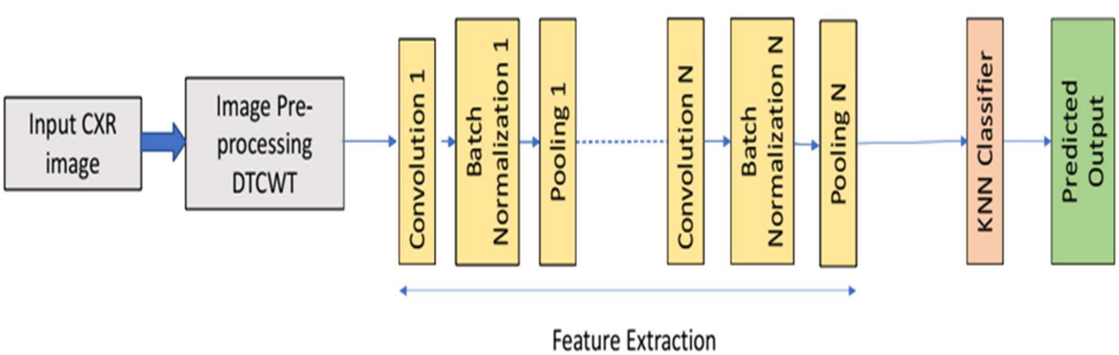


*Figure 3 Detailed overview of the proposed algorithm*

Journal of Theoretical and Applied Information Technology
31st January 2023. Vol.101. No 2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

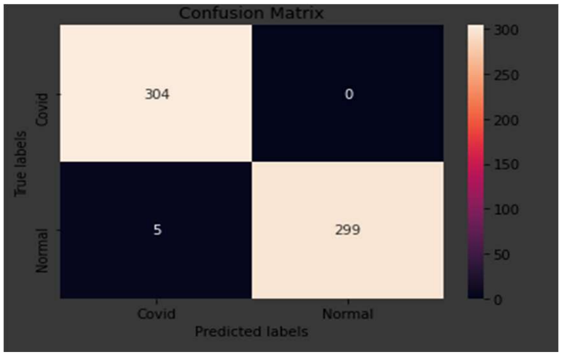


*Figure 4 Confusion matrix for the training dataset*

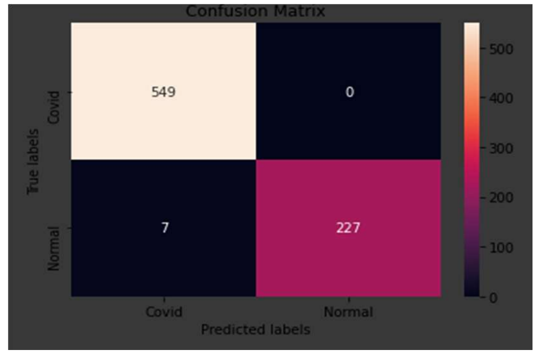


*Figure 5 Confusion matrix for testing dataset*

*Table I Various Parameters for Quantitative Analysis*

| S. No. | Parameter | Formulae |
|---|---|---|
| 1 | Accuracy | $Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$ |
| 2 | Precision | $Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$ |
| 3 | Recall | $Recall\ (Sentivity) = \frac{True\ Positive}{True\ Positive + False\ Negative}$ |
| 4 | F1 score | $F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$ |
| 5 | Specificity | $Specificity = \frac{True\ Negative}{True\ negative + False\ Positive}$ |

Journal of Theoretical and Applied Information Technology
31st January 2023. Vol.101. No 2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

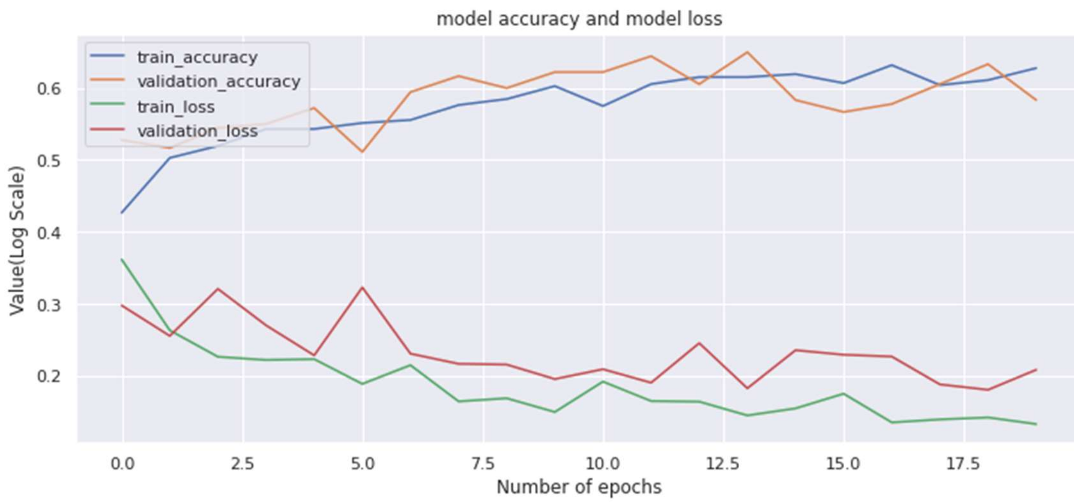


*Figure 6 Graphical Representation Of The Model Accuracy And Model Loss*

*Table II Performance Prediction Matrix For Proposed Model With Existing Model [24]*

| **Models** | **Confusion Matrix and Performance results (%)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **TP** | **TN** | **FP** | **FN** | **Accuracy** | **Macro Avg Recall** | **Macro Avg Precision** | **Macro Avg F1 Score** | **Average Performance** |
| **InceptionResnetV2 [24]** | 515 | 233 | 1 | 34 | 0.96 | 0.97 | 0.94 | 0.95 | Descent |
| **InceptionV3 [24]** | 544 | 222 | 12 | 5 | 0.98 | 0.97 | 0.98 | 0.97 | Good |
| **ResNet50 [24]** | 540 | 228 | 6 | 9 | 0.98 | 0.98 | 0.98 | 0.98 | Good |
| **DenseNet121** | 542 | 224 | 10 | 7 | 0.98 | 0.97 | 0.98 | 0.97 | Good |
| **KNN-WT Classifier (Proposed)** | 549 | 227 | 7 | 0 | 0.99 | 0.99 | 0.99 | 0.99 | Better than all |

(a) (b) (c)

*Figure 7 (A) Normal Patient CXR Image, (B) COVID Affected Patient CXR Image, (C) COVID Affected Patient CXR Image.*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table III Comparison Of The DTCWT-KNN Classifier With Other Methods*

| Author(s) | Dataset Type | Classification | Algorithm | Accuracy% |
|---|---|---|---|---|
| Wang et al. [25] | CXR image | 53 COVID-19+5526 COVID-19 – 8066 Normal | COVID-Net | 92.4 |
| Sethy et al. [26] | CXR image | 25 COVID-19 + 25 COVID-19 | ResNet50+SVM | 95.38 |
| Hemdan et al, [27] | CXR image | 25 COVID + 25 Normal | COVIDX-Net | 90 |
| Ying et al, [28] | Chest CT | 777 COVID + 708 Normal | DRE-Net | 86 |
| KNN-WT Classifier (Proposed Model) | CXR image | 626 (COVID + Normal) | KNN-WT | 99 |