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Deep learning based COVID and pneumonia detection using chest X-ray

Praveen Kumar[1], Mira Rakhimzhanova[1], Seema Rawat[2], Alibek Orynbek[1], Vikas Kamra[3]
[1]Department of Computer Engineering, Astana IT University, Astana, Kazakhstan
[2]Department of Information Technology, Amity University Uttar Pradesh, Noida, India
[3]Department of Computer Science and Engineering, Amity University Uttar Pradesh, Noida, India

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ABSTRACT

Since the outbreak, the novel coronavirus (COVID-19) has infected more than 180 million people and has taken a toll of 3.91 million lives globally as of June 2021. This virus causes symptoms like fever, cold, and fatigue, and can develop into Pneumonia which can be detected using chest X-rays (CXRs). Therefore, early detection of COVID-19 can help get early medical attention. However, a sudden rise in the number of cases in many countries caused by COVID waves increases the burden on their testing facilities. As a result, they sometimes fail to perform enough testing to contain the spread. This work proposes a deep learning model to detect COVID-19 and Pneumonia based on CXRs. The dataset for our COVID model contains a total of 3,400 CXRs images of COVID-19 patients and 3,400 normal CXRs. The dataset for our Pneumonia model contains 1,300 CXR images of Pneumonia patients and 1,300 normal CXRs. We use convolutional neural network provided by TensorFlow to build our model, which gave 94.17% and 93.55% accuracy for COVID model and Pneumonia model, respectively. Finally, we deployed our model on the web and added a web tracker, which gives us the cases, deaths, and recoveries state-wise and nationwide.

Corresponding Author:

Praveen Kumar
Department of Computer Engineering, Astana IT University
Mangilik El Avenue, 55/11, EXPO Business Center, block C1 Astana, 010000 Kazakhstan
Email: Praveen.Kumar@astanait.edu.kz

1. INTRODUCTION

An infectious disease called as COVID-19 (SARS-CoV-2) started spreading at the end of 2019. It initially started spreading in China which led to Pneumonia like illness. COVID-19 was declared a global pandemic in March 2020 by the WHO. Although COVID-19 influences the whole populace, youngsters who are influenced by COVID-19 show some symptoms like sore throat, headache, and rise in body temperature or remain asymptomatic. For elder people and particularly for senior citizens and patients with long-term sickness, COVID-19 may advance to other genuine indications like diarrhoea, dyspnea, Pneumonia, and demise [1], [2]. COVID-19 can cause severe Pneumonia in the lungs of infected patients. Pneumonia is a disease of the lower part of the respiratory system in which the aviation routes and lung parenchyma are influenced, and the alveolar spaces are combined. The side effects of the sickness can change and incorporate dyspnea, high fever, runny nose, and cough. COVID-19 can most regularly be analyzed utilizing the chest X-ray (CXR) visualizing examination for irregularities [3]. The determination of COVID-19 is performed by the RT-PCR test after an assortment of appropriate respiratory parcel examples, which is a lab-based test evaluation of a designated DNA particle. RT-PCR tests provide a high accuracy in detecting COVID-19 but it requires a lab with well-

maintained infrastructure and equipment [4], [5]. The expense of the gear and the necessary polymerase chain reaction (PCR) reagents is high, which makes this test costly and occasionally time-consuming. As the number of COVID-19 cases rises exponentially, artificisl intelligent (AI) can play a very important part in the detection and prevention of COVID-19 cases by making use of imaging technology [6], [7].

X-ray imaging is a technology which makes use of electromagnetic radiation to take pictures of interior human body parts in high contrast. X-Ray is one of the most established and ordinarily utilized clinical analytic tests. CXR has traditionally been used for imaging of sicknesses related to the chest such as Pneumonia infections. The X-ray imaging strategy gives various benefits as another option analysis strategy for COVID-19 over other testing systems. These advantages incorporate its minimal expense, the immense accessibility of X-ray offices, noninvasiveness, less time utilization, and gadget affordability [8].

Deep learning is a part of machine learning that helps us to extract a greater number of details from the given input dataset. Deep learning has given rise to techniques like convolutional neural networks (CNNs). CNN has offered incredible guarantees concerning clinical image investigation [9]. CNNs contain various layers like convolutional layers, and pooling layers, with some number of neurons. By making a handful of changes we can acquire a model that performs in a very different way than the other showing tremendous changes in accuracies [10]. CNN address a tremendous forward leap in image processing and characterization, where they are most regularly used. They comprise the input layer and an output layer, and between them, there are some hidden layers. These hidden layers accomplish the most work as far as computation. Convolutional layers can be found within the hidden layers [11].

This work proposes a COVID-19 and Pneumonia detection framework that can predict these diseases using CXRs. We have created two CNN models trained on CXR datasets. The datasets are collected from the COVID Radiology database available on Kaggle. After training these models, we saved both models and made predictions with the help of them [12].

2. LITERATURE REVIEW

Computer vision has discovered noticeable utilization in medical discoveries and diagnoses. It is valuable in the clinical fields that require visual diagnosis, like dermatology. Computer vision is also utilized to analyze whether a skin irregularity is a possible early pointer of skin disease. It is additionally used to identify internal injuries and issues with the tissues, arteries/veins, and many more [13]. It also finds its application in determining diabetic retinopathy to provide early treatment. It has therefore shown incredible accomplishment in medical procedures as well as remedies. Computer vision uses medical imaging technologies like X-rays, CT scans, MRIs, and so on to solve a range of medical problems [14].

According to various studies and research, medical imaging helps better detect lung diseases caused by viruses. In their work, Jaiswal *et al.* [6] have proposed a deep-learning model based on Mask-RCNN to detect Pneumonia using CXRs. Chouhan *et al.* [7] proposed a transfer learning model for the prediction of Pneumonia which gave an accuracy of 96.4% and gave a recall value of 99.62% on freshly introduced data. Similarly, deep learning has proved to be an effective way of detecting thoracic diseases [7]–[9], and gastric cancer detection [15], using X-rays. Some of these models use a large dataset to input their models and offer promising results [16].

Basset *et al.* [16] used RT-PCR as a reference to show that chest tomography (CT) can accurately detect COVID-19. Ng *et al.* [17] proposed a fully automated deep learning-based network for COVID-19 detection using CT scans. Several other works have been done to detect COVID-19 using CT scans with the help of CNN models [18]–[20]. In their work, Mahmud *et al.* [20] proposed a multi-objective differential CNN that detects COVID-19 using chest CT. A deep learning model utilizing 3D CT scans to detect COVID-19 which had an AUC of 96%, was proposed [21], [22].

Song *et al.* [23] proposed a weakly supervised deep learning model with an accuracy of 90.1%, which had 84% and 98.2% positive and negative predictive values, respectively. In their works, Rahimzadeh *et al.* [24] have inferred that CXRs are better than some other means of identifying COVID-19 due to their promising outcomes alongside the accessibility of CXR machines and their low support cost. Much research works have been done to identify COVID-19 with the help of CXR images [25]–[27]. As a result, Wang *et al.* [28] proposed an automatic COVID-19 detection model using ensemble learning with a total dataset of 1,006 CXR images giving a final classification accuracy of 91.62%. Panwar *et al.* [29] propose an nCOVnet deep learning model for fast prediction of COVID-19 using CXR. Kamra *et al.* [30] offer a deep learning-assisted method for early detection of COVID-19 using a dataset containing 286 CXR images by evaluating eight CNN out of which ResNET-34 gave the highest accuracy, 98.33%.

Our work proposed two CNN based deep learning models to detect COVID-19 and Pneumonia. We chose to build our models using simple CNN architecture with only two convolutional layers [31]. We prepared our CNN models by utilizing the Keras API provided by the TensorFlow library. In the previous works related to this topic, the authors have used small datasets due to the unavailability of COVID-19 CXRs as the pandemic was in its initial stage [32].

So, we decided to train our model on a larger dataset to make our models more effective, so we trained and validated our models on the CXRs collected from the COVID-19 Radiology database on Kaggle. We trained our COVID-19 and Pneumonia deep learning models on 6,800 and 2,600 CXR images in this work. The final accuracy of the COVID-19 model and the Pneumonia model came out to be 94.17% and 93.55%, respectively.

3. METHOD

This section presents the methodology we adopted to build both models to classify the X-ray as COVID-19 positive or normal and Pneumonia or normal. We first explain our dataset and divide it into a training set and test set to train and validate our model. Then, we explain how we use CNN to train our deep learning model and predict the results. Lastly, we describe how we save our model and deploy it on a web app using Flask. Figure 1 shows a flow chart of our work.

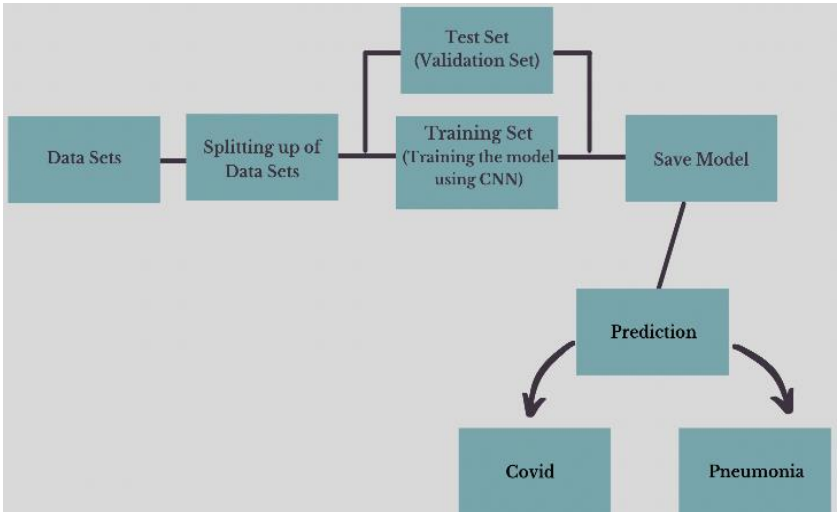

Figure 1. Flowchart of the work

3.1. Dataset

To train our model, we pick up the CXRs with the posterior-anterior and anterior-posterior view. We collected the CXR images from the COVID-19 Radiography Database on Kaggle. First, we divided our dataset into two main sets: the COVID-19 set and the Pneumonia set. The COVID-19 set contained 6,800 CXR images, out of which 3,400 are COVID positive and 3,400 of normal people. Next, we divide the COVID set into the training set and test set for the COVID model. The training set and test set for the COVID-19 model contain 5,400 (2,700 COVID positive and 2,700 healthy) and 1400 (700 COVID positive and 700 healthy) frontal-view CXRs, respectively. Table 1 shows splitting of datasets for COVID-19 model.

Table 1. Splitting of datasets for COVID-19 model

Dataset	Training set	Test set	Total images
COVID-19	2,700	700	3,400
Healthy	2,700	700	3,400

Similarly, we divided the Pneumonia set into the training and the test set to train the Pneumonia model. The training and test set for the Pneumonia model contain 2,000 (1,000 Pneumonia and 100 healthy) and 600 (300 Pneumonia and 300 healthy) frontal-view CXRs, respectively. We choose the images for the dataset in an ordered manner. We choose the first 3400 X-rays from COVID-19 and normal directories in the COVID-19 Radiology database. Similarly, we picked the first 1,300 images from the Pneumonia and normal directories from the Kaggle database. Table 2 shows splitting of datasets for Pneumonia model.

Table 2. Splitting of datasets for Pneumonia model

Dataset	Training set	Test set	Total images
Pneumonia	2,700	700	3,400
Healthy	2,700	700	3,400

All the images inside our dataset are in portable network graphics (PNG) format. Images had a resolution of 299 pixels. We further reduce their resolution to 200 pixels in the pre-processing phase before training our model. This transformation leads to the faster training of the deep learning models.

3.2. Model training

In this study, we trained two models COVID detection model and the Pneumonia detection model. We prepared both these models using the deep learning technique. We use the CNN provided by TensorFlow to train the models. TensorFlow is the library provided by Google for scalable machine learning that reduces the complexity of computations [28]. We use tf.keras.models.Sequential() to group all the layers in a linear stack. We add two Convolutional layers with rectified linear unit (ReLU) as the activation function to our CNN. Since our models predict the result as COVID-19 positive or healthy and Pneumonia or healthy, the CNN's output layer contains only one neuron with sigmoid as the activation function. Figure 2 shows the layers of CNN built using TensorFlow.

The models are compiled with loss calculation function as binary_crossentropy, Adam optimizer, and accuracy as metrics. Then, we train the models on the training set and use the test set as the validation hyperparameter. After trying many hyperparameters, we choose the number of epochs as 25 for both models. Finally, we save the model with the .h5 extension using the h5py package. The saved deep learning model is later loaded in our Flask web app for making predictions using the predict() method.

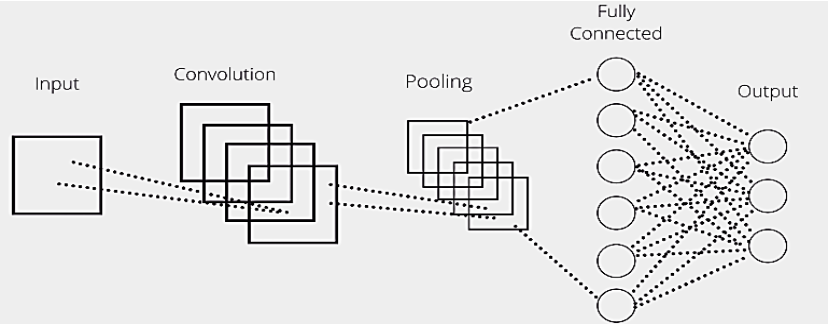

Figure 2. Layers of CNN built using TensorFlow

3.2.1. Tools used

We have used Jupyter Notebook on the PC with 8 GB DDR5 RAM, TensorFlow 2.5.0, and Python 3.9.5. We implement our model using Keras, a deep learning library provided by TensorFlow, to build and train the CNN models on the training sets discussed in section A of the methodology. We also use Matplotlib to visualize the loss and accuracy of data of the deep learning models. For the web development, we used Visual Studio Code as a code editor.

3.2.2. Evaluation metrics

We chose accuracy as the evaluation metric to test the performance of our models. The formula used to calculate accuracy:

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn}$$

Tp stands for true positive in the above equation, Tn for true negative, Fp for false- positive, and Fn for false negative. True positive in the context of our study means a correct prediction made for COVID-19 positive, and False positive means a routine CXR is predicted as COVID-19 positive. Similarly, True negative means an accurate prediction is made for normal, and Fn means a COVID-19-positive person's CXR is predicted as normal.

4. RESULTS AND DISCUSSIONS

We trained both our models with the same hyperparameters after testing our model against a range of values. We added the layers to our CNN model in a sequential manner using the Sequential class of Keras.models module. Our models contained two convolutional layers, which had 32 filters, kernel_size as three, and ReLU as the activation function. We added a pooling layer after each convolutional layer with pool_size and strides as 2. The full connection was made using the dense layer with 128 neurons and ReLU as the activation function. We decided the batch_size to be 32 for training our models. The summary of the model layer is shown in Figure 3.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 198, 198, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 99, 99, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 97, 97, 32)        9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 48, 48, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 73728)             0
_________________________________________________________________
dense (Dense)                (None, 128)               9437312
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 9,447,585
Trainable params: 9,447,585
Non-trainable params: 0
_________________________________________________________________
```

Figure 3. Sequential model output parameters

To start with our implementation, we have imported the libraries required to build our CNN model. After importing the libraries, we preprocessed the images. The images were fetched from the directory using the flow_from_directory() method of ImageDataGenerator. We divided them into training and test sets, after which we reduced the resolution of our images to 200×200 pixels for faster training of our COVID model. After the preprocessing phase, we chose to make our CNN model sequential using the Sequential class of Keras.models module of the TensorFlow library. The first convolutional layer of our model contained 32 filters and ReLU as the activation function. After adding the first convolutional layer to our model, we performed pooling using pool_size and strides as 2.

Then we added a second convolutional layer and performed pooling to it in the same manner as we did to the first convolutional layer. After this, we added a flattening layer to the model using the Flatten class of Keras.layers module. Further, we added a dense layer that receives the network from all the neurons in the previous layers. Finally, we added an output layer with only one neuron because it must only predict the results between the two classes. The activation function used in this layer was sigmoid. After adding this layer, we print the summary of the model. After building the CNN model, we completed it with the loss function being binary_crossEntropy, Adam as an optimizer, and accuracy as the metric. After compiling, we train our model on the training set and validate it on the test set. It takes a total of 25 epochs to train our model. Then we visualize the accuracy and validation accuracy of the models by plotting them using Matplotlib. Similarly, we also plot the loss and validation loss of our model. After visualizing the data, we save our COVID model in .h5 format. We also planned to test our model on an unseen dataset. We used the predict() method to make the prediction, which returned a 2D array with only one element inside of it, which is 1 when the model predicts a CXR to be of a healthy person and 0 when COVID-19 is detected.

To start with our implementation of our Pneumonia model, we have imported the libraries required to build our CNN model. After importing the libraries, we preprocessed the images. The images were fetched from the directory using the flow_from_directory() method of ImageDataGenerator. They were divided into training and test sets, after which we reduced the resolution of our images to 200×200 pixels for faster training of our COVID model. After the preprocessing phase, we chose to make our CNN model sequential using the Sequential class of Keras.models module of the TensorFlow library. The first convolutional layer of

our model contained 32 filters and a ReLU as the activation function. After adding the first convolutional layer to our model, we performed pooling on it using pool_size and strides as 2. Then we added a second convolutional layer and performed pooling to it in the same manner as we did to the first convolutional layer. After this, we added a flattening layer to the model using the Flatten class of Keras.layers module.

Further, we added a dense layer that receives the network from all the neurons in the previous layers. Finally, we added an output layer with only one neuron because it must only predict the results between the two classes. The activation function used in this layer was sigmoid. After adding this layer, we print the summary of the model. After building the CNN model, we completed it with the loss function being binary_crossEntropy, Adam as an optimizer, and accuracy as the metric. After compiling, we train our model on the training set and validate it on the test set. It takes a total of 25 epochs to train our model. Then we visualize the accuracy and validation accuracy of the models by plotting them using Matplotlib. Similarly, we also plot the loss and validation loss of our model. After visualizing the data, we save our Pneumonia model in .h5 format. We also planned to test our model on an unseen dataset. We used the predict() method to make the prediction which returned a 2D array with only one element inside of it, which is 0 when the model predicts a CXR to be of a healthy person and 1 when Pneumonia is detected. The COVID model gave a high accuracy of 94.17% and a validation accuracy of 91.43%, while our Pneumonia model gave an accuracy of 93.55% and a validation accuracy of 93%, as shown in Table 3.

Our models were trained on the training set and validated against the test set discussed in the methodology section of this work. In Figure 4, we have plotted the model accuracy and validation accuracy of the COVID model against the number of epochs. The model loss and validation loss of the COVID model is plotted against the number of epochs in Figure 5. Similarly, we have plotted the accuracy data and loss data of Pneumonia against the number of epochs has been plotted in Figures 6 and 7.

Table 3. Splitting of datasets for Pneumonia model

Model	Accuracy (%)	Validation accuracy (%)	Loss (%)	Validation loss (%)
COVID-19	94.17	91.43	13.98	20.24
Pneumonia	93.55	93.00	16.25	20.32

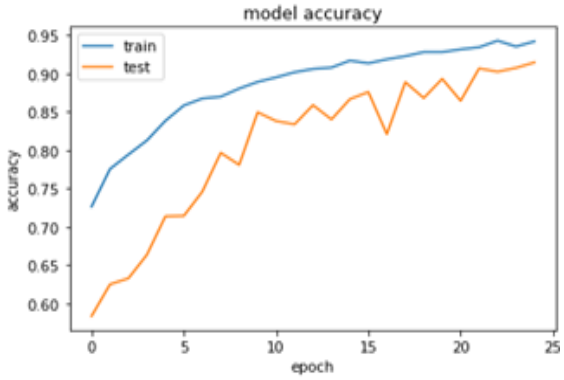

Figure 4. Plot of accuracy data for COVID model

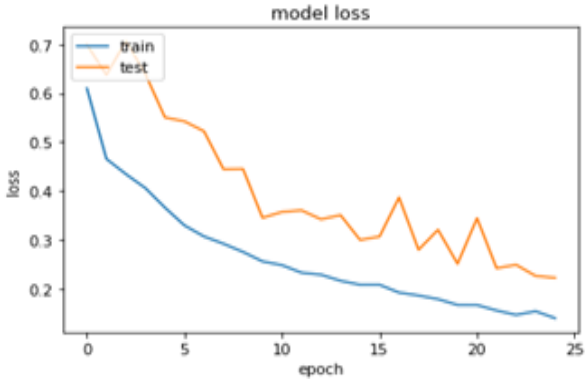

Figure 5. Plot of loss data for COVID model

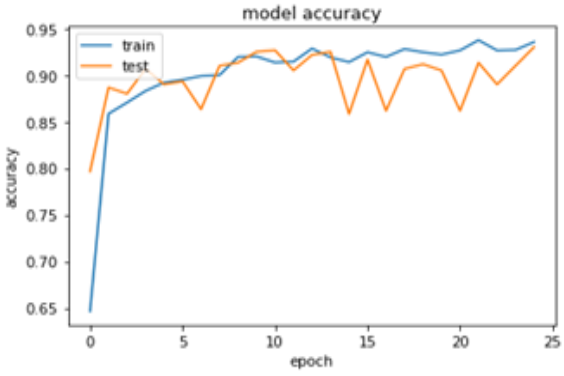

Figure 6. Plot of accuracy data for Pneumonia model

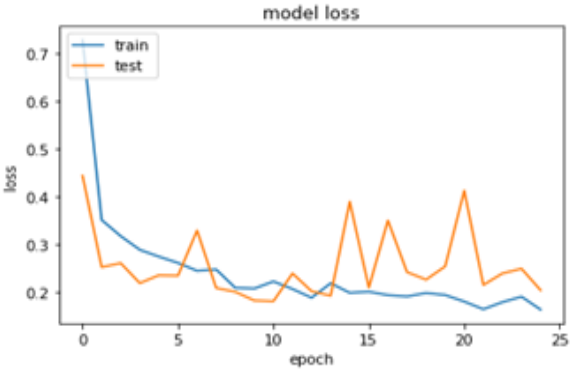

Figure 7. Plot of loss data for Pneumonia model

5. CONCLUSION AND FUTURE WORK

Hence, we proposed and implemented a framework for disease detection, which successfully predicts COVID-19 and Pneumonia using CXRs. Our project constituted two CNN models for COVID-19 detection and Pneumonia detection. These models showed high accuracy in prediction, 94.17% for the COVID model and 93.55% for the Pneumonia model. After saving these models, we deployed them on the web using Flask. The Flask has two forms which take an image as an input and feed that image to our models to make the prediction. After completing the deployment of our model on the web app, we integrated a COVID tracker for India, which shows the statistics about vaccination and COVID-19 cases, deaths, and recoveries around the country. As future work for our project, we will collect additional CXR images and train our models on a larger dataset to increase their effectiveness in predicting these diseases. We also want to add some more features to our website, such as a webpage where people can request resources like oxygen concentrators, and Remdesivir. Currently, we have been running our server on our localhost. In the future, we want to deploy our web app on Heroku servers so that it can be used by everyone, helping in the early detection of COVID-19, and preventing the spread.

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BIOGRAPHIES OF AUTHORS

Praveen Kumar is received his Ph.D. and M. Tech in Computer Science and Engineering. Currently he is working as Professor in Astana IT University, Kazakhstan. Previously he was the Professor and Head, Department of Information Technology and Engineering in Amity University Tashkent Uzbekistan. He has more than 17+ years' experience in teaching and research. He has been awarded as best Ph.D. thesis and Awarded as Fellow Member of Indian Institute of Machine Learning for outstanding contribution in Artificial Intelligence and Machine Learning, recognized by Government of West Bengal, India, Awarded as Best Teacher of Big Data Analytics, Corona worrier Award, Awarded for Excellence in Research-2023, Certified Microsoft Technology Associate (MTA). He has to his credit 09 Patents, 04 Copyright and published more than 0130+ research papers in International Journals and Conferences (Scopus Indexed). Also published 06-SCI paper, and 15 UGC Listed journal. and Published 01- Edited Book (01 – In process). He has organized and Session chaired in 62+ International and National Conferences and Evaluate 06 Ph.D. thesis Reviewed as an External Examiner He has visited various countries for various purposes like Uzbekistan, visited Tokyo, Japan as Indian Delegation sponsored by Japan Science and Technology (JST), Visited London, UK under Student Abroad program, Visited Paris, France for chairing a Technical Session in International Conference, visited Da Nang, Vietnam for Chairing a Technical and Keynote Speaker in International conference, Visited Dubai for Chairing a Special Session in International conference. He is an Active Senior member in IEEE, lifetime member of IETE, member of ACM, and member of IET(UK) and other renowned technical societies. He is associated with Corporates, and he is Technical Adviser of DeetyaSoft Pvt. Ltd. Noida, and MyDigital360. He can be contacted at email: Praveen.Kumar@astanait.edu.kz.

Mira Rakhimzhanova received her Ph.D. in computer science from the L.N.Gumilyov Eurasian National University, awarded in 2023. Currently, she works as Deputy Director of the Computer Engineering Department of Astana IT University. Mira Rakhimzhanova specializes in such advanced fields as methods of teaching computer science, computer graphics, big data, and artificial intelligence. She can be contacted at email: rakhimzhan.mira@gmail.com.

Seema Rawat did her Ph.D. in Computer Science and Engineering and currently she is working as an Associate Professor in Amity school of Engineering and Technology, Amity University Uttar Pradesh, Noida. She has more than 18+ years of experience in research, teaching, and content writing. His areas of interests include big data analytics, data mining, and machine learning. She has to her credit 12 Patents and published more than 80 research paper in international journals and conferences (Scopus Indexed). She is an editor and reviewer for many books and conferences. She has received the Award of "Faculty Innovation Excellence Award 2019" on World Intellectual Property Day. The award was given by The Secretary of Department of Science and Technology (DST) Government of India. She is an Active member in IEEE, member of ACM, and member of IET(UK) and other renowned technical societies. She can be contacted at email: srawat1@amity.edu.

Alibek Orynbek Sarsenbekuly is Senior Lecturer at Astana IT University, Kazakhstan. He is doing Ph.D. degree in Eurasian National University in specialization Mathematics. His research area then was math analysis in furrier series in generalized Haar systems. His research interests signal processing, big data, and machine learning. He can be contacted at email: mr.orynbek@gmail.com.

Vikas Kamra is working as an Assistant Professor (Grade-III) in Computer Science and Engineering Department at Amity School of Engineering and Technology, Amity University Uttar Pradesh, Noida, Delhi-NCR, India. He is a seasoned academician and researcher having 19 years of experience in the field of Computer Science and Engineering. He has done his Ph.D, in CSE, M.Tech in CSE and B.Tech in CSE. He has published 10 Indian Patents and 25 research papers in reputed journals and conferences. He worked as an organizer of many international conferences. He also contributed as a resource person in many faculty development programmers. His research area is machine learning and health informatics. He has developed an artificial intelligence based model for prediction of psychological diseases like Bipolar Disorder, Obsessive Compulsive Disorder and Schizophrenia. He can be contacted at email: kamra1984@gmail.com.