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Revolutionizing healthcare image analysis in pandemic-based fog-cloud computing architectures

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Article Info	ABSTRACT
	Healthcare data analysis has become essential after epidemic outbreaks. The manual examination of medical images such as X-rays and computed tomography (CT) scans became one of these challenges. This paper introduces a healthcare architecture that tackles the analysis efficiency and accuracy challenges by harnessing artificial intelligence (AI) capabilities. This architecture utilizes fog computing and presents a modified convolutional neural network (CNN) designed specifically for image analysis. Different architectures of CNN layers are thoroughly explored and evaluated to optimize overall performance. To demonstrate the effectiveness of the proposed approach, a dataset of X-ray images is utilized for analysis and evaluation. Comparative assessments are conducted against recent models such as VGG16, VGG19, MobileNet, and related research papers. Notably, the proposed approach achieves an exceptional accuracy rate of 99.88% in classifying normal cases, accompanied by a validation rate of 96.5%, precision and recall rates of 100%, and an F1 score of 100%. These results highlight the immense potential of fog computing and modified CNNs in revolutionizing healthcare image analysis and diagnosis, not only during pandemics but also in the future. By leveraging these technologies, healthcare professionals can improve the efficacy and accuracy of medical image analysis, leading to improved patient care and outcomes.

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1. INTRODUCTION

The field of healthcare data analysis has undergone a significant transformation, particularly in response to pandemics, which have heightened the demand for efficient solutions. During such critical times, healthcare professionals and researchers face a significant challenge in manually analyzing medical images, including X-rays and computed tomography (CT) scans [1]. This task is time-consuming and complicated by the logistical hurdles of transferring these large image datasets to centralized cloud computing servers. Moreover, the speed and accuracy of image analysis are crucial factors in effective healthcare image management.

Cloud computing, a technology which permits users to access computing resources which include data storage and processing power via the internet, has the likelihood to enhance the safety, quality, and efficiency of healthcare. One application of cloud computing in healthcare involves storing and analyzing extensive patient data to identify trends and patterns which could aid in more efficient disease diagnosis and management [1]. Additionally, cloud computing can facilitate the remote delivery of healthcare services,

particularly benefiting patients residing in rural areas or those facing challenges in visiting a doctor's office [2]. However, the traditional cloud computing architecture for medical and healthcare purposes relies on a centralized approach for data transmission, which poses several challenges [3]:

i)   Security: centralized data storage increases vulnerability to cyberattacks.
ii) Scalability: scaling centralized data storage to meet the needs of a growing number of users can be challenging.
iii) Compliance: healthcare organizations must adhere to strict regulations governing the privacy and security of patient data, which can be difficult with a centralized storage system.
iv) Latency: the time it takes for data to travel from the network's edge to the cloud and back may be too long for time-sensitive healthcare applications, particularly those requiring rapid response in emergency situations.
v)   Cost: transferring huge amounts of data to the cloud can be expensive.

These challenges have led some healthcare organizations to adopt fog computing as an alternative to cloud computing. Fog computing, a distributed cloud computing architecture, is better suited for healthcare applications. Fog computing nodes are positioned closer to the network's edge, reducing latency and improving security. Moreover, fog computing could be a more cost-effective solution for health care applications that involve significant data transfer. Fog computing holds great promise for healthcare and is expected to witness increased adoption in the future [4].

Deep learning (DL), a subset of artificial intelligence (AI), is being leveraged to enhance healthcare in various ways. DL algorithms can analyse medical images and data to diagnose diseases, develop new treatments, and deliver personalized care [5], [6]. It is also instrumental in developing healthcare applications which include virtual assistants as well as chatbots. DL is a rapidly evolving field that is poised to have a significant impact on healthcare in the years to come [7], [8].

The advancement of science and technology has historically been driven by medicine and healthcare [9], [10]. Recent research has focused on integrating fog computing into internet of health technology (IoHT) applications, yielding positive outcomes such as reduced service response time, improved system performance, and increased energy efficacy. For instance, Xue et al. [11] developed the analytic network technique to identify and rank fog computing-based internet of things (IoT) solutions for health system supervising. Fog computing in health care includes establishing a distributed intermediate layer between the cloud and sensor hubs using IoT frameworks.

Gia et al. [12] demonstrated the use of fog computing as a gateway to enhance health monitoring systems. They created fog computing features, including interoperability, a distributed database, a real-time notification mechanism, position awareness, and a graphical user interface with access management. Additionally, they presented a lightweight, customizable framework for extracting electrocardiography (ECG) features (such as pulse, P, and T waves). Elhadad et al. [13] have suggested a fog-based health monitoring framework which utilizes fog gateways in the context of medical decision-making according to data collected from sensors embedded in wearable devices. These sensors which include temperature sensors, ECG sensors, and blood pressure (BP) sensors, measure a patient's temperature, pulse, and BP respectively.

Al-Khafajiy et al. [14] introduced the concept of IoT-fog computing in IoT-based healthcare systems, suggesting a methodology for improving fog performance through collaborative policies among fog nodes for optimal workload and job distribution. Similarly, El-Rashidy et al. [15] presented a detailed strategy to monitor pregnant females by utilizing a data replacement and prediction framework (DRPF) divided into three layers: (i) IoT, (ii) fog, and (iii) cloud. Their findings indicated strong associations between patient age, body mass index (BMI), BP, lymphocyte vitamin E levels, and the diagnosis of gestational diabetes.

Quy et al. [16] presented an all-in-one computer architectural framework and conducted a survey of IoT applications according to fog computing in the health care industry. They explored the application potential, challenges, and future research objectives in this field. Similarly, Shi et al. [17] evaluated the vision and essential characteristics of fog computing, which aims to address the latency issue caused by IoT by distributing processing, storage, and networking resources to the network edge, interacting with the cloud.

Arunkumar et al. [18] recommended HealthFog-CCNN, a fog-based smart healthcare system to automatically diagnose cardiac disorders that combines DL and IoT. Their research focused on the medical aspects of heart disease patients, utilizing DL in edge computing devices for real-time analysis of cardiac problems. Lastly, Mutlag et al. [19] aimed to contribute to the existing knowledge by providing specific examples categorized into four groups: fog computing approaches in healthcare applications, system development in fog computing for healthcare applications, and evaluation and surveys of fog computing in healthcare applications.

While fog computing and artificial intelligence (AI) have been effectively utilized in the healthcare field, no effective framework has been used for heavy healthcare processing, particularly during a pandemic.

Furthermore, most papers examine small datasets for efficiency testing. Therefore, the current paper suggests a new framework according to a distributed data ingestion/collection layer, with distributed data processing and integration layers to simplify the processing of similar data on specific devices. The collected data is then forwarded to fog nodes for additional analysis. The next section offers a detailed description of the proposed framework.

To address these formidable challenges, this research paper introduces an innovative healthcare architecture that aims to achieve both analysis efficiency and accuracy. At its core, this architecture harnesses the power of AI. Specifically, it presents a novel framework that combines the fog computing paradigm with a meticulously designed modification of convolutional neural networks (CNNs), tailored explicitly for image analysis. A comprehensive exploration of various CNN layer architectures is conducted and subjected to rigorous evaluation to optimize performance.

To empirically validate the efficiency of the recommended approach, a curated dataset of COVID-19-related X-ray images is used for analysis and evaluation. These images serve as a practical testbed to enable comparative assessments against contemporary models such as VGG16, VGG19, and MobileNet. The outcomes of these assessments unequivocally demonstrate the exceptional potential of the proposed framework.

These compelling results underscore the transformative potential that emerges from the intersection of fog computing and modified CNNs in the domain of healthcare image analysis. In a world grappling with the challenges posed by pandemics, the convergence of cutting-edge technology and medical science holds the promise of revolutionizing healthcare image analysis and diagnosis, not only during times of crisis but also in the broader landscape of healthcare delivery. This research represents a critical step forward in realizing this promise and provides a glimpse into a future where the fusion of AI and healthcare unlocks boundless potential.

The remainder of the current paper is planned as follows: section two discusses previous work in the field. Section three defines the proposed framework. Section four presents the CNNs architecture. Section 5 introduces mathematical formulas for the proposed model. Section 6 discusses database for chest X-rays (CXR). Section 7 discusses the experimental results. Section 8 evaluation of three layers of the CNN model with different epochs. Finally, section 9 concludes the paper by summarizing the outcomes and outlining upcoming research directions.

2. METHOD

The integration of fog computing, cloud resources and AI technologies in the proposed healthcare framework creates a comprehensive and efficient healthcare ecosystem [9], [10] as depicted in Figure 1. The framework aims to improve patient care, streamline healthcare processes, and support research and innovation. It consists of several interconnected layers, each with its unique roles and functionalities.

The first layer is the end layer, which has an essential role in collecting and assimilating diverse data from sources which include medical devices, sensors, electronic health records, and patient-generated data. Its main functions include data collection, transformation, quality assurance, and aggregation. This layer ensures data compatibility, reliability, and security through encryption and authentication. It also prioritizes scalability, reliability, adherence to healthcare regulations, and interoperability for efficient data sharing and collaboration [11], [12].

The second layer is the edge/fog computing layer, that serves as a critical bridge between the data sources and the centralized cloud infrastructure. Positioned closer to the data sources, this layer allows real-time or near-real-time data processing, in particular essential for low-latency healthcare applications like patient monitoring and emergency care. It leverages distributed edge or fog computing nodes to execute data analytics and computational tasks at the source, reducing the burden on central cloud resources and optimizing bandwidth usage. This layer ensures local data processing, secure data storage, and efficient resource allocation to enhance system scalability, reliability, and rapid decision-making [13]–[16]. The proposed model is in this layer in order to analyse images to detect disease.

The third layer is the cloud layer, which serves as the central component of the healthcare system, providing hardware resources and high-capacity computer services as data centres for data computation and storage. It encompasses data analysis and pre-processing procedures, supporting medical professionals in making long-term treatment decisions. This layer involves various processing tasks, including normalization and data preparation, before training machine learning algorithms such as CNN for disease diagnosis, predictive modeling, anomaly detection, and data-driven decision support. It contributes to improved healthcare outcomes and drives innovation within the healthcare ecosystem [18], [19]. This layer contains the pre-trained CNN model to ensure the validity of the results.

In summary, the proposed healthcare framework integrates fog computing, cloud resources, and AI technologies to create a holistic and efficient healthcare ecosystem. The framework consists of the data ingestion layer, data processing and integration layer, edge/fog computing layer, and cloud layer, each playing an essential role in collecting, processing, analyzing, and storing healthcare data to support improved patient care and decision-making.
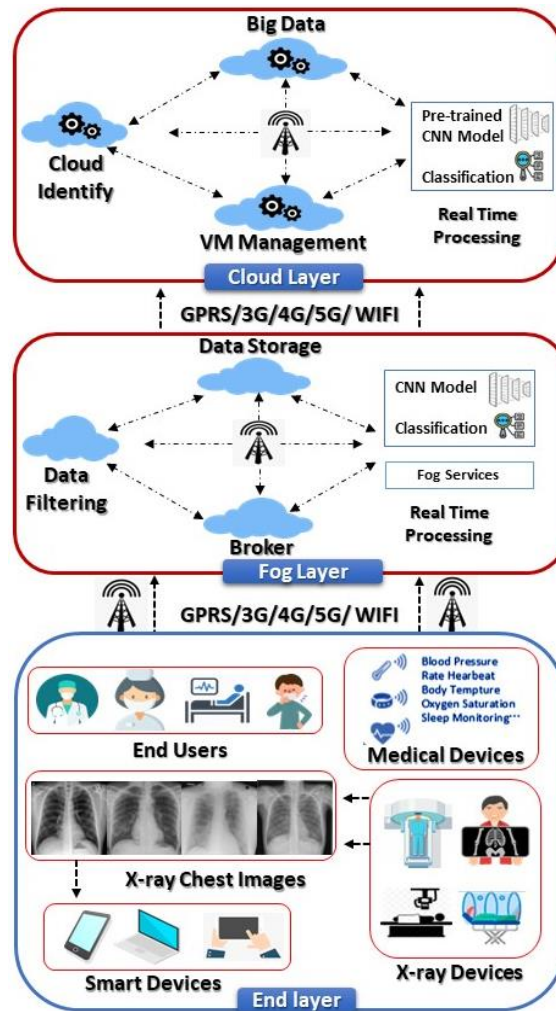

Figure 1. The framework based on IoT fog-cloud computing architecture

2.1. The CNN architecture

Like other domains, the healthcare field has successfully implemented several DL applications that have revealed significant results in various medical scenarios. This success can be attributed to two main factors: i) the ability of DL models to learn from labeled or unlabeled datasets and ii) the inherent risk of human error in diagnosing cases, regardless of the doctors' expertise level. Consequently, the medical research community has developed numerous healthcare systems based on DL methods.

One specific DL technique, called CNN, has been designed to excel in image identification, classification, and prediction tasks. CNN's ability to automatically extract features from images and perform in-depth analysis makes it ideally suited for training in the recommended architecture. In this study, a CNN-based model is proposed for detecting chest diseases in patients using chest radiography images. The model's objective is to classify and identify chest diseases by distinguishing between normal X-rays and abnormal CXR, as depicted in Figure 2.

For CNN to operate effectively, the input images must undergo processing to extract visual patterns. This process involves a linear operation where two functions represented by matrices are multiplied to produce an output. Initially, the images are transformed into a matrix format to facilitate information

extraction. CNN comprises several layers that work together to perform these operations efficiently, including as shown Figure 3:

i)   Input data layer: this layer reads a pre-processed collection of images. In our case, the X-ray and CT images are pre-processed separately.

ii) Convolutional layer: serving as the core of our proposed model, this layer is responsible for extracting features from the image collection while preserving the spatial relation between pixels.

iii) Batch normalization layer: this layer is a crucial training strategy in deep neural networks as it ensures the stability and proper training of convolutional features.

iv) Rectified linear unit (ReLU) layer: This layer replaces negative pixel values in the convolved features with zero, generating a non-linearity map of the CNN network's features.

v)   Fully connected layer: this layer categorizes the convolved features from the image datasets into the desired classes.

vi) Softmax layer: interpreting the probability values of the activation function from the previous layer, this layer is particularly relevant for illness diagnosis. The results can be interpreted as two classes: '0' for negative (normal CXR or CT) and '1' for positive disease.

vii) Output layer: this final layer of the CNN model labels the results obtained from the previous layer accordingly [20].
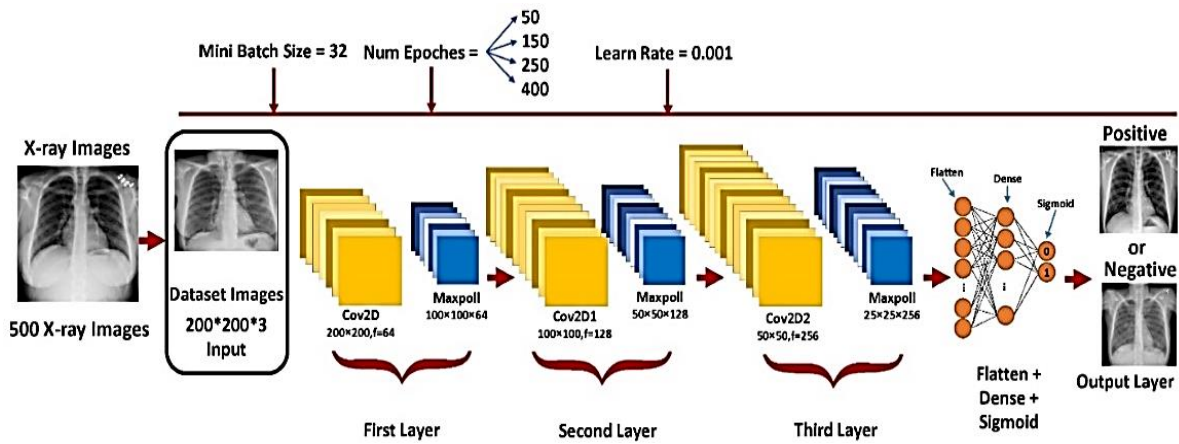

Figure 2. The proposed model is according to CNN architecture
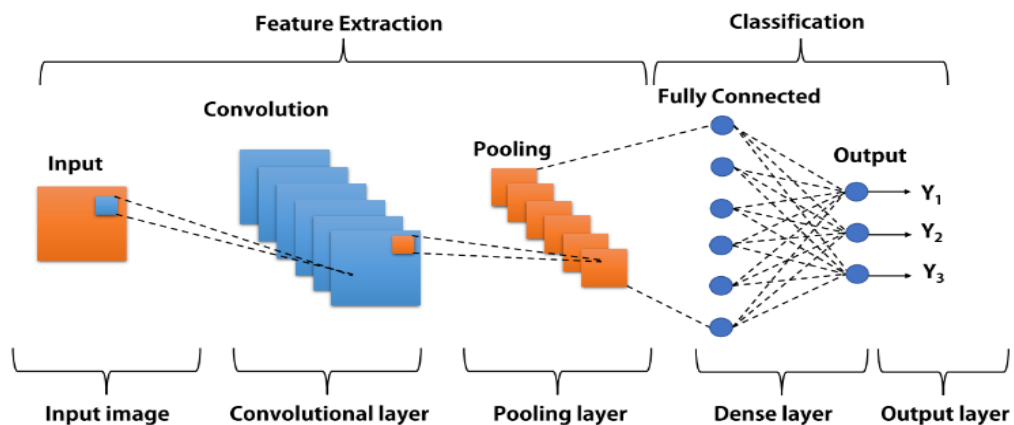

Figure 3. The CNN architecture layers

In conclusion, the healthcare field has embraced DL applications, leveraging the remarkable capabilities of DL models in various medical scenarios. The proposed architecture incorporates CNN, a specialized DL technique for image identification, classification, and prediction, to detect chest diseases from

chest radiography images. The CNN model consists of multiple layers, each playing a distinct role in efficiently processing and analyzing the input data to classify and identify chest diseases [20].

3.   RESULTS AND DISCUSSION
The experiments were conducted on an HP EliteBook operating on Windows 10 Pro 64-bit. The system specifications included a 3.8 GHz Core i7 processor, 16 GB of RAM, an Intel HD Graphics 4600 GPU, and 1 TB of storage. The experiments were implemented using Python 3.9 with the Keras and TensorFlow libraries within the PyCharm program.

3.1. Database for chest X-rays
A collaborative team of authors from Qatar University, the University of Dhaka in Bangladesh, besides their partners from Pakistan and Malaysia, collaborated with medical professionals to develop a comprehensive database of CXR image. This database includes cases of COVID-19-positive individuals, as well as normal and viral pneumonitis cases. The dataset is being made available in stages, with the initial release comprising 219 COVID-19, 1,341 normal, and 1,345 viral pneumonia CXR images. Subsequently, the COVID-19 class was expanded to include 1,200 CXR images in the first update. In the second update, the database was further expanded to encompass 1,345 viral pneumonia cases, 3,616 COVID-19 positive cases, 10,192 normal cases, 6,012 instances of lung opacity (non-COVID lung infections), and an additional 6,012 COVID-19 positive cases. For our research, we are specifically interested in two datasets: one containing 10,192 normal CXR and another containing 3616 COVID-19 positive CXR [21].

The dataset curated by Chowdhury *et al.* [22] consists of 13,808 chest images captured in the posterior/anterior (PA) or anterior-posterior (AP) view. Each sample in the database has a resolution of 1,024×1,024 pixels and is stored in portable network graphics (PNG) format. To facilitate compatibility with popular CNNs, the images were resized to standard dimensions of 224×224 or 227×227.

In this study, the dataset of 13,808 images was divided into training, validation, and test sets with a ratio of 80:10:10. The corresponding counts for each dataset are as follows:
i)   Training dataset: this dataset comprises a total of 13,808 images, with 2,894 being COVID-19 positive CXR and 8,154 being normal CXR.
ii) Validation dataset: the validation dataset consists of 1,381 images, including 361 COVID-19 positive CXR and 1,019 normal CXR.
iii) Testing dataset: the testing dataset contains 1,381 images, with 361 COVID-19 positive CXR and 1,019 normal CXR.

Table 1 provides an overview of the distribution of images across the training, validation, and test sets. In the dataset, normal cases equal (0), and COVID-19 positive cases equal (1), as shown in Figure 4.

Table 1. Distribution of chest X-ray images after splitting

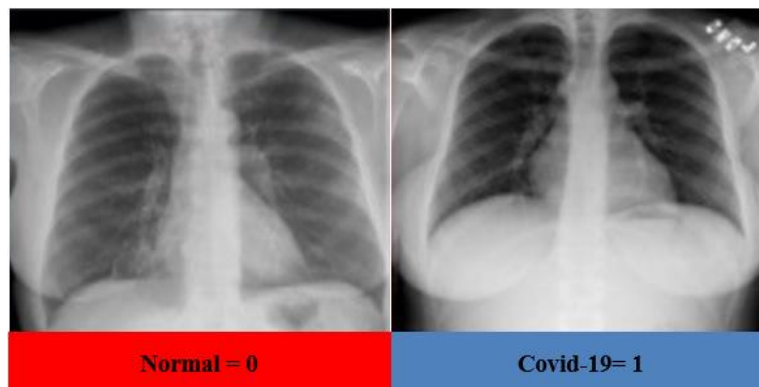| Classes	Training set	Validation set	Testing set	Total
COVID-19	2,894	361	361	3,616
NORMAL	8,154	1,019	1,019	10,192

Figure 4. The dataset of normal cases and COVID-19-positive cases

3.2. Performance measures

In this paper, to evaluate our model, the cross-entropy log loss function between correct and predicted labels is used as an evaluation criterion. The mathematical formula for calculating log loss is written as (1):

$$\text{Log Loss} = -\frac{1}{K} \sum_{i=1}^{K} \sum_{j=1}^{S} g_{ij} \, log \, (F_{ij}) \tag{1}$$

here, K denotes the number of samples, and S denotes the number of classes. The true label of the class is represented by g, and the probability of the given sample is represented by F. The natural logarithm is used in the formula.

In terms of the current model assessment, we used the next classification metrics: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). We calculate recall, TP rate (TPR), false positive rate (FPR), precision, specificity, sensitivity, F1 score, and accuracy using these measures.

Recall: it represents a model's ability to find all relevant cases within a dataset. Mathematically, recall is defined as the number of TP divided by the total number of TP plus the number of FN.

$$\text{Recall} = \text{TPR} = \frac{TP}{TP+FN} \tag{2}$$

Precision: it indicates a classification model's ability to identify only relevant data points. Precision is defined as the number of TP divided by the number of TP plus the number of false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

Specificity refers to the number of correctly predicted negative records. It helps determine how well our model predicts the class that we want to label as the negative class. In some ways, it is like Recall for the negative class.

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{4}$$

Sensitivity refers to the number of positive records correctly predicted. For the class that we want to declare as the positive class, sensitivity is the same as recall.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{5}$$

Additionally, accuracy is another evaluation metric used to assess the performance of our model. It is mathematically defined as (6).

$$\text{Accuracy} = \frac{Tp+Tn}{Tp+TN+FP+FN} \tag{6}$$

The F1-score is the harmonic mean of precision and recall, using the following equation to account for both metrics as (7).

$$F1 - score = 2 * \left(\frac{Precision*Recall}{Precision + Recall}\right) \tag{7}$$

The results of our proposed framework showcased exceptional performance in classifying COVID-19 and normal cases, accomplishing an accuracy of 99.88% and a validation rate of 96.50%. A summary of the classification results is presented in Table 2. According to Table 2, our proposed approach achieves the highest accuracy of 99.88% in classifying COVID-19 and normal cases. It is accompanied by a validation rate of 96.5%, precision and recall rates of 100%, and an F1-score of 100% based on the training rate. However, for the validation rate, the precision and recall rates are 98%, and the F1-score is 98.45% with a precision of 98.88% and recall rate of 98%.

Figure 5 provides a visual representation comparing the pooling of a 3-by-3 image with a stride of 2 and the pooling of a 2-by-2 image with a stride of 3. The illustration concludes that while reducing the image features, minimal information loss occurs. Before the completely linked CNN layer, feature maps from the three sequential layers are concatenated. Weights are calculated using the Glorot technique [23], the Adam

optimizer [24], and a learning rate of 0.001, 400 epochs, and 32 mini-batch sizes. Table 3 depicts the proposed model based on CNN's structure.

Table 2. Classification results

Metrics	Precision	Recall	F1-score	Accuracy
Training	100%	100%	100%	99.88%
validation	98.88%	98%	98.45%	96.50%
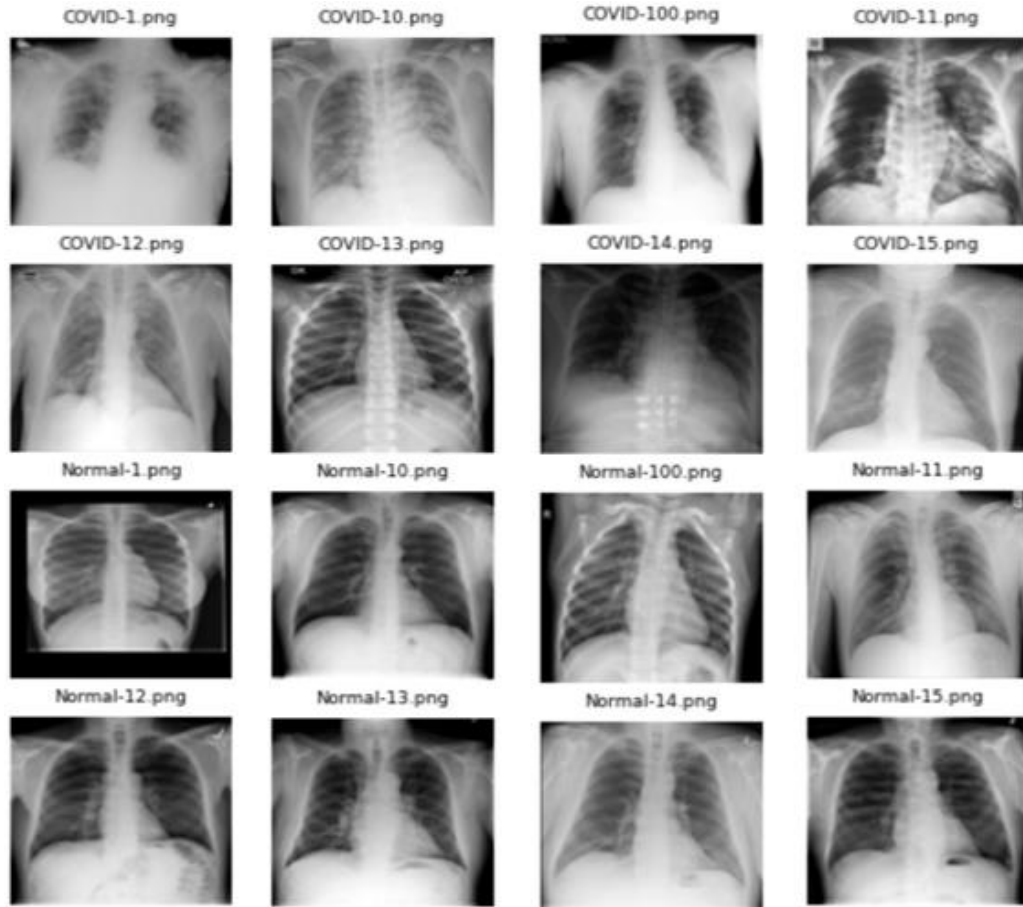
Figure 5. Effect of stride and pooling on image resolution

Table 3. Proposed model based on CNN

Layer (type)	Output shape	Parameter
Conv2d (Conv2D)	(None, 200, 200, 64)	6,976
Max_pooling2d (Maxpooling2D)	(None, 100, 100, 64)	0
Dropout (Dropout)	(None, 100, 100, 64)	0
Conv2d_1(Conv2D)	(None, 100, 100, 128)	295,040
Max_pooling2d_1(Maxpooling2D)	(None, 50, 50, 128)	0
Dropout_1 (Dropout)	(None, 50, 50, 128)	0
Conv2d_2(Conv2D)	(None, 50, 50, 256)	1,179,904
Max_pooling2d_2(Maxpooling2D)	(None, 25, 25, 256)	0
Dropout_2 (Dropout)	(None, 25, 25, 256)	0
Flatten (Flatten)	(None, 160,000)	0
Dense (Dense)	(None, 512)	81,920,512
Dropout_3 (Dropout)	(None, 512)	0
Dense_1 (Dense)	(None, 1)	513

3.3. Evaluation of three layers of the CNN model with 400 epochs

To validate the output of the presented approach, we implemented and tested the approach using (400) epochs with three layers of the CNN model. A series of experiments were conducted to assess the performance of the proposed model. The results encompass different performance metrics, comprising accuracy, precision, recall, and F1-score.

3.3.1. Using 400 epochs

Deep-COVID-19, our proposed model according to CNN, was trained for 400 epochs with early stopping. It was tested on the remaining 20% of the dataset after all models were trained on 80% of it. Figure 6 demonstrates the relation between the number of epochs and the loss value. At the first epoch, the loss values for the training and validation sets are 0.3852 and 0.4419 for the three-layer model. The loss values for the three-layer model decrease dramatically to 0 0.3229 at the fifth epoch. The training loss for the three-layer model gradually decreases to 0.0011 at 361 epochs. The validation losses for the three-layer model gradually decrease to 0.1418 at 75 epochs.

Figure 7 shows the relation between the number of epochs and the accuracy value. At the first epoch, the accuracy values for the training and validation sets are 0.845 and 0.785 for the three-layer model. The accuracy values for three-layer model increase dramatically to 0.9013 at the fifth epoch. The training the training accuracy for the three-layer model gradually increases to 0.9988 at 373 epochs. The validation accuracy for the three-layer model gradually increases to 0.965 at 159 epochs.
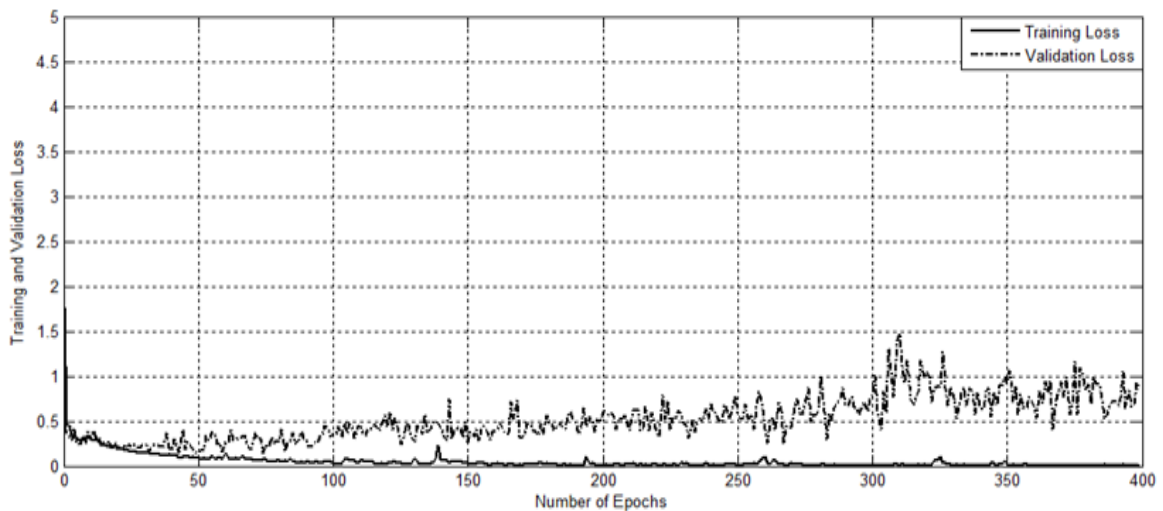

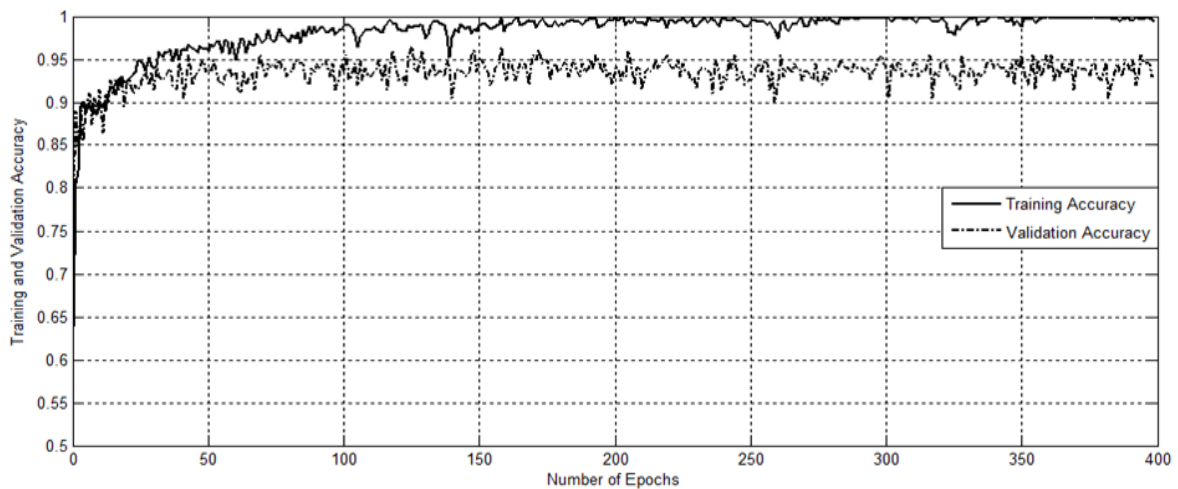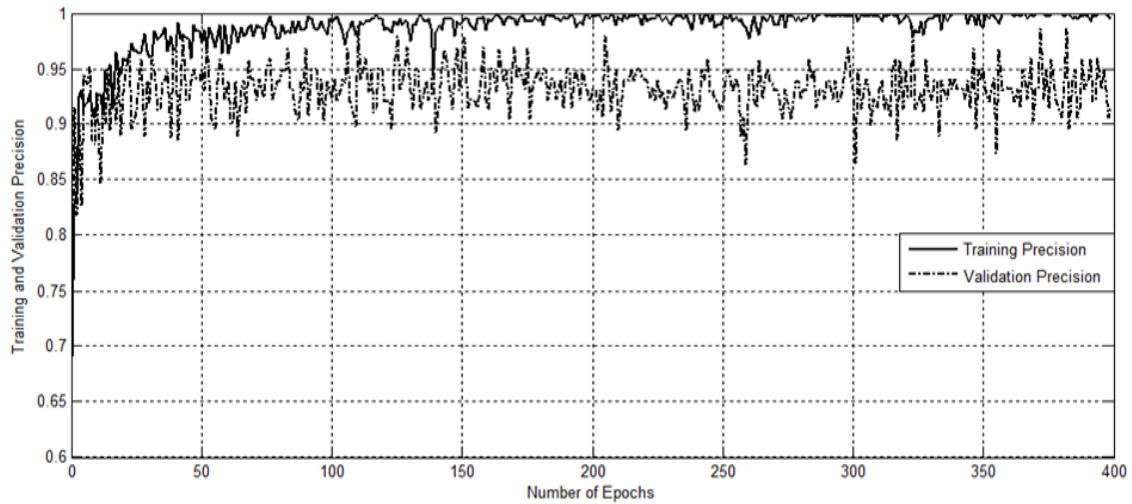Figure 6. model loss of our Proposed model based on CNN using three layers

Figure 7. model accuracy of our Proposed model according to CNN using three layers

Figure 8 shows the relation between the number of epochs and the precision value. At the first epoch, the precision values for the training and validation sets are 0.8485 and 0.728 for the three-layer model. The precision values for the three-layer model increase dramatically to 0.9303 at the fifth epoch. The training precision for the three-layer model gradually increases to 1 at 188 epochs. The validation precision for the three-layer model gradually increases to 0.9888 at 324 epochs.

Figure 8. Model precision of our proposed model according to CNN using three layers

Figure 9 shows the relation between the number of epochs and the recall value. At the first epoch, the recall values for the training and validation sets are 0.84 and 0.91 for the three-layer model. The recall values for the three-layer model increase dramatically to 0.8675 at the fifth epoch. The training recall for the three-layer model gradually increases to 0.98 at 360 epochs.
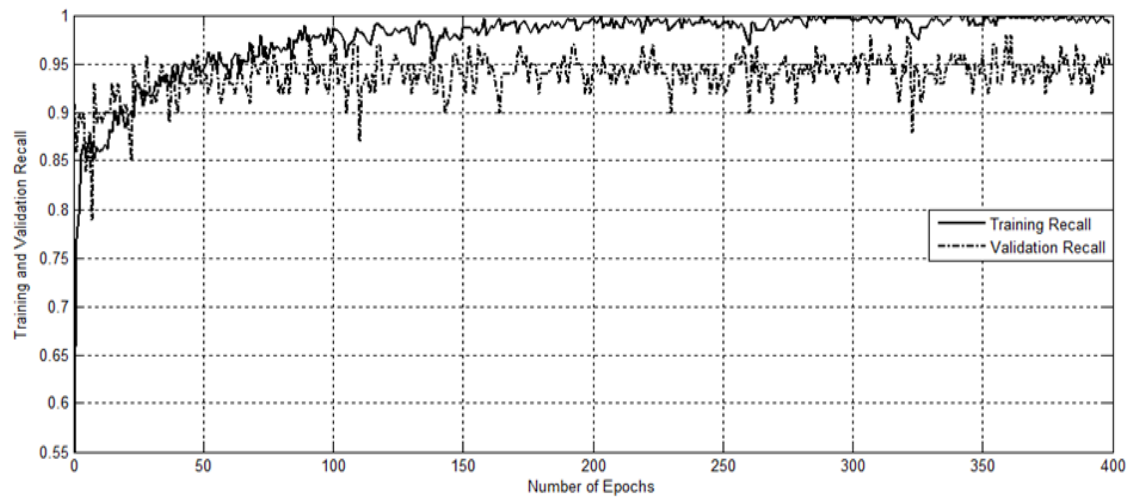

Figure 9. model recall of our proposed model according to CNN using three layers

Figure 10 shows the relation between the number of epochs and the F1 score value for the three-layer CNN model. At the first epoch, the F1 scores for the training and validation sets are 3.36 and 3.64 for the three-layer model. The F1 scores for the three-layer model increase dramatically to 3.47 at the fifth epoch. The training F1 score for the three-layer model gradually increases to 4 at 204 epochs.

The validation F1 score for the three-layer model gradually increases to 3.92 at 360 epochs. By comparing the results of our proposed model based on CNN with other models in the literature, it was clear that our model has higher accuracy in classifying COVID-19 and normal cases. Our model achieved an accuracy of 99.88%, a validation rate of 96.5%, a precision of 100%, a recall of 100%, and an F1 score of 100%.
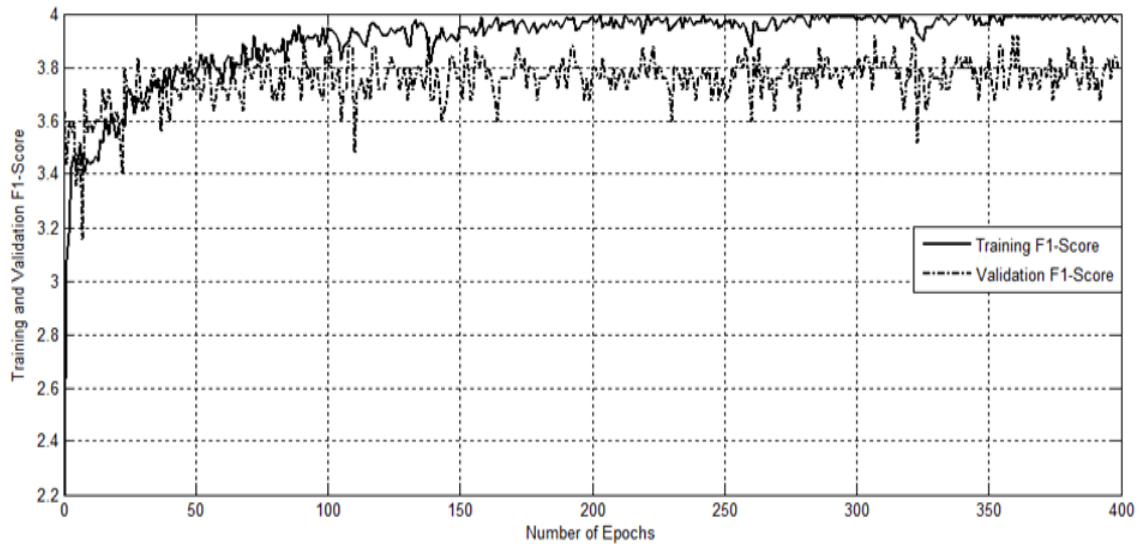

Figure 10. Model F1-score of our proposed model according to CNN using three layers

3.4. Comparison of deep learning models for the diagnosis of COVID-19

In this section we compared our proposed model according to CNN with three pre-trained models: VGG16, VGG19, and MobileNet. We used the same dataset for all models. Transfer learning has been considered as a popular practice in computer vision. A pre-trained model is one that has been trained on a major benchmark dataset for problem solving comparable to the one we want to solve. Because of the computational charge of training these models, it is frequent practice to import and utilize models from documented literatures (e.g., VGG16, VGG19, MobileNet).

Transfer learning is a powerful technique in computer vision as it permits us to build precise models in a timely manner. With transfer learning, we do not start from scratch; instead, we start from patterns that have been established when solving dissimilar problems. This allows us to build on existing knowledge rather than starting from scratch [25], [26].

Figure 11 shows the relation between the number of epochs and the accuracy value for the three pre-trained models. At the first epoch, the training and validation accuracy for all three models are low. However, the accuracy for all models gradually increases over time. Figure 11(a) to 11(c) shows that for 400 epochs, the training accuracy for VGG16, VGG19, and MobileNet are 0.925, 0.946, and 0.957, respectively. The validation accuracy for VGG16, VGG19, and MobileNet are 0.895, 0.927, and 0.935, respectively.

Therefore, the proposed model outperforms the three pre-trained models. Our model achieved a higher accuracy at 400 epochs than the three pre-trained models. Due to the limited scope of the current study, we have summarized the results of the comparison in the Table 4.

Table 4. Classification results

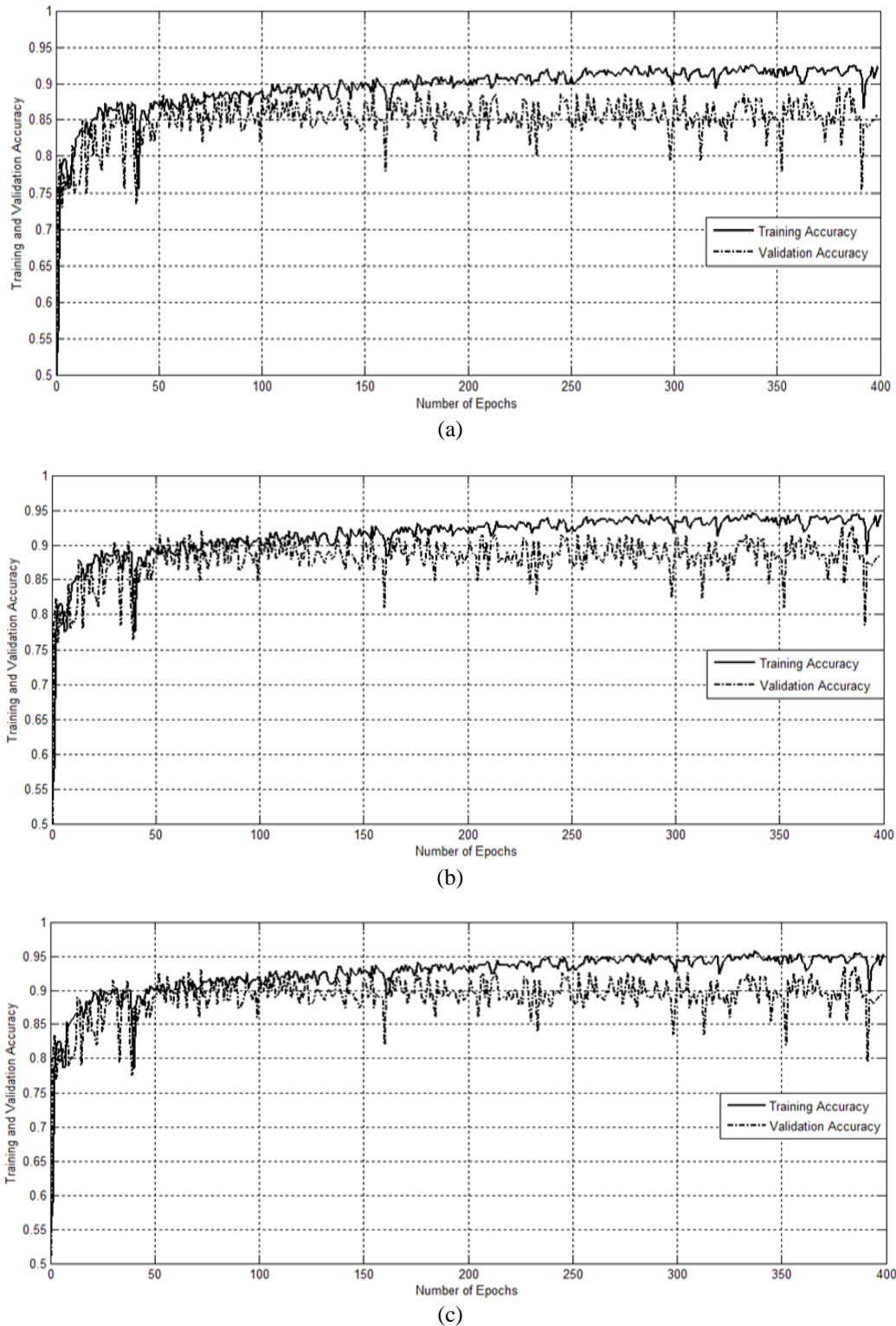| Models	Dataset	Precision	Recall	F1-score	Accuracy
VGG16	Train	71%	70%	70.5%	92.5%
	Valid	68.9%	67%	67.9%	89.5%
VGG19	Train	82%	82%	82%	94.6%
	Valid	79.3%	78%	78.6%	92.7%
MobileNet	Train	93%	93%	93%	95.7%
	Valid	89.6%	87%	88.3%	93.5%
Proposed model based on CNN	Train	100%	100%	100%	99.88%
	Valid	98.88%	98%	98.45%	96.50%

(a)

(b)

(c)

Figure 11. Model accuracy of three pre-trained models: (a) VGG16, (b) VGG19 and (c) MobileNet

4.   CONCLUSION

This paper presents a framework according to an IoT fog-cloud computing architecture for identifying COVID-19. We also propose a model based on CNN that is deployed and implemented on a fog computing layer to detect COVID-19 from CXR images. We evaluate the performance of the proposed model by studying its categorization accuracy. The proposed model was experimented by utilizing three

layers of CNN, and the results demonstrated that the training and validation accuracy gradually increased to 99.87% and 95.50%, correspondingly.

The proposed model was also experimented with three layers of CNN. The results revealed that the training and validation accuracy increased to 99.88% and 96.50%, correspondingly. The proposed model was then compared with other studies and with three pre-trained models: VGG16, VGG19, and MobileNet. The results showed that the accuracy of the proposed model was higher than the other models. The proposed model attained an accuracy of 99.88% in classifying COVID-19 and normal cases, along with a validation rate of 96.5%, precision of 100%, recall of 100%, and F1 score of 100%. In the future, we plan to: i) secure user multimedia data in the cloud using fog computing; ii) focus on authentication and key agreement using different authentication algorithms; iii) use ECG to detect COVID-19, as recent forms of COVID-19 can affect the cardiovascular system; and iv) investigate the use of empirical wavelet transform (EWT) and principal component analysis (PCA) for data filtering.

REFERENCES

[1]   A. M.-H. Kuo, "Opportunities and challenges of cloud computing to improve health care services," *Journal of Medical Internet Research*, vol. 13, no. 3, p. e67, Sep. 2011, doi: 10.2196/jmir.1867.
[2]   T. Alam, "Cloud computing and its role in the information technology," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 1, no. 2, pp. 108–115, Feb. 2020, doi: 10.34306/itsdi.v1i2.103.
[3]   S. Dash, S. K. Shakyawar, M. Sharma, and S. Kaushik, "Big data in healthcare: management, analysis and future prospects," *Journal of Big Data*, vol. 6, no. 1, p. 54, Dec. 2019, doi: 10.1186/s40537-019-0217-0.
[4]   F. Emmert-Streib, Z. Yang, H. Feng, S. Tripathi, and M. Dehmer, "An introductory review of deep learning for prediction models with big data," *Frontiers in Artificial Intelligence*, vol. 3, p. 4, Feb. 2020, doi: 10.3389/frai.2020.00004.
[5]   Q. Althebyan, Q. Yaseen, Y. Jararweh, and M. Al-Ayyoub, "Cloud support for large scale e-healthcare systems," *Annals of Telecommunications*, vol. 71, no. 9–10, pp. 503–515, Oct. 2016, doi: 10.1007/s12243-016-0496-9.
[6]   K. Bhargava and S. Ivanov, "A fog computing approach for localization in WSN," in *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Oct. 2017, pp. 1–7, doi: 10.1109/PIMRC.2017.8292245.
[7]   A. Canziani, A. Paszke, and E. Culurciello, "An analysis of deep neural network models for practical applications," *arXiv preprint*, 2016, [Online]. Available: http://arxiv.org/abs/1605.07678.
[8]   Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.
[9]   V. Chamola, V. Hassija, S. Gupta, A. Goyal, M. Guizani, and B. Sikdar, "Disaster and pandemic management using machine learning: a survey," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 16047–16071, Nov. 2021, doi: 10.1109/JIOT.2020.3044966.
[10] A. Feriani, A. Refaey, and E. Hossain, "Tracking pandemics: a MEC-enabled IoT ecosystem with learning capability," *IEEE Internet of Things Magazine*, vol. 3, no. 3, pp. 40–45, Sep. 2020, doi: 10.1109/IOTM.0001.2000142.
[11] D. Xue, S. Nazir, Z. Peng, and H. Khattak, "Selection and ranking of fog computing-based IoT for monitoring of health using the analytic network approach," *Complexity*, vol. 2021, pp. 1–11, Aug. 2021, doi: 10.1155/2021/9964303.
[12] T. N. Gia, M. Jiang, A.-M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, "Fog Computing in healthcare internet of things: a case study on ECG feature extraction," in *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, Oct. 2015, pp. 356–363, doi: 10.1109/CIT/IUCC/DASC/PICOM.2015.51.
[13] A. Elhadad, F. Alanazi, A. I. Taloba, and A. Abozeid, "Fog computing service in the healthcare monitoring system for managing the real-time notification," *Journal of Healthcare Engineering*, vol. 2022, pp. 1–11, Mar. 2022, doi: 10.1155/2022/5337733.
[14] M. Al-khafajiy, L. Webster, T. Baker, and A. Waraich, "Towards fog driven IoT healthcare," in *Proceedings of the 2nd International Conference on Future Networks and Distributed Systems*, Jun. 2018, pp. 1–7, doi: 10.1145/3231053.3231062.
[15] N. El-Rashidy, N. E. ElSayed, A. El-Ghamry, and F. M. Talaat, "Utilizing fog computing and explainable deep learning techniques for gestational diabetes prediction," *Neural Computing and Applications*, vol. 35, no. 10, pp. 7423–7442, Apr. 2023, doi: 10.1007/s00521-022-08007-5.
[16] V. K. Quy, N. Van Hau, D. Van Anh, and L. A. Ngoc, "Smart healthcare IoT applications based on fog computing: architecture, applications and challenges," *Complex & Intelligent Systems*, vol. 8, no. 5, pp. 3805–3815, Oct. 2022, doi: 10.1007/s40747-021-00582-9.
[17] Y. Shi, G. Ding, H. Wang, H. Eduardo Roman, and S. Lu, "The fog computing service for healthcare," in *2015 2nd International Symposium on Future Information and Communication Technologies for Ubiquitous HealthCare, Ubi-HealthTech 2015*, 2015, pp. 70–74, doi: 10.1109/Ubi-HealthTech.2015.7203325.
[18] P. M. Arunkumar, M. Masud, S. Aljahdali, and M. Abouhawwash, "Healthcare monitoring using ensemble classifiers in fog computing framework," *Computer Systems Science and Engineering*, vol. 45, no. 2, pp. 2265–2280, 2023, doi: 10.32604/csse.2023.032571.
[19] A. A. Mutlag, M. K. Abd Ghani, N. Arunkumar, M. A. Mohammed, and O. Mohd, "Enabling technologies for fog computing in healthcare IoT systems," *Future Generation Computer Systems*, vol. 90, pp. 62–78, Jan. 2019, doi: 10.1016/j.future.2018.07.049.
[20] T. Bezdan and N. Bačanin Džakula, "Convolutional neural network layers and architectures," in *Proceedings of the International Scientific Conference - Sinteza 2019*, 2019, pp. 445–451, doi: 10.15308/Sinteza-2019-445-451.
[21] T. Rahman, M. Chowdhury, and A. Khandakar, "COVID-19 radiography database," *www.kaggle.com*, 2021. https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database.
[22] M. E. H. Chowdhury *et al.*, "Can AI help in screening viral and COVID-19 pneumonia?," *IEEE Access*, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.
[23] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," *Journal of Machine Learning Research*, vol. 9, pp. 249–256, 2010.
[24] D. P. Kingma and J. L. Ba, "Adam: a method for stochastic optimization," in *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, 2015, pp. 1–15.

[25]   H. Chen *et al.*, "Pre-trained image processing transformer," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2021, pp. 12294–12305, doi: 10.1109/CVPR46437.2021.01212.

[26]   X. Han *et al.*, "Pre-trained models: past, present and future," *AI Open*, vol. 2, pp. 225–250, 2021, doi: 10.1016/j.aiopen.2021.08.002.

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