مجلة الدلتا الدولية للعلوم التجارية ونظم المعلومات

https://djicsi. journals.eKb.eg

Information Intelligent System for COVID-19

Submitted by:

Mahmoud Khaled Elsayed Ramadan

Demonstrator in Delta higher institute for Management and accounting information system

ABSTRACT

The new coronavirus (COVID-19) outbreak in 2019 was one of the most significant crises, as the World Health Organization (WHO) declared it a public health emergency of international concern. Researchers across the globe are utilizing various models to predict virus outbreaks, make informed decisions, and implement effective control measures. Simple statistical and epidemiological methods have garnered significant attention from both researchers and authorities. A primary challenge in controlling the spread of COVID-19 has been the shortage and limited availability of medical tests for detecting and identifying the virus. To mitigate this issue, several statistical techniques have been developed to provide partial solutions. In response to the medical challenges posed by COVID-19, a broad range of Artificial Intelligence (AI) systems, frameworks, and tools that leverage Machine Learning (ML) and Deep Learning (DL) have been proposed. These technologies are particularly suited for developing effective COVID-19 diagnostic solutions due to their ability to recognize and predict patterns in large and complex datasets

COVID-19 diagnosis. machine learning; deep learning; convolutional neural network.

INTRODUCTION

At the end of 2019, a new virus from the coronavirus family, named COVID-19, emerged in Asia and spread globally, causing a new wave of respiratory infections. By March 2020, the World Health Organization (WHO) had classified it as a pandemic and declared it a "Public Health Emergency of International Concern"[1]. As of February 2023, the illness had affected 673.3 million individuals worldwide, with 6.8 million confirmed deaths [2]. One of the most common methods for identifying coronavirus is the Reverse Transcription Polymerase Chain Reaction (RT-PCR), which uses respiratory samples and provides results within a few hours to two days. However, this diagnostic test is both time-consuming and costly. Therefore, developing new viral detection techniques remains a significant challenge for researchers, especially as a definitive medical treatment has yet to be discovered. Previous studies have employed machine learning and deep learning architectures to detect COVID-19 in lung CT and X-ray images. Yan et al. [3] aimed to create a mathematical modeling strategy based on advanced interpretable machine learning algorithms, identifying the most discriminative indicators of patient survival. Nasiri et al. [4], on the other hand, used a pre-trained DenseNet169 network to extract features from X-ray images via analysis of variance (ANOVA) and classified them using eXtreme Gradient Boosting (XGBoost). Similarly, Öztürk et al. [5] developed a technique for analyzing CT and X-ray data with ML algorithms to detect viral outbreaks. They also classified the images into six categories, including coronavirus images, using a two-stage data augmentation approach. Saha et al. [6] proposed a convolutional neural network (CNN) architecture to detect COVID-19 in radiographs by concatenation. They developed a multi-label algorithm to distinguish between standard X-ray images, viral pneumonia, and COVID-19. Bhargava et al. [7] provided an automated learning method to assess nine datasets and identify COVID-19. Absar et al. [8] used the SVM machine learning algorithm to diagnose COVID-19 based on chest radiograph images. In Islam et al. [9], Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to CT images to enhance image quality. They then created a new convolutional neural network model using 2482 CT images to extract 100 key features, which were subsequently applied to various machine learning methods. Finally, they recommended an integrated approach for categorizing COVID-19 medical images. Shan et al. [10] deployed a deep network to identify COVID-19 affected regions using CT images for deeper understanding. Kogilavani et al. [11] developed neural network models like DenseNet121, NASNet, EfficientNet, and Xception to detect COVID-19 using lung images. Mishra et al. [12] reviewed various deep CNN-based methods for identifying COVID-19 in chest CT images. Rehman et al. [13] proposed a deep learning methodology using radiographs to diagnose approximately 15 chest diseases.

Aboughazala et al. [14] built a network to classify COVID-19 images from radiographs into negative or positive cases. Conversely, Diaz-Escobar et al. [15] compared and evaluated the efficiency of different methods for detecting COVID-19 using lung images and pre-trained deep learning architectures such as VGG19, InceptionV3, Xception, and ResNet50. Malik et al. [16] trained a combination of VGG-19 and CNN on a publicly available benchmark database to recognize respiratory diseases from chest radiographs. Rahman et al. [17] used a deep network and a graph of oriented variations framework to classify the data into multiple lung disease types, in addition to normal cases, and to identify the most discriminating anomalies in anterior lung radiograph images. Sarkar [18] utilized Vision Pro Deep Learning, a deep learning tool from COGNEX, to classify chest X-rays from the COVIDx dataset. Vision Pro DL is used across various industries, including life sciences and factory automation. Saood et al. [19] used two well-known deep network models, U-NET and SegNet, for data classification. SegNet is described as a network for image segmentation, while U-NET is a tool for medical segmentation. Moreover, multi-class segmentation was utilized with both networks to identify the type of chest infection and to differentiate diseased lung cells from healthy ones using binary components. In the context of diagnosing and determining COVID-19 patients through chest radiographs, Hassantabar et al. [20] developed a three-supervised learning architecture, while Imani [21] created convolutional filters that reduced contextual features. Both lung X-rays and abdominal CT scans were employed to extract shape and textural information as contextual feature maps. Notably, chest CT images are beneficial even before symptoms appear, as they reliably detect abnormal features that may not be visible in early-stage lung X-rays. Combining the features of these two types of images enhances classification accuracy. Various methods have been developed to distinguish COVID-19 from other lung infections using X-ray and CT images, with numerous deep learning architectures employed. Khalifa et al. [22] proposed a deep learning methodology that combines deep transfer learning with generative adversarial networks (GAN). They also used GAN to increase the sample size for training deep transfer models, specifically AlexNet and GoogleNet, to detect pneumonia from lung X-rays. Ibrahim et al. [23] used a combination of X-ray and CT images to train a multi-classification model to detect lung cancer, pneumonia, and COVID-19, expanding the dataset by linking lung X-rays and CT images, which improved classification accuracy. They also considered four distinct deep learning architectures during model training. Despite promising results, these methods still have limitations. The first limitation, noted in articles [11, 17, 18, 20, 22], is the infrequent consideration of the heterogeneity between various imaging techniques [5, 21, 23]; most studies used chest X-rays or CT scans independently for diagnosing lung disorders. To address this issue, a combined learning process using both CT and X-ray scans can be employed. The second limitation identified in these studies [5, 13, 19, 20] is that the models were trained in two stages: initially using various augmentation techniques to enhance the dataset and subsequently training the deep-learning models with both original and augmented images. This two-stage process can be simplified by developing a deep learning architecture capable of recognizing COVID-19 in a single learning operation. The third limitation found in these studies [10, 11, 19] is that they typically diagnosed only two types of lung diseases, whereas multiple lung ailments, such as lung cancer and COVID-19, exist. To address this, a deep learning arxchitecture that diagnoses various lung diseases using a combination of lung X-ray and CT images is proposed.

١. Literature Review

Table 1 : Applications of ML for resolving some COVID-19 issues

Author	Year	Dataset	Method
[25].el	2020	COVID-19 Time Series dataset	LR,LASSO, Support Vector Machine (SVM), ER
[26].el	2020	CT Image dataset	Residual Neural Network
[27].el	2020	COVID-19 data of various countries	Support Vector Regression (SVR)
[28].el	2020	COVID data of 5 countries	MLP, ANFIS
[29].el	2020	COVID-19 dataset of 1,182 hospitalized patients	SVM
[30].el	2020	COVID-19 patients data of Massachusetts, Georgia, and New Jersey.	GB (Gradient Boosting) algorithm
[31].el	2020	COVID-19 Patient Dataset	ML algorithm
[32].el	2020	COVID-19 Indian Dataset	Support vector Kuhntucker model
[33].el	2020	COVID-19 data from Mindstream-ai	ANN
[34].el	2020	COVID-19 Data	Logistic Model + Prophet method
[35].el	2020	CT dataset	AD3D-MIL algorithm (A Deep 3D-Multiple Instance Learning)
[36].el	2020	JHU CSSE database	-
[37].el	2020	Two COVID-19 chest X-ray datasets	KNN (K Nearest Neighbor) + Manta-Ray Foraging

			Optimization (MRFO)
[38].el	2020	COVID-19 patient data	XGB (Extreme Gradient Boosting), Decision Tree (DT), Random Forest (RF), SVM, GBM (Gradient Boosting Machine)
[39].el	2020		
[40].el	2020	COVID-19 time series dataset	Ensemble Empirical Mode Decomposition (EEMD) + ANN)
[41].el	2020	CT images dataset	CNN, RF, NB, SVM, as well as JRIP
[42].el	2020	COVID_CT dataset	Enhanced KNN
[43].el	2020	COVID-19 pandemic data	NN (Neural Network)
[44].el	2020	Corona virus dataset	LR, Naive Bayes (NB), Linear Regression (LiR), KNN
[45].el	2020	Hungary dataset of COVID-19 data	ANFIS (Adaptive Network-based Fuzzy Inference System) & MLP-ICA (Multi Layered Perceptron-Imperialist Competitive Algorithm)
[46].el	2020	COVID-19 patients data	k-Means algorithm
[47].el	2020	COVID-19 patients data	Support Vector Regression (SVR), RF
[48].el	2020	COVID-19 patient blood sample data	KNN, LR, RF, SVM
[49].el	2020	COVID-19 Synthetic dataset	SVR

On the basis of previous literature Table 1, classification tasks for COVID-19 were different in terms of aspects related to the accuracy of results, in spite of the differences of the overall performance. Previous literature was solely focused on accuracy enhancement, time reduction or even overall performance improvements for the classification. Furthermore, differences exist in previous literature with respect to classification techniques, phases and classification procedures. On the one hand, the developed COVID-19 classification techniques in the analyzed studies provide three COVID-19 classification tasks (i.e. binary classification, multi-class classification and hierarchical classification). On the other hand, Ref. [50] indicated that all relevant label distribution in a classification problem changes, which explains why four classification types can be performed in the AI techniques, namely, binary, multi-class, multi-labelled and hierarchical classifications. Multi-labelled classification is described in Ref. [50] as follows: ‘the input is to be classified into several of non-overlapping classes. When the learning task is document topic classification, multi-labelling is often referred as multi-topic classification. In the multi-labelled classification problem, categories are isolated and their relations are not considered important.' However, no study has provided multi-labelled classification for the detection of COVID-19 medical images. This is considered the first research gab identified in the literature reviewed. Furthermore, the growing number of classification techniques developed for COVID-19 is considered a major problem for health organizations and other treatment centers. The reason behind that these medical organizations that aim to adopt classification techniques for detection of COVID-19 will be encountered a challenge on how to select the best and an appropriate classification technique that would provide an accurate and rapid detection of COVID-19 medical images. Apart from the disparity in COVID-19 classification techniques in terms of their overall performance, all results confirm the difficulty of making a decision to choose a better technique amongst others. In the analyzed studies, there is no evidence or proposed solution confirmed to be superior over the rest. Moreover, although multi-labelled classification AI techniques used in the detection of COVID-19 have not been developed, they might be developed in the near future. In the case of this development, another important question will arise: 'which classification technique is appropriate for such purpose?' According to the included final set of articles that met the search query used, no study has provided a comprehensive evaluation and benchmarking solution for AI classification techniques (i.e. binary, multi-class, multi-labelled and hierarchical classifications) used in the detection of COVID-19 medical images. This is considered the second research gab identified in the literature reviewed. Ref. [51] recommended that an evaluation and benchmarking solution for multi-labelled and/or hierarchical classification techniques could be beneficial and essential to determine which AI technique is appropriate amongst others. To explain the detailed solution for the identified gabs, two problems should be discussed: 'what are the evaluation criteria used in each classification type (i.e. binary, multi-class, multi-labelled and hierarchical classifications), and what are the calculation processes of these criteria? Each of these classification methods has its own evaluation criterion. The calculation procedure for each evaluation criteria is completely different from each classification type [51,50]. Thus, the evaluation and benchmarking procedure will be different within each classification method (the evaluation criteria and calculation procedures are specified in detail in the methodology section). This study attempts to fill the gap in the evaluation and benchmarking of different classification types that will be used in the detection of COVID-19. The proposed solution shall assist the administrations of health organisations to evaluate and benchmark COVID-19 AI classification techniques. It can also ensure that the selected classification techniques meet all necessary requirements. OS Albahri et al [24]

3.Background technology

3.1. Artificial neural network background (ANN)

3.1.1 AlexNet Architecture

AlexNet CNN Architecture In the outlined work, AlexNet CNN's deep learning architecture is used for each image class (one for X-ray and the other for CT). The elements of the architecture are explained in Fig. 2.

The suggested system employs five convolutional layers with rectified linear units (ReLUs) and three max-pooling layers: In the First Convolutional Layer, Filters: 96, Kernel Size: 11×11, Stride:

4. In the Second Convolutional Layer, Filters: 256, Kernel Size: 5×5. In the Third and Fourth Convolutional Layers, Filters: 384, Kernel Size: 3×3. In the Fifth Convolutional Layer, Filters: 256, Kernel Size: 3×3. Each convolutional layer produces a feature map. The feature maps from the first, second, and fifth layers are combined with pooling layers of size 3×3 and a stride of 2×2. The system has 100 nodes and an eight-layer architecture, allowing for trainable feature maps, which means feature extraction processes occur at these levels.

Fully connected layers (FC) are used to place these feature maps, and Softmax activation is used to calculate the classification probabilities. The dataset has only four classes, although the Softmax layer can provide classification for up to 1000 different classes.

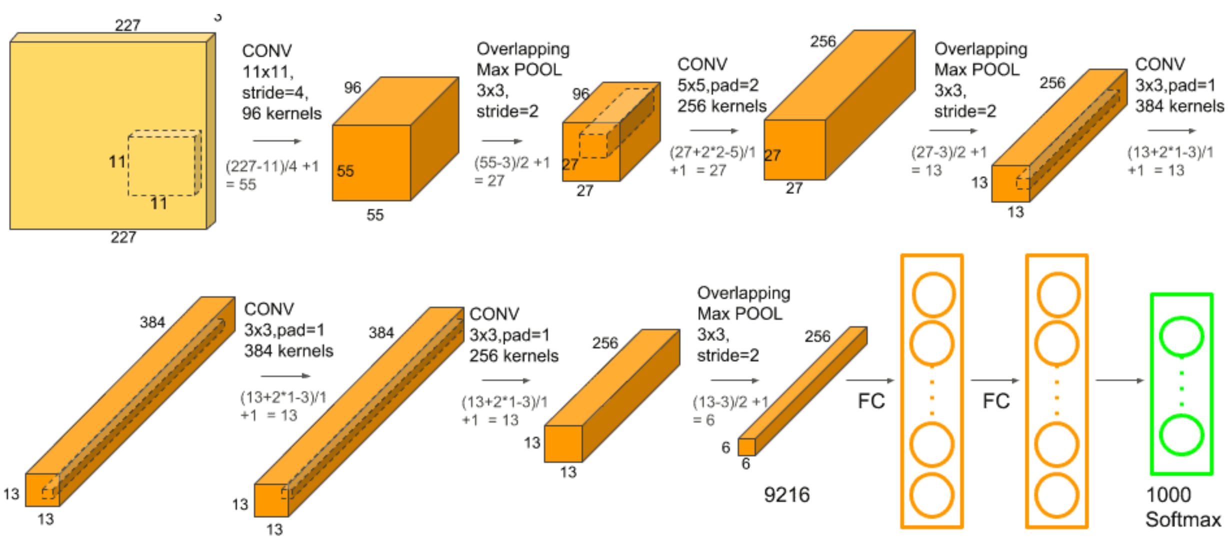


Fig.2. AlexNet convolution neural network architecture [3]

٣,١,٢ Convolution Layer

This layer generates the feature maps that are used as input to classification layers. It includes a kernel to create the feature map as the output. Matrix multiplication and result integration are performed at every point on the input. The definition of the generated feature map is as follows

$$N_x^r = \frac{N_x^{r-1} - L_x^r}{S_x^r} + 1 \; ; N_y^r = \frac{N_y^{r-1} - L_y^r}{S_y^r} + 1 \qquad (1)$$

[4]

Where (Nx, Ny) is the width and height of the output feature map of the last layer and (Lx, Ly) is the kernel size, (Sx, Sy) that defines the number of pixels skipped by the kernel in horizontal and vertical directions and index r indicates the layer, i.e., r = 1. Convolution is applied on the input feature map and a kernel to get the output feature map that is defined as:

$$X_1(m.n) = (J * R)(m.n)$$

(2) [4]

X1 (m, n) expresses a feature map with two dimensions, m and n. R is the kernel of size (Lx, Ly) and feature map input J. To illustrate the convolution between J and R, use *. Convolution is expressed as the following:

$$X_1(m.n) = \sum_{p=-\frac{L_x}{2}}^{p=+\frac{L_x}{2}} \sum_{q=-\frac{L_y}{2}}^{q=+\frac{L_y}{2}} J(m-p.n-q)R(p.q) \qquad (3) \quad [4]$$

In the suggested framework, five CONV layers with a RELU layer are used to accurately train the dataset and extract the most feature maps possible from the input frames.

3.1.3 Rectified Linear Unit (ReLU) Layer

A RELU activation function makes the proposed network non-linear and applies to all the trainable layers. This layer appropriately considers the nonlinearities and is utilized with the final feature map generated by the convolutional layer. The non-linear gradient descent is covered using tanh(.)and the RELU activation function.Tanh (.)is expressed as:

$$X_2(m.n) = tanh\big(X_1(m.n)\big) = \frac{sinh\big(X_1(m.n)\big)}{cosh\big(X_1(m.n)\big)} = 1 + \frac{1-e^{-2*X_1(m.n)}}{1+e^{-2*X_1(m.n)}} \qquad (4) \quad [4]$$

Where X2(m, n) is a two-dimensional output feature map after applying tanh(.) on the input feature map X1(m, n), which is achieved after passing through the convolutional layer.

The values in the final feature map are obtained after applying the RELU function as follows:

$$X(m.n) = \begin{cases} ٠. & if X_{٢}(m.n < ٠) \\ X_{٢}(m.n). & if X_{٢}(m.n \geq ٠) \end{cases} \qquad (5) \quad [4]$$

In eq. (5), X (m, n) is produced by turning the negative numbers into zero, and it returns the same result when it receives a positive value. The RELU layer speeds the training of deep convolutional neural networks.

3.1.4 Maximum Pooling Layer

The proposed architecture includes a pooling layer after the first, second, and fifth convolution layers to reduce each frame's computational expense and spatial dimension for the deep learning framework. The pooling process typically selects the average or maximum value of each image slice. In the suggested work, maximum pooling is used because it yielded better outcomes. The use of the maximum pooling layer for downsampling the images on the activation output is illustrated in Fig. 3.

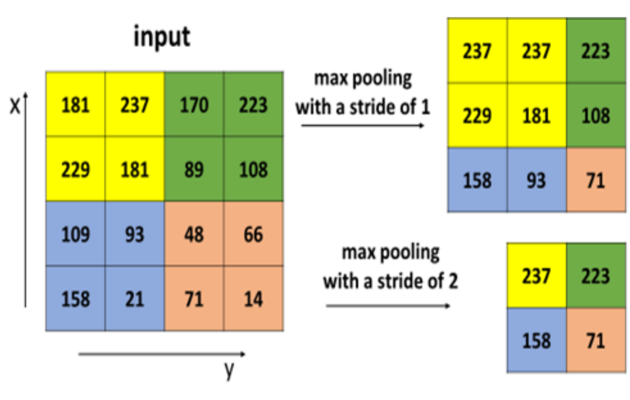


Fig.3. Maximum pooling layer [5]

٣,١,٥ Dropout Layer

The first two fully connected layers implement dropout to prevent overfitting. This technique effectively regularizes the training data by averaging multiple neural network models. The dropout layer reduces overfitting by randomly setting a fraction of input units to zero during training, which helps in creating a more robust model.

In the proposed architecture, maximum pooling is used to generate feature maps by selecting the highest pixel value from each map, considering the convolutional layer kernel sizes and their stride factors. The output from the top layers is then connected to a 1D feature vector through a fully connected layer. It is crucial for the output unit for the class label to be fully connected to the top layer to capture advanced training features. Figure 4 shows the regularization technique applied to the fully connected layers before and after using dropout.

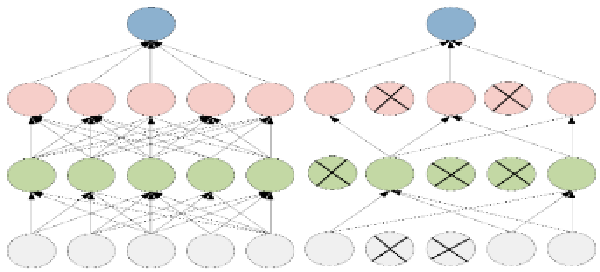


Fig.4. Fully connected layers (FC) before and after applying dropout [4]

٣,١,٦ Deep feature concatenation

Concatenating features is a valuable technique for combining many features to improve categorization. In this study, the proposed CNNs are used to extract X-ray and CT characteristics, and then the DFC is employed; as seen in Fig. 5, the classification descriptor is then formed by connecting these features:

$$FinalFeatureDescriptor = F^{(CT)} \cup F^{(X-ray)} \qquad (6)\ [6]$$

F (CT) denotes the features of CT images, and F (X-ray) is the features of X-ray images.

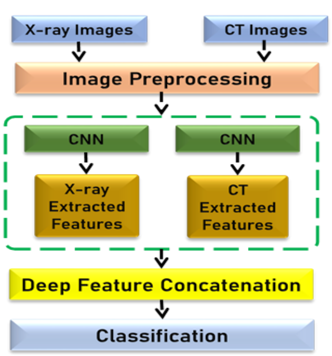


Fig. 5. Deep feature concatenation architecture [6]

3.2. Covid-19 Diagnosis Using Artificial Intelligence:

The synergy between AI and imaging in medicine is crucial for achieving precise COVID-19 diagnosis. The utilization of medical imaging techniques like Chest CT, which involves numerous slices, often requires a substantial number of medical radiologists for accurate COVID-19 symptom diagnosis. Consequently, many respiratory-related diseases exhibit morphological similarities[7]. The use of AI-assisted diagnostics, however, intends to speed up the procedure by offering quick and precise assessments to identifying COVID-19 from other lung conditions, like pneumonia.

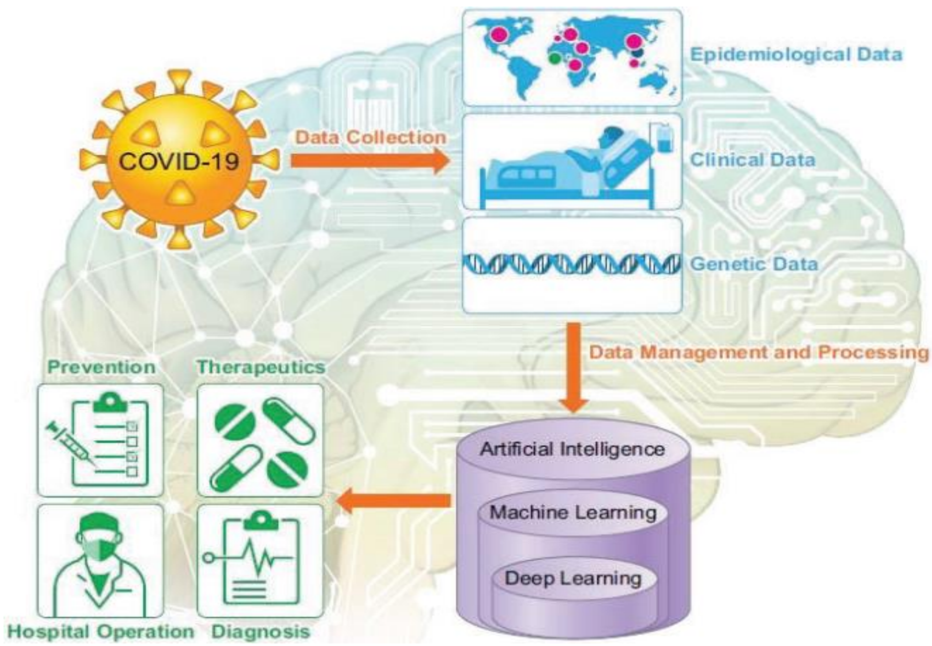


Figure 2.1. Role of AI in COVID-19 fight. [8].

3.3. Application of Machine Learning to the Diagnosis of COVID-19

Approaches for machine learning (ML) are invaluable methods for predicting accurate results in various aspects. The Institute for AI, in collaboration with prominent research organizations, has released an open-source, regularly updated COVID-19 Open Research Dataset. This dataset continually compiles articles related to COVID-19, expediting novel research projects that depend on real-time data. Numerous research groups are diligently gathering data and devising solutions on a daily basis.

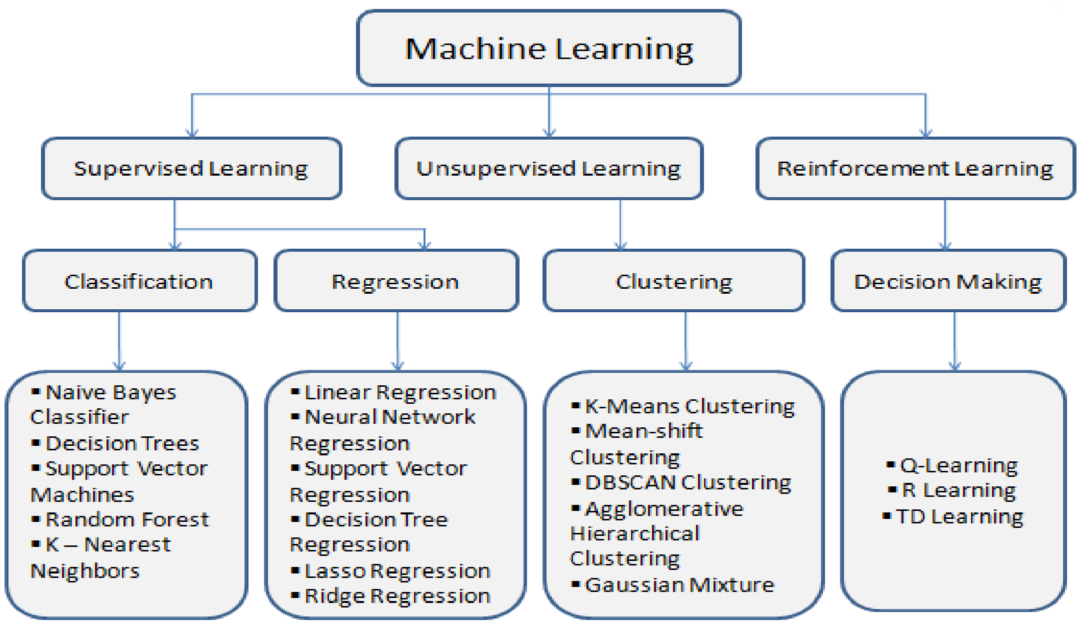
ML focuses on developing intelligent applications that can learn from data and improve their accuracy without explicit programming. This is achieved through training algorithms, which enable the system to identify trends and characteristics in data, using them to make accurate judgments and forecasts when presented with new data.

The ML process involves several steps:

- **Definition and Preparation of a Training Dataset**
- **Selection of an Appropriate Algorithm**
- **Training the Algorithm to Produce the Desired Model**
- **Utilization and Refinement of the Model**

Machine learning algorithms come in various types, including:

- **Supervised Machine Learning**: Involves training the model on labeled data.
- **Unsupervised Machine Learning**: Involves identifying patterns in unlabeled data.
- **Reinforcement Learning**: Involves training the model through rewards and penalties based on actions taken.



These types are illustrated in the accompanying figure.

Figure 2.2. Overview of Machine Learning.

3.4. Medical Imaging

Another subset of deep learning is used in medical imaging applications, which classify COVID-19, cancer, and pneumonia-related symptoms. The ability to identify pneumonia using chest X-ray and CT imaging is becoming more widely available, which is important for the detection of COVID-19 [13].

3.5. Covid-19 chest X-ray and CT classification:

Regarding the classification of COVID-19 chest images, the disease can be readily identified through various classification models, yielding accurate results. Imaging is crucial for disease classification, especially for differentiating COVID-19 from similar conditions like cancer and pneumonia. Techniques such as transformation, normalization, resizing, and patching are employed on chest images to facilitate this process. Deep learning applications are used to assess the performance of the algorithms after configuration within the models. According to various studies, the classification method proves highly effective in COVID-19 detection. Don Sheng Ji's research outlines several phases in the virus detection process through X-ray imaging, including scaling, rotation, size adjustment, and position translation.

Computed tomography (CT) imaging is essential for clinically diagnosing diseases. CT scans are used to analyze and identify images in detecting and evaluating COVID-19, enabling the determination of infection levels and its distribution throughout the body. Additionally, CT scans use transfer learning and additional neural networks for COVID-19 identification, as depicted in Figure 2.3 .

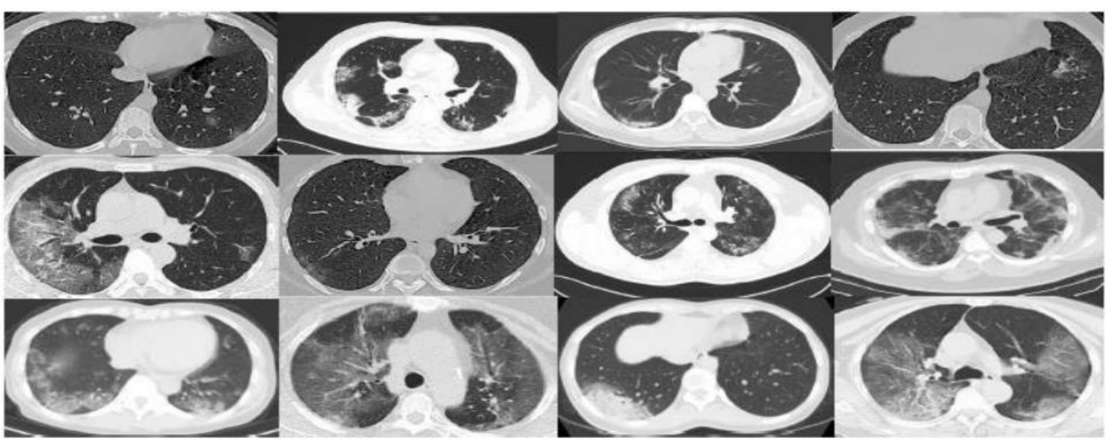


Figure 2.3. Positive COVID-19 CT Scan

٤ Conclusion

The COVID-19 pandemic has a tremendous impact on the life of people around the world, and the number of infected patients has considerably increased. COVID-19 quickly gained a foothold, and nations, governments and scholars are attempting to address this worldwide crisis. Different medical tests are used in the detection of COVID-19. Several studies have used X-rays and CT scans to support and reveal anomalies indicative of COVID-19. CT scan and X-ray tests are utilised as initial detection tools to evaluate the severity of COVID-19, monitor the emergency conditions of patients and predict disease progression. The growing developments of AI techniques have led to the challenges of choosing evaluation and benchmarking AI techniques and which technique is suitable for the diagnosis and classification of COVID-19 medical images. Thus, this study presented a systematic review of AI techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking. The results showed that only 11 studies utilised AI techniques in detecting and classifying COVID-19 with different case studies. However, this study proved that the process of evaluating and benchmarking of AI classification techniques (i.e. binary, multi-class, multi-labelled and hierarchical classifications), which could be used in the detection and diagnosis of COVID-19 medical image, is a critical gap of related literature. The challenges of such gap are discussed, and the process of evaluation and benchmarking of COVID-19 AI classification techniques is considered a multi-complex attribute problem. Thus, using MCDA is essential. As a potential future research direction, this study provided a detailed methodology for the evaluation and benchmarking of AI classification techniques used in the detection of COVID-19 medical images. Such methodology is presented on the basis of three sequential phases (i.e. identification, development and validation).

٥ Future works

For future studies, incorporating other types of images such as PET and MRI alongside CT and X-ray images in the datasets, increasing the number of training epochs, and utilizing different architectures like GAN for classification and augmentation could improve the performance of the proposed model. Additionally, leveraging public media data to forecast illness cases and inform timely responses would also be beneficial

References

1. Albahli, S.J.I.j.o.m.s., *Efficient GAN-based Chest Radiographs (CXR) augmentation to diagnose coronavirus disease pneumonia*. International journal of medical sciences, 2020. 17(10): p. 1439. (JCR(Citescore:5.5,https://www.scopus.com/sourceid/130020))
2. *WHO. Coronavirus (COVID-19)dashboard* https://COVID19.who.int/. Accessed 10 May 2023. , (JCR(Citescore:-,-))
3. Yan, L. et al., *A machine learning-based model for survival prediction in patients with severe COVID-19 infection.* Nature Machine Intelligence 2020. https://doi.org/10.1101/2020.02.27.20028027 , (JCR(Citescore:25.7,https://www.scopus.com/sourceid/21101007236))
4. Nasiri, H. and S.A. Alavi, *A novel framework based on deep learning and ANOVA feature selection method for diagnosis of COVID-19* cases from chest X-ray images. Computational intelligence and neuroscience, 2022. , (JCR(Citescore:3.9,https://www.scopus.com/sourceid/7000153240))
5. Öztürk, Ş., U. Özkaya, and M. Barstuğan, *Classification of Coronavirus (COVID‐19) from X‐ray and CT images using shrunken features.* International Journal of Imaging Systems and Technology, 2021. 31(1): p. 5-15. , (JCR(Citescore:5.4,https://www.scopus.com/sourceid/35932))
6. Saha, P. and S. Neogy, *Concat_CNN: A Model to Detect COVID-19 from Chest X-ray Images with Deep Learning.* SN Computer Science, 2022. 3(4): p. 1-11. , (JCR(Citescore:4.1,https://www.scopus.com/sourceid/21101083109))
7. Bhargava, A., A. Bansal, and V. Goyal, *Machine learning-based automatic detection of novel coronavirus (COVID-19) disease.* Multimedia Tools and Applications, 2022. 81(10): p. 13731-13750. , (JCR(Citescore:5.6,https://www.scopus.com/sourceid/25627))
8. Absar, N., et al., *Development of a computer-aided tool for detection of COVID-19 pneumonia from CXR images using machine learning algorithm.* Journal of Radiation Research and Applied Sciences, 2022. 15(1): p. 32-43. , (JCR(Citescore:-,-))
9. Islam, M.R. and M. Nahiduzzaman, *Complex features extraction with deep learning model for the detection of COVID19 from CT scan images using ensemble based machine learning approach.* Expert Systems with Applications, 2022. 195: p. 116554. , (JCR(Citescore:10.2,https://www.scopus.com/sourceid/24201))
10. Shan, F., et al., *Lung infection quantification of COVID-19 in CT images with deep learning.* arXiv preprint arXiv:2003.04655, 2020. , (JCR(Citescore:-,-))
11. Kogilavani, S., et al., *COVID-19 Detection Based on Lung Ct Scan Using Deep Learning Techniques.* Computational and Mathematical Methods in Medicine, 2022. , (JCR(Citescore:2.3,https://www.scopus.com/sourceid/11000153760))

12. Mishra, A.K., et al., *Identifying COVID19 from chest CT images: a deep convolutional neural networks based approach.* Journal of Healthcare Engineering, 2020. , (JCR(Citescore:6.5,https://www.scopus.com/sourceid/21100205972))
13. Rehman, N.-u., et al., *A self-activated cnn approach for multi-class chest-related COVID-19 detection.* Applied Sciences, 2021. 11(19): p. 9023. , (JCR(Citescore:0.8,https://www.scopus.com/sourceid/25193))
14. Aboughazala, L.M., *Automated detection of COVID-19 coronavirus cases using deep neural networks with X-ray images.* Al-Azhar University Journal of Virus Researches and Studies, 2020. 2(1): p. 1-12. , (JCR(Citescore:-,-))
15. Diaz-Escobar, J., et al., *Deep-learning based detection of COVID-19 using lung ultrasound imagery.* Plos one, 2021. 16(8): p. e0255886. , (JCR(Citescore:4.3,https://www.scopus.com/sourceid/10600153309))
16. Malik, H. and T. Anees, *BDCNet: multi-classification convolutional neural network model for classification of COVID-19, pneumonia, and lung cancer from chest radiographs.* Multimedia Systems, 2022: p. 1-15. , (JCR(Citescore:5.0,https://www.scopus.com/sourceid/25626))
17. Rahman, M.M., et al., *HOG+ CNN Net: Diagnosing COVID-19 and pneumonia by deep neural network from chest X-Ray images.* Sn Computer Science, 2021. 2(5): p. 1-15. , (JCR(Citescore:4.1,https://www.scopus.com/sourceid/21101083109))
18. Sarkar, A., et al., *Detection of COVID-19 from Chest X-rays using Deep Learning: Comparing COGNEX VisionPro Deep Learning 1.0TM Software with Open Source Convolutional Neural Networks.* https://www.researchgate.net/publication/343414434_Detection_of_COVID-19_from_Chest_X-rays_using_Deep_Learning_Comparing_COGNEX_VisionPro_Deep_Learning_10_Software_with_Open_Source_Convolutional_Neural_Networks?enrichId=rgreq-5d1abe2723f80061645dbcb12b1fbb49-XXX&enrichSource=Y292ZXJQYWdlOzM0MzQxNDQzNDtBUzo5MjU4NTgxOTc5NDIyNzhAMTU5Nzc1MzIwNDcwMQ%3D%3D&el=1_x_2&_esc=publicationCoverPdf 2020. , (JCR(Citescore:-,-))
19. Saood, A. and I. Hatem, *COVID-19 lung CT image segmentation using deep learning methods: U-Net versus SegNet.* BMC Medical Imaging, 2021. 21(1): p. 1-10. , (JCR(Citescore:4.1,https://www.scopus.com/sourceid/16561))
20. Hassantabar, S., M. Ahmadi, and A. Sharifi, *Diagnosis and detection of infected tissue of COVID-19 patients based on lung X-ray image using convolutional neural network approaches.* Chaos, Solitons and Fractals, 2020. 140: p. 110170. , (JCR(Citescore:8.2,https://www.scopus.com/sourceid/25347))
21. Imani, M., *Automatic diagnosis of coronavirus (COVID-19) using shape and texture characteristics extracted from X-ray and CT-Scan images.* Biomedical Signal Processing and Control, 2021. 68: p. 102602. (JCR(Citescore:7.8,https://www.scopus.com/sourceid/4700152237))
22. Khalifa, N.E.M., et al., *Detection of coronavirus (COVID-19) associated pneumonia based on generative adversarial networks and a fine-tuned deep transfer learning model using chest X-ray dataset.* International Conference on Advanced Intelligent Systems and Informatics, 2022. (JCR(Citescore:0.9, https://www.scopus.com/sourceid/5100152904))
23. Ibrahim, D.M., et al., *Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases*. Computers in biology and medicine, 2021. **132**: p. 104348. (JCR(Citescore:9.7, https://www.scopus.com/sourceid/17957))
24. OS Albahri, AA Zaidan, AS Albahri, BB Zaidan *Systematic review of artificial intelligence techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking: Taxonomy analysis, challenges, future solutions and*

methodological aspects. Journal of infection and public health, 2020. https://doi.org/10.1016/j.jiph.2020.06.028 (JCR(Citescore:6.9, https://www.scopus.com/sourceid/16800154711))

25. Rustam F, Reshi AA,Mehmood A, Ullah S, On B, AslamW, Choi GS, *COVID-19 future forecasting using supervised machine learning models*. IEEE Access, 2020. 8:101489–101499. https://doi.org/10.1109/ACCESS.2020.2997311 , (JCR(Citescore:6.6,https://www.scopus.com/sourceid/21100374601))
26. Sharma S, *Drawing insights from COVID-19-infected patients using CT scan images and machine learning techniques: a study on 200 patients*. Environmental Science and Pollution Research, 2020. 27:37115–37163. https://doi.org/10.1007/s11356-020-10133-3 , (JCR(Citescore:8.1,https://www.scopus.com/sourceid/23918))
27. Peng Y, Nagata MH, *An empirical overview of nonlinearity and overfitting in machine learning using COVID-19 data*. Chaos, Solitons and Fractals, 2020. 139:110055 , (JCR(Citescore:8.2,https://www.scopus.com/sourceid/25347))
28. Ardabili SF, Mosavi A, Ghamisi P, Ferdinand F, Varkonyi-Koczy AR, Reuter U, Rabczuk T, Atkinson PM, *COVID-1*9 outbreak prediction with machine learning. Algorithms, 2020. Available at SSRN3580188 , (JCR(Citescore:3.2,https://www.scopus.com/sourceid/21100199795))
29. Nemati M, Ansary J, Nemati N, *Machine learning approaches in COVID-19 survival analysis and discharge time likelihood prediction using clinical data*. Patterns, 2020. 1:100074 , (JCR(Citescore:9.9,https://www.scopus.com/sourceid/21101028388))
30. Sun CLF, Zuccarelli E, Zerhouni EGA, Lee J, Muller J, Scott KM, Lujan AM, Levi R, *Predicting COVID-1*9 infection risk and related risk drivers in nursing homes: a machine learning *approach*. J Am Med Dir Assoc 21(11):1533-1538.e6, 2020. https://doi.org/10.1016/j.jamda.2020.08.030 , (JCR(Citescore:-,-))
31. Burdick H, Lam C, Mataraso S, Siefkas A, Braden G, McCoy A, Vincen JL, Green-Saxena A, Barnes G, Hoffman J, Calvert J, Pellegrini E, Das R, *Prediction of respiratory decompensation in Covid-19 patients using machine learning: The READY trial*. Computers in biology and medicine, 2020. 124:103949. https://doi.org/10.1016/j.compbiomed.2020.103949 , (JCR(Citescore:9.7,https://www.scopus.com/sourceid/17957))
32. Kavadi DP, Patan R, Ramachandran M, Gandomi AH, *Partial derivative nonlinear global pandemic machine learning prediction of covid 19*. Chaos, Solitons and Fractals, 2020. 139:110056 , (JCR(Citescore:8.2,https://www.scopus.com/sourceid/25347))
33. BanerjeeA, Ray S,Vorselaars B, Kitson J, Mamalakis M,Weeks S, Mackenzie LS, *Use of machine learning and artificial intelligence to predict SARS-CoV*-2 infection f*rom full blood counts in a population*. International immunopharmacology, 2020. 86:106705 , (JCR(Citescore:5.8,https://www.scopus.com/sourceid/22432))
34. Wang P, Zheng X, Li J, Zhu B (2020) *Prediction of epidemic trends in COVID-19 with logistic model and machine learning technics*. Chaos, Solitons and Fractals 139:110058 , (JCR(Citescore:8.2,https://www.scopus.com/sourceid/25347))
35. Han Z, Wei B, Hong Y, Li T, Cong J, Zhu X, Zhang W, *Accurate screening of COVID*-19 using *attention based deep 3D multiple instance learning*. IEEE transactions on medical imaging, 2020. 39(8):2584–2594 , (JCR(Citescore:13.7,https://www.scopus.com/sourceid/16733))
36. Vaid S, Cakan C, Bhandari M, *Using machine learning to estimate unobserved COVID*-19 *infections in North America*. JBJS, 2020. 102(13):e70. https://doi.org/10.2106/JBJS.20.00715 , (JCR(Citescore:3.7,https://www.scopus.com/sourceid/21100984155))
37. Elaziz MA, Hosny KM, Salah A, Darwish MM, Lu S, Sahlol AT, *New machine learning method for image-based diagnosis of COVID-1*9. PLoS One, 2020. 15(6):e0235187 , (JCR(Citescore:4.3,https://www.scopus.com/sourceid/10600153309))

38. Ahamad MM, Aktar S, Rashed-Al-Mahfuz M, Uddin S, Liò P, Xu H,…MoniMA, *A machine learning model to identify early stage symptoms of SARS-Cov-2 infected patients.* Expert systems with applications, 2020. 160:113661 , (JCR(Citescore:10.2,https://www.scopus.com/sourceid/24201))
39. Brinati D, Campagner A, Ferrari D, Locatelli M, Banfi G, Cabitza F (2020) *Detection of COVID-19 infection from routine blood exams with machine learning: a feasibility study.* Journal of medical systems, 2020. 44:135. https://doi.org/10.1007/s10916-020-01597-4 , (JCR(Citescore:5.9,https://www.scopus.com/sourceid/23710))
40. Hasan N, *A methodological approach for predicting COVID-19 epidemic using EEMD-ANN hybrid model*. Internet of things, 2020. 11:100228 , (JCR(Citescore:6.9,https://www.scopus.com/sourceid/21101141804))
41. Farid AA, Selim GI, Khater HAA, *A novel approach of CT images feature analysis and prediction to screen for corona virus disease (COVID-19*). Int J Sci Eng Res, 2020. 11(3):1–9 , (JCR(Citescore:-,-))
42. Shaban WM, Rabie AH, Saleh AI, Abo-Elsoud MA, *A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier*. Knowledge-Based Systems, 2020. 205:106270 , (JCR(Citescore:11.8,https://www.scopus.com/sourceid/24772))
43. Ou S, He X, Ji W, Chen W, Sui L, Gan Y, Lu Z, Lin Z, Deng S, Przesmitzki S, Bouchard J, *Machine learning model to project the impact of COVID-19* on US motor gasoline demand. Nature Energy, 2020. 5:666–673. https://doi.org/10.1038/s41560-020-0662-1 , (JCR(Citescore:55.7,https://www.scopus.com/sourceid/21100812579))
44. Samuel J, Ali GG, RahmanM, Esawi E, Samuel Y, *Covid-19 public sentiment insights and machine learning for tweets classification*. Information, 2020. 11(6):314 , (JCR(Citescore:-,-))
45. Pinter G, Felde I, Mosavi A, Ghamisi P, Gloaguen R, *COVID-19 pandemic prediction for hungary; a hybrid machine learning approach*. Mathematics, 2020. 8(6):890 , https://doi.org/10.3390/math8060890 , (JCR(Citescore:-,-))
46. Carrillo-Larco RM, Castillo-Cara M,*Using country-level variables to classify countries according to the number of confirmed COVID-19* cases: an unsupervised machine learning approach. Wellcome open research, 2020. 5(56):56 , (JCR(Citescore:3.2,https://www.scopus.com/sourceid/21100842667))
47. Benıtez-Pena S, Carrizosa E, Guerrero V, Dolores M, *Shortterm predictions of the evolution of COVID-19 in Andalusia. An ensemble method*. Preprint, 2020. https://www.researchgate.net/publication/340716304_Short-Term_Predictions_of_the_Evolution_of_COVID-19_in_Andalusia_An_Ensemble_Method. Accessed 21 November 2020 , (JCR(Citescore:-,-))
48. Zhong L,Mu L, Li J,Wang J, Yin Z, Liu D, *Early prediction of the 2019 novel corona virus outbreak in the mainland China based on simplemathematical model*. IEEE access, 2020. 8:51761–51769 , (JCR(Citescore:6.6,https://www.scopus.com/sourceid/21100374601))
49. Yadav M, Perumal M, Srinivas M, *Analysis on novel coronavirus (covid-19) using machine learning methods*. Chaos, Solitons and Fractals, 2020. 139:110050 , (JCR(Citescore:8.2,https://www.scopus.com/sourceid/25347))
50. M. Sokolova, G. Lapalme *A systematic analysis of performance measures for classification tasks,* Information processing & management, 2009, pp. 427-437 , (JCR(Citescore:13.3,https://www.scopus.com/sourceid/12689))
51. M. Alsalem, et al. *Multiclass benchmarking framework for automated acute Leukaemia detection and classification based on BWM and group-VIKOR J Med Syst,* Journal of medical systems, 2019, p. 212 , (JCR(Citescore:5.9,https://www.scopus.com/sourceid/23710))