Deep Learning Models Used to Identify and Classify COVID-19 : A Review

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ABSTRACT

The novel coronavirus disease 2019 (COVID-19) became a challenging issue and added tremendous pressure on healthcare services worldwide. The early detection is of covid19 became very important to control the spread and to reduce pressure on healthcare services. the most common approach to detect covid19 is to use the nasal swab technique. X-ray radiographs are also a primary method used to detect lung infections and allow physicians to assess and plan a course of treatment. Although the usage of X-ray machines are a preferable first approach , the usage of X-ray radiographs requires radiologists to assess ever X-ray image of the chest and hence proved to be quite challenging. Hence, various machine learning techniques have been proposed to assist and speed up the diagnoses and decision-making process.

Keyword: - *Deep Learning, Covid-19, Classification, Artificial Intelligence, Deep Learning Models, Review*

1.INTRODUCTION

The novel coronavirus disease 2019 (COVID-19) rapidly spread around the world causing global pandemic. The first case of infection due to the virus was identified in early December 2019 in Wuhan, the People's Republic of China. Strong measures such as isolation close monitoring and shutdowns were applied to control the spread of infection. These measures that were applied have caused economic crisis, recession, and affected the mental well-being of many individuals around the world [1], [2], [3]. The World Health Organization (WHO) declared the COVID-19 outbreak as a global pandemic on March 11th, 2020 [4]. The governments, medical teams and hospitals faced many challenges in the first few months of the pandemic to test and control the infected people. Due to the rapid spread of the virus the need for early detection of COVID-19 and faster diagnosis has also increased [5] Reverse Transcription Polymerase Chain Reaction test (RT-PCR) is the current standard tool used to detect COVID-19 infection. However, in RT-PCR there is a fairly high chance of obtaining false-negative rates, which might lead for inefficiency in treatment or failure [6], [7]. Other methods, such as Computed Tomography (CT) have been made use in assisting and increasing the accuracy of the testing process. However, in many countries it is expensive to conduct diagnosis based on RT-PCR and CT scans due to insufficient facilities. Other methods that are based on chest X-rays, have shown potential improvements in detecting COVID-19. Inspection of X-ray to diagnose COVID-19 adds to the burden of radiologists as they have to review and interpret lung X-ray images. Although this method takes a lot of time from a radiologist to interpret the images, X-ray evidence may be more accurate as opposed to reverse transcription polymerase chain reaction (RT-PCR) [8]. Researchers have proposed many methods that are based on machine learning algorithms to analyse X-rays of COVID-19 cases and hence automating the diagnostic process as well as promoting the early detection and treatment.

2. DEEP LEARNING

Deep learning-based approaches have become one of the most popular algorithms in the field machine learning. These approaches have outperformed and achieved state-of- the art performance in many learning-based research problems [9], [10], [11]. The popularity of deep learning started when a deep-learning approach based on convolutional neural networks (CNNs) outperformed all other methods in the best-known computer-vision competition, ImageNet [19]. CNNs are designed in a way that it could take advantage of a two-dimensional input, that employ series of convolutional layers that extracts features at various different spatial locations. One of the unique ability of deep learning methods are to automatically learn a hierarchical feature representation of input data, make them an excellent choice when compared with traditional machine learning methods that depend on hand engineering features [12]. CNNs are powerful tool that could extract features from the input images and differentiate the importance among the features. It could also process 3-dimensional (3D) images along with 2- dimensional (2D) images. Recently, CNNs are being used in various different fields, including imaging analysis. The general architecture of CNN model consist of convolutional layers, activation functions (e.g. rectified linear unit (RELU)), pooling layers, and fully connected layers as shown in Figure 2. When an image is fed as input into a convolutional layer, raw pixels are detected by the layer .Using a low-level features, a ReLU layer produces a feature map that has higher features, such as a cell or cytoplasm. A convolutional layer has three major mechanisms (sparse connection, weight sharing, and sub- sampling) that reduces the degrees of freedom in a model. In a sparse connection only some inputs are connected to the next layer. Sharing of weights allows the network to decrease the number of weights that are updated in a convolutional layer and decrease the time taken for training. Deep learning approach could be categorized into transfer learning and training from scratch.

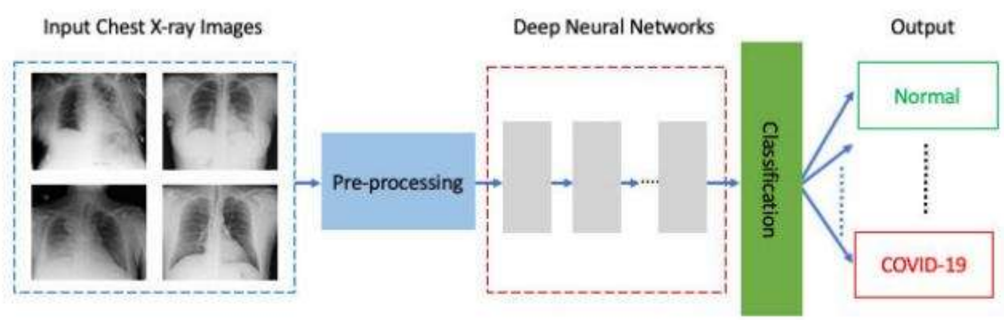

Fig 1: General classification process using CNN

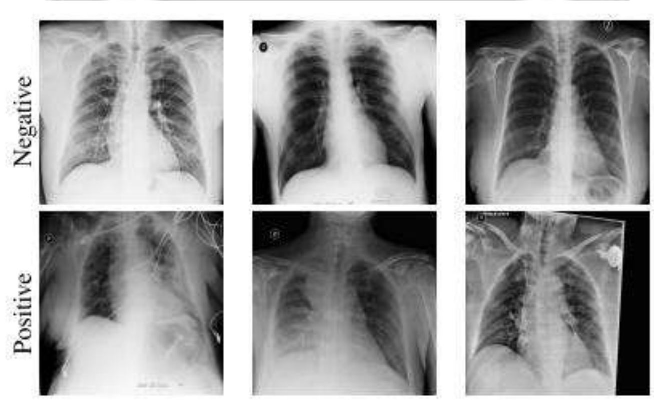

Fig 2: Chest X-Ray Samples

3. CHEST X-RAY DATASETS

Physicians require X-Ray images to understand and diagnose many ailments. These X-Ray images are used to gather features that are used to train learning algorithms. The COVID-19 patient X-Rays as well as non-COVID-19 patient X-Rays are considered for analysis. Analysis of different datasets was done to find the most appropriate and useful datasets[13]. Certain criteria such as patient demographics, kurtosis, and so on were used to assess the datasets. Additionally, the quality of the image was also taken into consideration due to variations in angle of images, scan protocols, field of view, etc. Figure 3, shows some examples of COVID-19 positive and negative X-ray images. Biases can occur due to different factors. The size of a dataset is one such parameter. CoronaHack Chest X-Ray dataset [14] has 1% of its dataset with COVID-19 confirmed patients, hence skewing the outcome. Therefore, a larger and more diverse dataset may be needed. Inconsistencies in different parameters such as field of view, age and image parameters can also be found in some datasets[15]. Image artifacts such as cables can also affect the training models The NIH dataset [16] is a well-established and documented pneumonia imaging data that may be used as a preliminary check for researchers to test their approach. a slope, it can also refer to winning something by a large margin. Hence, the noise and context can decrease the accuracy of this method.

Dataset Reference	chest X-ray image category				Total number of images
	Pneumonia	Normal	COVID19	Other	
[[31] Available online	✓				79
[[32] Available online		✓		✓	247
[[33] Available online			✓		468
[[34] Available online		✓		✓	1107
[[35] Available online		✓	✓	✓	5381
[[36] Available online	✓	✓			5856
[[37] Available online	✓	✓			5856
[[38] Available online	✓		✓		5933
[[39] Available online	✓	✓	✓		13975
[[40] Available online	✓	✓	✓	✓	21173
[[41] Available online	✓	✓			29700
[[42] Available online	✓	✓		✓	112120
[[43] Available online		✓	✓		13609
[[44] Not Available online		✓	✓		610

Table 1: Chest X-Ray datasets summary

4. DEEP LEARNING USED FOR DETECTION OF COVID-19

There are various approaches for detection of COVID-19 using chest X-Ray. We have found that there are primarily two major methods used:

1) Transfer learning: This uses trained models and fine- tuning them, or extracting features from trained models and then using classification.

2)Training from scratch: This could be done using single model Convoluted Neural Networks or multiple Deep Learning models

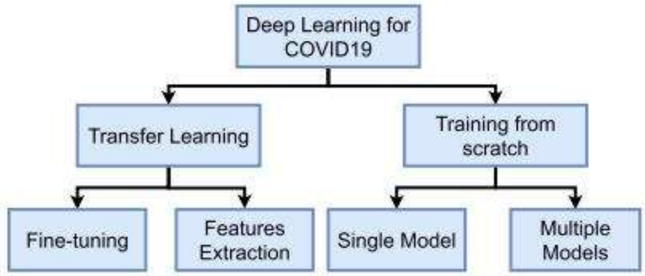

Figure 3: Deep Learning Models classification

4.1 Transfer-Learning Based approach

Transfer learning approaches can be divided into two categories:
1) Fine-tuning based methods
2) Features extraction which is then followed by classification methods.

1) Fine-Tuning based approach: When training a deep learning model for a specific task, fine-tuning is the act of employing knowledge transferred from a different domain as initial weights.To enable learning models efficiently for smaller labelled datasets, our technique leverages models trained on big labelled datasets In [17], the authors applied an ensemble of the predictions from the seven pre-trained fine-tuned deep learning models, The pre-trained models were: VGG16, VGG19 [18], InceptionResNetV2 [19], Xception [20], InceptionV3 [21], MobileNet [22], and DenseNet121 [16]. The authors used a public datasets of chest X-ray images for fine-tuning the pre-trained models. They classified each image into one of three classes: normal, COVID-19, or pneumonia. Another fine-tuning approach was presented by El-Gannour et al. in [23], where the best performing model was Xception with an accuracy of 98% and precision of 100%.

An evaluation of different fine-tuning deep learning models was done in [24]. The pre-trained deep learning models include: AlexNet [19], SqueezNet [26], GoogleNet [27], ResNet-50 [18], DarkNet-53 [28], DarkNet-19 [28], ShuttleNet [29], NasNet-Mobile [30], Xception [20], Plae365- GoogLeNet [27], MobileNet-v2 [22], DenseNet- 201 [16], ResNet-18 [18], Inception-ResNet-v28 [19], Inceptionv3 [21], ResNet-101 [18], and VGG19 [18]. Publicly available datasets were used, where it showed that DarkNet-19 had the best performance of accuracy, about 94.28%, whereas ResNet-50 accuracy was 93.69% on the test set.

Some approaches combined multiple datasets together to get larger training data, as there was a lack of datasets. In [31], a study was done on different state-of the-art deep learning models using combined datasets from multiple publicly available imaging datasets was done.

Inceptionv3 model using ImageNet dataset was fine-tuned in [32]. Four fully connected layers were used in place of the head. The last fully connected layer outputs classification for three classes: COVID-19, pneumonia, and normal, where an accuracy of 98% was shown. Similarly, VGG16 model was done fine tuned [65] . All the layers except for the last three layers were frozen. The performance on the validation was high at 99.45% (accuracy) using 5-fold cross-validation, however the data was imbalanced.

CoroNet[33] is a method that balances the data before fine- tuning deep learning, which fine-tunes Xception neural network trained on ImageNet. Here, two fully connected layers replaced with the head of the neural network. This model was used for binary classification, three classes based classification, and four classes based classification. The classes for the binary classification were COVID-19 and normal,whereas the three classes classification were: COVID-19, normal, and pneumonia. The four classes classification were: COVID-19, normal, pneumonia-bacterial, and pneumonia viral. This approach yielded 99% (accuracy for binary classification) ,95% (accuracy for three classes classification) and 89.6% (accuracy for four classes classification).

A three steps approach with fine-tuning of the VGG16 model pre-trained on ImageNet was done in [34]. The approach will first classify a chest X-ray image as healthy versus infected (for an infected patient with pulmonary diseases, which include COVID-19). The second step is applied when the image is classified as infected, where it further classifies the disease and checks for Covid-19 aims to detect if the pulmonary infection was pneumonia or COVID-19. The accuracy of the model in the first step was 96% and in the second step was 98%.

Using Inception v3 network pre-trained on ImageNet, a transfer learning and fine-tuning approach was done in [35]. The authors tried six experiments where different datasets were considered, yielding an accuracy of 100% from the best result, with the caveat being the serious data imbalance using this approach.

A transfer learning approach using three ResNet models were trained to classify chest X-ray images [36]. The first model classified images as normal or diseased. The second model categorized images as pneumonia or non-pneumonia. The third model was trained to classify COVID-19 vs. non- COVID-19.Upon training, the models were combined and all layers were frozen except the classification layers, with new layers being added. Then fine-tuning of the models to classify chest X-ray images of classes: COVID-19, normal, and pneumonia were done. 95.5% was the best accuracy of this approach.

Early detection of COVID-19 infections using X-ray images using convolution support estimator network (CSEN) was proposed in [37]. This was compared to neural networks such as DenseNet ,where CSEN showed lower accuracy for COVID-19 detection.

An ensemble of CNNs had a superior results over radiologists when a comparison between an ensemble of ten convolution neural networks (CNN) and radiologists was done in [38]. The authors used TRACE4 system to fine-tune ResNet-50 pre-trained neural network to classify X-ray images into COVID-19 and non-COVID-19. Another approach for assessing the severity of COVID-19 progression was proposed in [39]. This approach uses transfer learning of VGG16 pre-trained on pneumonia dataset [40] for fine-tuning. This approach classifies X-ray images into normal, mild, moderate, and severe.

2) Features Extraction: In this section, we discuss papers that extract deep or traditional features from chest X-ray images to apply classification algorithms to detect COVID- 19. Explain proposed methods for detecting COVID-19 using features extracted from chest X-rays. [41] proposed a cascade-based deep learning approach to detect COVID-19 in chest X-rays. The extracted features were fed into Capsule-Net, followed by two-class classification levels and multi-class classification. The proposed method was evaluated with chest X-ray image data [42]. The classifications for the two classes were: COVID-19-positive vs. COVID-19 negative, while multiclass classifications were: viral pneumonia, normal, and COVID-19 positive.

A comparative study on the transfer of pre-trained deep learning models with ImageNet was conducted [43]. The authors extracted features from each model and fed the features to a perceptron neural network to classify each chest X-ray into one of three categories: normal, pneumonia and COVID-19. The dataset for this study was based on two publicly available datasets: chest X-ray and CT datasets [44] and [45]. The best accuracy was achieved with features extracted from Inception_Resnet_v2, with an accuracy of 92.18%.

An approach for identifying the COVID-19 in a chest X-ray dataset was proposed in [46]. The dataset was named RYDLS-20 and was provided by the authors. This approach extracts manually created surface textures and depth features from chest X-ray images to train multiple classifiers. The results of a trained neural network that classified chest x-rays as normal, pneumonia or COVID-19 were 98. 82% (accuracy), while the accuracy of CNN was 95.48%.

In [47], the authors proposed a deep learning approach called ConStacknet based on StackNet meta-modeling combined with CNN to learn characteristics of X-ray images. The authors used a VGG16 architecture pretrained on ImageNet to extract deep features from chest X-ray images. Then feature processing like standardization was done. After that, Stacknet was launched. The accuracy of the Stacknet model was 97% on the test set. A feature combination approach was proposed in [48]. His approach combines traditional features and deep features extracted from X-ray images to learn how to detect COVID-19. The authors showed that combining features performs better than classifiers using deep features and traditional features independently.

4.2 Training from Scratch

1)Single Model Approach: Convolutional Neural Networks (CNN) is a type of neural network that can learn spatial features and weights. A CNN trained to detect the COVID-19 case using a neural network was trained using data from three publicly available datasets. 1) Joeseph Paul dataset containing 542 chest X-ray from 262 patients [44] 2) the COVID-19 radiographic dataset [49], [50]. The combined data set was divided into training, validation and test set, where the accuracy of the test set was 99.2%.

The quality of X-ray images is critical for high- performance deep learning models. Hence, in [51] an approach is done that involves the pre-processing of chest x-ray images for performance improvement. CNNs trained to classify chest X-rays included four convolutional layers with two connected layers. CNN training was done with two datasets: 1) COVID-19 Radiography dataset which had 219 positive COVID-19 chest X-ray images [52], and 2) chest x-ray radiographic dataset created by Murali Kummitha, which included 107 chest radiographs of effusion disease and 1000 chest radiographs of normal cases [53]. The high-performance result shown with pre- processed images than non-processed images for both the classes: two classification classes (i.e., COVID-19 vs normal) and three classes classification (i.e., COVID-19 vs normal vs effusion). The accuracy in the deep learning model using histogram equalization pre-processing step for two classes and three classes classification was 98.62% and 95.77%.

A semi-supervised method was proposed in [130] for the classification of X-ray images of COVID-19 .Feature Extraction was made from the pretrained network, after which the latent features were fed into different classification networks. [54] proposed an approach to validate the deep learning results of the classification of COVID-19 using X-ray images. This approach is called hiding, which uses modified versions of the training, validation, and test sets. The changes include cutting out lungs from X-ray images to study the effect on deep learning, learning and performance. A deep anomaly detection method called reliable anomaly detection (CAAD) was proposed in [55]. This approach consists of feature learning and extraction, outlier detection, and reliable prediction modules. This approach was used to identify cases of viral pneumonia using an indoor radiographic dataset.

2)Multiple Model Based Approach: Several model-based approaches are presented in this sub-section relating to how multiple models are combined and trained. A deep learning model that uses chest x-rays to detect COVID-19.

In [56], the auto-encoder latent space was used to train a CNN. This method shows 2% better accuracy compared to the VGG16 model. A dataset of 400 COVID-19 chest x- rays was taken. There are positive cases and normal cases.

Another approach, involved combining Xception and ResNet50v2 networks for COVID-19 detection using learning capabilities and chest x-rays. The image dataset was proposed in Movements of these approaches are Network Xception and ResNet50-v2 in parallel. The function of size 10 x 10 x 2048 from each of the two networks are chained. Then a convolutional layer was applied of 1×1, This approach classifies chest radiographs and Pictures of normal, COVID-19, and pneumonia. We also proposed a training mechanism for imbalanced data. When the majority of classes are split into many subsets of size of equal minority. Then each subset is combined form a training set together with the minority class. Deep learning a model was trained for each combined training set. It led to trained models, the dataset used for training and Validation of this approach was based on the RSNA pneumonia detection dataset. This approach showed 91.40% accuracy, and the detection accuracy of COVID-19 was 99.56%

5. Conclusion and Further Research

Deep learning shows many promising avenues Detection of COVID-19 cases using chest radiograph data pictures. Combinations are a promising future direction of research Multiple sources of information for deep learning models. To B. Adding information from the patient's clinical record such as medical history and vital signs in combination with Model-driven information from chest X-ray Deep learning models need to be enhanced to further support radiologists' decisions. For deep learning models, combining information when training the model should help in the detection of COVID-19 more effectively improving accuracy and generalizability. This overview paper summarizes deep learning approaches A chest X-ray is used to detect COVID-19 in her. Additionally, this article summarizes available breast datasets. X-ray images were used in the reviewed approach. again, The article presents a discussion of the reviewed approaches, Indicating opportunities for improvement. I will also explain to them the Future directions for her COVID-19 detection using a chest X-ray picture.

6. Summary of Deep Learning Models architecture and visualization

Image classification is a very time-consuming process. Training a model with high accuracy requires a large model A dataset containing labeled data. But collecting these records is Complex and expensive. learning approach Pre-trained deep learning models could be a solution to solve these problems. In transfer learning, a deep neural network model is pre-trained on common large datasets such: as ImageNet. Then transfer the model to another dataset same domain. Two approaches can be followed in transfer learning Applications: Feature extraction and fine-tuning

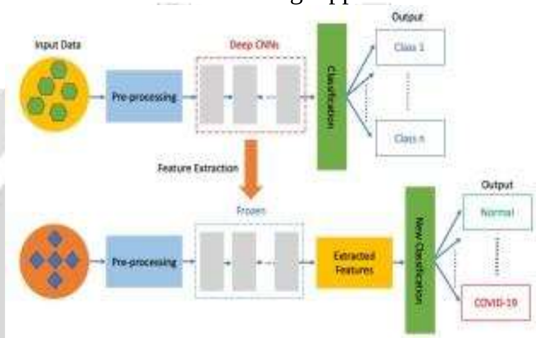

Figure 4: Feature extraction in transfer learning

F-4 Describes the general concept of feature extraction with transfer learning. A pre-trained network is used for extraction Works from a new dataset. Then the input image can be classified with the resulting features by simply replacing it with the new one Such as the application of a classifier layer or classification algorithm Support Vector Machine (SVM). Now the new model is Classify images in new data set using extracted features New classification layer is reused to classify images with a new record.

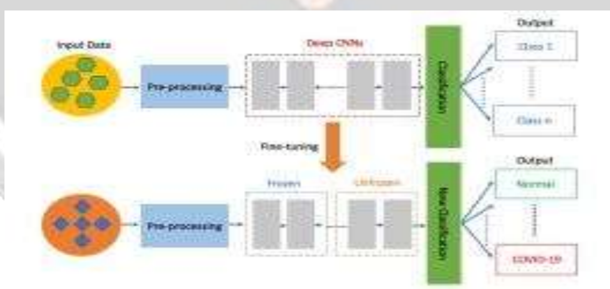

Figure 5: Fine-tune in transfer learning

F-5 Illustrate the fine-tuning model scenario. something deep A convolutional neural network (DCNN) model is trained first. with another larger dataset. early strata DCNN is more general, but later layers are more dataset-dependent. Tweaking refers to freezing the initial layer, Then unpacking some top layers of the pre-trained model, and eventually replacing the new classifier layer. The decompressed layer and new classifier are trained from scratch on the new layer record. Learned features have been tweaked to be more relevant to a new record.

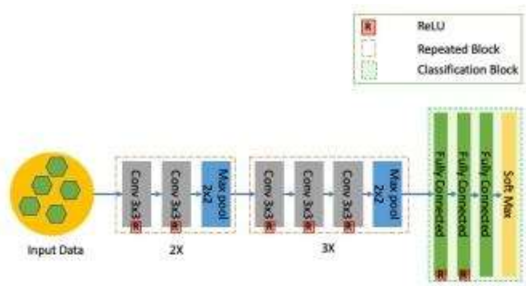

Figure 6: VGG-16

F-6 We present the VGG-16 (or OxfordNet) model architecture. VGG-16 was proposed by Karen and Simonyan Andrew Zisserman [18] in 2014. It contains 16 layers of convolution and achieves a top 5 test accuracy of 92.7%. ImageNet dataset with over 14 million images 1000 class. VGG-16 is still widely used for image classification and localization problems. Stack of convolutions Layers follow fully connected layers and the softmax activation layer

Figure 7: ResNet-50

F-7 We discuss the ResNet-50 model, one of the convolutional neural networks. ResNet-50 has 50 layers, Activation functions, and pooling layers. different from Other convolutional neural networks that learn from features The ResNet 50 model follows a deep residual learning framework where the model learns from residuals and skips some. Connections between layers. ResNet-50 aims to reduce complexity and improve learning accuracy. ResNet-50 is used for training computer vision tasks such as Image classification and object recognition

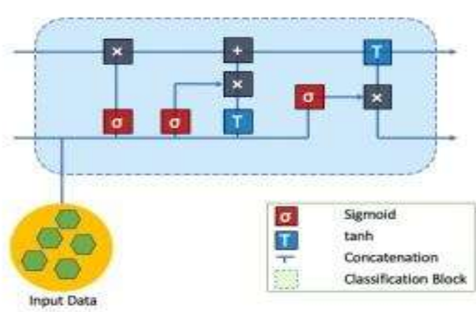

Figure 8: LSTM

F-8 Shows long short-term memory (LSTM) neural network. Sepp Hochreiter and Jürgen Schmidhuber 1997 [57 suggest a special kind of Recurrent Neural Network (RNN). LSTM was designed Addresses RNN's inability to remember dates preventing the model from learning from it for too long A long data sequence. LSTM on the other hand allows this to Store information longer, learn new information, and Decide what information to keep or delete. For this reason, LSTMs can solve many problems that RNNs could not effectively solve. LSTMs are commonly used for detection. A pattern in a data sequence that changes over time. Similarly, LSTM shows promise for speech recognition, language modeling, machine translation, handwriting recognition, image recognition, etc.

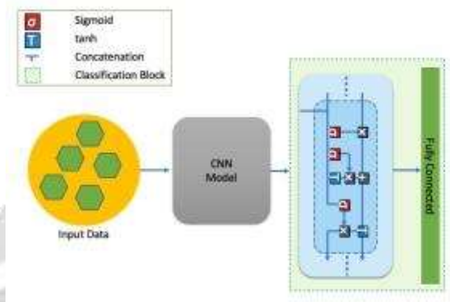

Figure 9: CNN-LSTM

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