Deep Learning for COVID-19 Prognosis: A Systematic Review

H. Swapna Rekha, Himansu Sekhar Behera, Janmenjoy Nayak, and Bighnaraj Naik

Abstract In the twenty-first century, the novel coronavirus (COVID-19) with its origin in the city of Wuhan has been spreading expeditiously and infecting more than 4.9 million population of the world as of May 19, 2020. As it is inducing serious threat to the global health, it is necessary to develop accurate prediction models and early diagnosis tools of COVID-19 to empower healthcare specialist and government authorities to control the spread of the pandemic. The latest advances in the intelligent computing particularly deep learning approaches are providing a wide range of efficient methods, paradigms and tools in the interpretation and prophecy of COVID-19. In this paper, a perspective research on the ongoing deep learning approaches has been carried out. In this study, an analysis of the different approaches of deep learning techniques in the forecasting, classification and detection of COVID-19 has been performed. The main motive of this research is to facilitate the researchers and technocrats with some critical research briefing that may further assist in developing more adequate prototypes for the analysis and diagnosis of COVID-19.

Keywords COVID-19 · Deep learning · Coronavirus

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1 Introduction

Over the past, several epidemics have been emerging and causing a serious threat to the public health all over the world. The outbreak of small pox has slayed approximately 500 million population all over the world over 3000 years ago [1]. An approximate of 17–100 million populations has been assassinated due to the surge of Spanish influenza in the year 1918 [2]. In the twenty-first century, human coronaviruses such as SARS and MERS coronavirus that have developed from the repositories of animals have induced world-wide epidemic with high fatality rate as per the World Health Organization (WHO). In December 2019, another outbreak was recognized when the local hospitals in the city of Wuhan in South China were reported with unidentified pneumonia-infected cases [3]. Most of the infected patients were associated to the Wuhan merchandise which is renowned for selling collection of distinct animals and seafoods such as poultry, bats, snakes [4]. The reason behind the unidentified cases was not identified in its early period as its symptoms are similar to the common pneumonia. But, on January 7, 2020, after making an analysis of the throat swab, the virus was declared as novel coronavirus pneumonia (NCP) by center for disease control (CDC) authorities [5]. Later, it was renamed as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) by the International Committee on Taxonomy of Viruses [6, 7]. On February 11, 2020, the disease was named as novel COVID-19 by the WHO [8]. On January 30, 2020, the outbreak was declared as Public Health Emergency of International Concern (PHEIC) by the WHO when the coronavirus infection disseminated to 18 countries of the world through person-to-person transmission. On March 11, 2020, the WHO declared the outbreak as pandemic when the number of cases other than china has raised 13 times imposing a serious threat to public health globally. Since March, the virus is spreading rapidly resulting in total of 4,951,752 confirmed cases and 322,948 deaths all over the world as on May 19, 2020. Figure 1 depicts the number of confirmed cases in top 15 countries of the world as on May 19, 2020.

The standard approach utilized for the detection of novel coronavirus is Reverse Transcription Polymerase Chain Reaction (RT-PCR). The limitations of RT-PCR are low sensitivity, more time and limited number of available kits. To conquer the limitations of RT-PCR, rapid screening can be performed through the interpretation of medical images such as X-ray and computer tomography. Therefore, the spread of the pandemic can be controlled by developing appropriate forecasting and prediction models. From the past decade, as computer intelligence techniques are vastly used in preventing the spread of diseases, the present global emergency is also exploring the support of intelligent computing approaches in developing more accurate forecasting and prediction models to control the dynamics of COVID-19. The assessment of human loss and the prophecy of mortality for a particular period of time or up to the finish of the pandemic can be performed using mathematical models and statistical models. As mathematical model does not include all aspects of the pandemic, these models cannot generate more accurate predictions. Due to the advancement of intelligent computing approaches in healthcare, these approaches have been widely

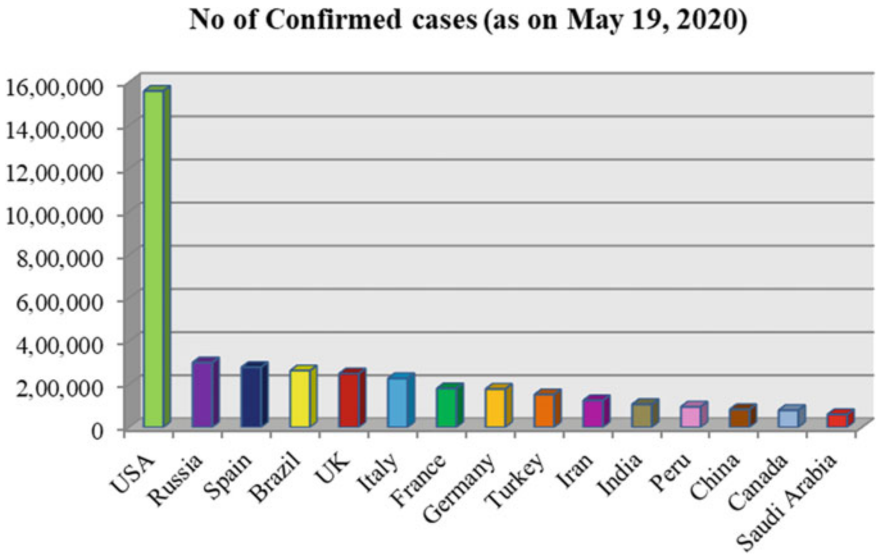

Fig. 1 Number of confirmed cases in top 15 countries as on May 19, 2020

used by the researchers and modeling developers to develop appropriate models and tools that help the physicians in diagnosing the COVID-19 infection and the government for taking appropriate actions to avoid the spread of the COVID-19 pandemic. Therefore, the present nCOVID-19 pandemic can be efficiently tackled by using distinct techniques of machine learning. Batista et al. [9] have suggested the usage of different approaches of machine learning in the prognosis of novel coronavirus. Further, the performance of various approaches of machine leaning has been evaluated by training these models using 70% of sample data and 30% of new data. From the results, it is identified that support vector machine achieves better performance with 0.68 sensitivity, 0.85 specificity, 0.85 AUC and 0.16 Brier score over random forests, logistic regression and gradient boosting trees techniques. There still exist some constraints with machine learning approaches such as exhaustive usage of medical data, inconsistency, dependency on temporal data, paucity, discrepancy and owing to high dimensionality for not generating the accurate forecastings and predictions [10–12].

Nowadays, deep learning approaches (DL) have exhibited excellence over the machine learning methods in the medical image analysis due to the availability of sufficient number of annotated images [13]. In addition, deep learning approaches have proven to be the best precise models for analyzing the medical datasets such as finding the abnormalities of brain, categorization of biomedical images, identification of tumors because of its deep architectural design [14–17]. The features of deep learning approaches such as superior performance, capability of handling composite and multimodal data, end-to-end learning along with feature learning, etc. has made the deep learning approaches to provide advanced facilities in the domain of biomedical informatics. Because of its powerful feature learning capacity, deep learning approaches can automatically mine clinical features from CT images which are somewhat troublesome for the humans to sense. Several studies reveal the importance of deep learning paradigms in the effective segmentation and identification of pneumonia from other infections on radiography. In recent years, prototypes of deep learning have been employed in the segmentation and recognition of pneumonia from radiography images [18]. The model performs pixel-wise segmentation by utilizing both global and local characteristics. The durability of the system has been obtained with the alteration of training process and post-processing step. Moreover, results also indicate that the proposed model achieves better performance in the detection of pneumonitis from radiography images. Benefiting from the features such as excellent accomplishment, capability of feature derivation without human interference, lack of engineering benefit in training phase, the prototypes of deep learning approaches have also been extensively utilized in the forecasting and prediction of present COVID-19 outbreak.

The main intention of this article is to emphasize the importance of distinct deep learning approaches in the recognition, categorization and forecasting of novel COVID-19. Initially, a study on the applicability of different deep learning methods along with its applications in the categorization, forecasting and identification of COVID-19 has been represented. Further, an investigation on number of publications published using various approaches in the estimation, identification and categorization of COVID-19 depending on input data and contribution of articles on the current outbreak has been presented. Lastly, some of the issues in the ongoing research are highlighted at the end of the paper to provide further scope of research for the researchers. The rest of the paper is organized as specified. Section 1 describes about the cause of SARS-CoV-2 and its effect on public health and the advantages of deep learning approaches in the analysis of COVID-19. The applicability of different techniques of deep learning in the recognition, categorization and forecasting of nCOVID-19 is described in Sects. 2 and 3. Section 4 describes the analytical investigation of different types of DL methods used in the forecasting and detection of coronavirus depending on data type and growth of publications. Section 5 describes the challenges that need to be addressed for the advancement of precise models. Finally, conclusion along with further scope of research is represented in Sect. 6.

2 Application of Deep Learning Techniques in the Prophecy of nCOVID-19

Deep learning is a branch of machine learning (ML) that tries to learn top-level abstractions in data by exploiting hierarchical frameworks. Deep learning can be used to solve complicated artificial intelligent problems because of its multiple processing layers. The main aspect of the deep learning technique is that the layers of deep learning are not created by human techies instead they are created from data by applying a learning procedure. Relevant clinical success has been achieved in the healthcare because of its advantages such as higher accomplishment, combined feature learning along with end-to-end learning scheme, ability to control composite intelligence problems. Due to the significant use of DL techniques in the analysis of medical images, presently, these approaches have also been applied in the recognition and screening of coronavirus pandemic. Several researchers and modeling developers have applied autoencoders, convolutional neural network (CNN), generative adversarial networks (GAN) and long short-term memory (LSTM), in the visualization, forecasting and analysis of the coronavirus pandemic.

2.1 Convolutional Neural Network (CNN)

Convolutional neural network is a deep learning approach that has been successfully enforced in the study of medical images. Basically, CNN consists of input, convolutional, pooling, fully connected and output layers. The basic advantage of CNN is its capability to extract features automatically from the images of specific domain without human interference. To optimize the medical resources and to perform early detection of COVID-19, a fully automated DL scheme has been recommended by Wang et al. [19]. The proposed system makes use of DenseNet129-FPN for performing the lung segmentation and COVID-19Net for performing the prognostic and symptomatic analysis of COVID-19. Initially, the proposed model was pre-trained with CT images and gene information of 4106 patients. Then the model was evaluated using CT images of 1266 patients of which 924 belong to COVID-19, 471 CT images have follow-up for more than five days and 342 of other pneumonia cases. From the findings, it has been observed that the proposed method attains better accomplishment with AUC of 0.87 and 0.88 for COVID-19 and AUC of 0.86 for other viral pneumonia. Moreover, the proposed deep learning scheme is also useful in classifying the infected patients into groups of high-risk and low-risk patients. To accurately identify the COVID-19 infection without annotating, a weakly supervised deep learning system that makes use of 3D CT volumes has been developed by Zheng et al. [20]. In the proposed system, pre-trained UNet was used to classify the lung region and the possibility of COVID-19 infection was identified using 3D deep neural network. Initially, the proposed system has been evaluated using 499 CT images and then validated using 131 CT images. The results show that the proposed system achieves an ROC AUC of 0.959 and PR AUC of 0.976 with 0.907 and 0.959 sensitivity and specificity in the ROC curve. Moreover, the algorithm has also achieved 0.901 accuracy, 0.840 positive predictive value and a very high 0.982 negative predictive value. To perform an efficient analysis of COVID-19 infection, pre-trained deep learning systems have been suggested by Razzak et al. [21]. The vigorous features of the images can be extracted automatically using these pre-trained models. Further, the effectiveness of the different CNN frameworks has been assessed using evaluative measures such as true positive, true negative, false positive, false negative and accuracy. In addition, using the pre-trained models, the

Table 1 Applicability of convolutional neural network in the diagnosis of nCOVID-19

Approach	Input data	Outcome	References
Tailored CNN models	145 COVID-19-infected chest X-ray images	DenseNet169 average classification accuracy = 95.72%	[22]
Custom CNN and pre-trained CNN models	Pediatric CXR, RSNACXR, Twitter COVID-19 CXR, Montreal COVID-19 CXR dataset	Accuracy = 99.01% AUC = 0.9972	[23]
Deep convolutional neural network ResNet50	135 COVID-19 X-ray and 320 other pneumonia X-ray images	Accuracy = 94.4% AUC = 0.99	[24]
Multiple 3D CNN models	618 CT samples	Overall accuracy = 86.7%	[25]
Mobile net using CNN framework	3905 diseases	Accuracy = 99.18% Sensitivity = 97.36% Specificity = 99.42%	[26]
CNN based COVIDX-Net model	50 images of chest X-ray with 25 X-ray images of confirmed COVID-19 cases	VGG19 f1-score = 0.89 DenseNet f1-score = 0.91	[27]
ResNet50, InceptionV3 and Inception-ResNetV2 pre-models	50 cases of COVID-19 and 50 images of normal chest X-ray	ResNet50 classification of accuracy = 95%	[28]

system has obtained an overall accuracy of 98.75% in distinguishing novel coronavirus from other bacterial pneumonia and 98.51% accuracy to identify coronavirus from other viral pneumonia. The appropriateness of convolutional neural networks in the diagnosis of nCOVID-19 infection has been represented in Table 1.

2.2 *Long Short-Term Memory Network (LSTM)*

LSTM network is a special kind of the recurrent neural network (RNN) that consists of a cell, an input and output gate and forget gate. As LSTM can be successfully utilized in training heavy architectures, they have been employed in deep learning approaches. Because LSTM can retain knowledge of earlier states, these are the best models for training the networks that requires memory. In time series analysis, LSTM is one of the excellent models used for performing more accurate forecasting of the outcome [29]. To predict the future trend of coronavirus cases in Iran, different models have been analyzed by the Kafieh et al. [30]. Initially, the models were trained with SARS data and then they were re-trained using COVID-19. The performance of the models has been evaluated using MAPE metrics. From these results, it can be concluded that M-LSTM has achieved better performance with 0.81% MAPE value when compared with other models in predicting the future trend of coronavirus cases. To determine best therapeutic options, LSTM model was suggested by Patankar [31]. Initially, the model was pre-trained using IC50 binding data from PDB database and 310,000 drug-like compounds from the ZINC. Further, the generative semi-supervised variational autoencoder (SSVAE) has been trained with 310,000 molecules along with their identified IC50s values. Moreover, it has been observed that new molecules generated by the proposed model produce the lower binding energies when compared to the binding energies of the prior drugs. To identify meaningful topics and sentiment classification of comments on COVID-19 from healthcare symposium, a novel NLP based on LSTM model has been recommended by Jelodar et al. [32]. Further, the findings illustrate that the model proposed may assist in enhancing the practical scenarios of healthcare services related to COVID-19. Other analysis on the prediction of COVID-19 using LSTM approach has been represented in Table 2.

Table 2 Diagnosis of novel COVID-19 using LSTM

Approach	Input data	Results	References
LSTM and curve fitting model	Time series data from COVID-19 in data source	To forecast the number of cases in India for one month and the effect of prevention measures	[33]
Modified SEIR and LSTM model	Daily COVID-19 cases reported by National Health Commission of China	Prediction of the COVID-19 epidemic peaks and sizes	[34]
LSTM	Time series data from Worldometer	LSTM model generated an RMSE value of 27.187	[35]
Variational LSTM-autoencoder	Data of COVID-19 cases published by John Hopkins University	Short-term and long-term forecast of the coronavirus around the world	[36]
ConvLSTM	Time series data of new cases in different regions along with some spatiotemporal features	Achieved 5.57 and 0.3% mean absolute percentage error for total no of predicted cases for five days in USA and Italy	[37]
RNN with LSTM	Datasets of World Health Organization and Johns Hopkins University	Generated low root mean squared logarithmic error between predicted and validated data and trends	[38]
LSTM-GRU-RNN	Time series data from Kaggle	Generated an accuracy of 87, 67.8, 62 and 40.5% for confirmed, negative, deceased and released cases	[39]

2.3 Generative Adversarial Network (GAN)

Generative adversarial network is a kind of deep learning technique that consists of two network modules, namely generator and discriminative network. The fake data that is similar to training data has been generated using generator, while the discriminative network is responsible for differentiating between the real and fake data that has been obtained using generator network. The mostly widely used applications of GAN are image, video and voice generation. To detect the inflames in the X-ray images of the COVID-19-infected patients, a model established on GAN and fine-tuned transfer learning technique was proposed by Khalifa et al. [40]. The efficiency and robustness of the proposed model has been proved by generating 90% of the images from the dataset by training only 10% of dataset. For identifying the pneumonia in the X-ray images, deep transfer learning models such as AlexNet, GoogLeNet, Squeeznet and Resnet18 have been used because of less number of layers in their architecture that further results in reducing the complexity of the models. Moreover, results conclude that Resnet18 using GAN as augmenter achieves 99% testing accuracy with performance metrics such as recall, F1 score and precision.

2.4 Autoencoders

Autoencoder is a kind of neural network in which the input is similar to output. It utilizes unsupervised algorithm for the minimization of dimensionality in the input data and then for regenerating the output from the original data. Data denoising and dimensionality reduction for data visualization are the most widely used application areas of Autoencoders. To model the transmission progress of the COVID-19, a RIN architecture based on RNN autoencoder was proposed by Ge et al. [41]. The proposed model has been validated using data from January 22, 2020 to April 18, 2020 to estimate the number of cases around the world. The results indicate that the proposed model estimates a total of new cases and cumulative cases, and the maximum number of cumulative cases across the world as 103,872, 2,104,800 and 2,271,648, respectively, with one-week later invention. The analysis of COVID-19 using GAN and autoencoder has been depicted in Table 3.

3 Analysis of Deep Learning Techniques in Prediction and Diagnosis of COVID-19

In the analysis of COVID-19 pandemic, different approaches of deep learning have been used in the process of forecasting the future dynamics of COVID-19, categorization of COVID-19 radiography images from the radiography images of pneumonia and in the prediction of COVID-19 epidemic. These analyses done using deep

Table 3 Utilization of GANs and autoencoder in the prediction of COVID-19

Approach	Input data	Results	References
GAN and CNN	2143 chest CT images	Achieves +2.82% Pearson coefficient to enhance the quantification of COVID-19	[42]
GAN and deep transfer language	306 X-ray images	Achieved 100% testing accuracy for two classes using three deep transfer learning models and validation accuracy of 99.9% using GoogLeNet	[43]
Topological autoencoder	Center for Systems Science and Engineering (CSSE) time series data of nCOVID-19	Used in the data visualization of global trends of coronavirus transmission	[44]
Variational autoencoder with QED and SA	Moses benchmarking dataset	Generates _ 3000 novel COVID-19 drug candidates	[45]
Modified autoencoder	Time series data of COVID-19 from WHO	Estimates a total of cumulative, new and maximum number of cumulative cases could reach 75,249,909, 10,086,085 and 255,392,154, respectively, with later intervention and January 10, 2021 as case ending time	[46]
Generative deep learning approach	Protease dataset from Dr. Rao's laboratory	Developed cost and time efficient models to provide different treatment against COVID-19	[47]

learning techniques help the government authorities in implementing proper actions and the clinical experts in performing early diagnosis to inhibit the spread of the COVID-19 outbreak.

3.1 Forecasting

The loom of infectious diseases poses a serious threat to human population across the world. Advances in disease vigilance system and information technology have produced the early warning systems that are not only appropriate but also repel the spread of epidemics. Epidemic avoidance and control competence can be achieved through the development of accurate forecasting models. The process of making

Table 4 Usage of DL techniques in forecasting of coronavirus infection

Author	Approach	Input data	Outcome	Month and year	References
Chimmula et al.	LSTM	Time series data from Johns Hopkins University and Canadian Health Authority	Predicted that the probable closing point of the COVID will be approximately by June 2020 in Canada	May 2020	[48]
Yudistira	LSTM	Time series data	LSTM outperformed RNN by 281.95	May 2020	[49]
Caicedo-Torres	IseeU2 deep learning model	MIMIC-III dataset	Predicts mortality of coronavirus with ROC of 0.8629	May 2020	[50]
Azarafza et al.	LSTM	Time series data from Iran Ministry of Health and Medical Education, IRNA and ISNA	Predicted total number of cases as of May 13, 2020, was 112,725 I IRAN	January 2020	[51]
Huang et al.	CNN	Time series data from Surging News Network and WHO	RMSE of CNN for six and one-input factors are 109.439, 325.857	January 2020	[52]

predictions of the future based on the historical data is known as forecasting. The existing traditional models mainly consist of linear and nonlinear models are well suited for short-term forecasting. The application of traditional models for long-term predictions may result in gradient problem. As the LSTM of deep learning approach allows to store and access information over long periods, it reduces the gradient problem. Hence, accurate long-term predictions can be achieved using approaches of deep learning. The succeeding Table 4 represents the applicability of deep learning techniques in the estimation of COVID-19 pandemic.

3.2 *Classification of COVID-19 Images*

Due to the limited availability and low sensitivity of RT-PCR, radiological imaging such as X-ray and CT images is utilized in the early interpretation of nCOVID-19 disease. As deep learning enables the development of end-to-end models without

Table 5 Classification of COVID-19-infected medical images by applying DL paradigms

Author	Procedure	Input data	Outcome	Month and year	References
Angelov et al.	Deep transfer learning CNN model	852 CT images	Achieves training accuracy = 96.2264% and testing accuracy = 93.0189% respectively	May 2020	[56]
Ozkaya et al.	CNN framework utilizing deep features fusion and ranking technique	150 CT images	Accuracy = 98.27%, sensitivity = 98.93%, specificity = 97.60%, precision = 97.63% F1-score = 98.28%, MCC = 96.54%	April 2020	[57]
Abbas et al.	DeTrac CNN	196 sample X-ray images	Achieves accuracy of 95.12% in classification of X-ray images from other	March 2020	[58]
Asnaoui et al.	Deep CNN architectures	5856 X-ray images	Fine-tuned version of Resnet50, MobileNet_V2 and Inception_Resnet_V2 shows accuracy > 96%	March 2020	[59]
Amyar et al.	Multitask learning model	1044 CT images	Achieves dice coefficient > 0.78 for segmentation and ROC > 93% for the classification	January 2020	[60]

the need of human for extracting features, they have widely utilized in the screening of medical images over the machine learning approaches. Since deep learning has been profitably used in the classification of many problems such as skin cancer classification [53], breast cancer classification [54], lung segmentation [55], the present COVID-19 epidemics is also requiring the expertise of deep learning approaches in preventing the disease. The utilization of deep learning approaches in the categorization of COVID-19 images is shown in Table 5.

3.3 Diagnosis of COVID-19

As the techniques of deep learning approaches can learn from raw data during training, they can be utilized to resolve problems that are difficult to solve using traditional approaches. Compared to standard approaches, deep learning approaches have multiple hidden layers that make them well suited to learn from heterogeneous information. Several studies of deep learning revealed the capabilities of deep learning such as image recognition [61], learning from complex data [62] and so

Table 6 Diagnosis of coronavirus-infected medical images using procedures of deep learning

Author	Approach	Input data	Outcome	Month and year	References
Javaheri et al.	CovidCTNet	287 CT images	Accuracy = 90%	May 2020	[64]
Ozturk et al.	DarkCovidNet model	125 COVID-19 positive images and 500 no-findings X-ray images	Accuracy = 98.08	April 2020	[65]
Apostolopoulos et al.	VGG-19	224 positive COVID-19 and 700 pneumonia 504 no-findings X-ray images	Accuracy = 93.48	April 2020	[66]
Sethy et al.	ResNet50 and SVM	25 COVID positive and 25 COVID negative images X-ray images	Accuracy = 95.38	March 2020	[67]
He et al.	Self-trans networks	349 COVID-19 positive CT scans and 397 negative CT scans	F1 score = 0.85 ROC = 0.94	January 2020	[68]

on. Diagnosis of medical images is one the main application of deep learning [63]. Hence, deep learning is used in the diagnosis of current coronavirus pandemic. During the screening of COVID-19, appropriate deep learning approach should assist the radiologist in accurate detection of COVID-19 and to provide user-friendly tools that should assist medical community in the automatic detection of pandemic without the knowledge of computer. The applicability of procedures of DL in the identification of COVID-19 has been depicted in Table 6.

4 Critical Investigation

Based on deep learning technologies, a precise study of papers relevant to COVID-19 has been accomplished. The capability of distinguishing between bacteria and other viral pneumonia, extracting features from multimodal clinical dataset, early prediction and visualization of epidemic patterns, etc. made the prototypes of deep learning appropriate for the analysis of the datasets related to medical field. From the studies, it can be noted that the distinct DL techniques have been profitably applied in the identification and detection of COVID-19. In this section, an analysis on the contribution of articles using various schemes of the deep learning in classification, forecasting and prediction of the novel SARS-CoV2, distribution of total number of articles in present pandemic depending on the type of input data and the analysis of the articles published week wise on COVID-19 has been represented. This investigation may assist the researches in developing more appropriate techniques for the control of the COVID-19 pandemic

4.1 Distribution of Articles Using Deep Learning Approaches Over Other Intelligent Computing Approaches

Figure 2 reveals that predominant work on the prediction and detection of COVID-19 has been supervised using the techniques of deep learning (42%). Next, 32% of research has been explored by applying the various techniques of machine learning. Only 24% of the activity has been experimented using the prototypes of the mathematical and statistical methods in the forecasting and identification of novel corona virus. From Fig. 2, it is determined that majority of the work in the prediction of present

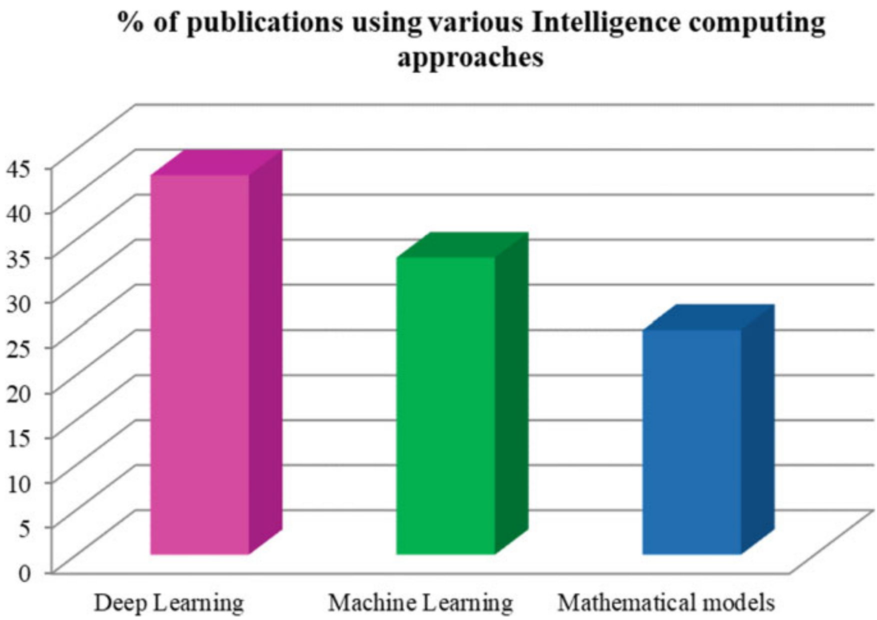

Fig. 2 Distribution of articles on COVID-19 using different approaches

pandemic has been accomplished using techniques of DL over other techniques because of the advantages such as performance excellence, handling of complex intelligent tasks, extraction of rich features without human interference.

4.2 Distribution of Articles Using Different Deep Learning Approaches

From Fig. 3, it is concluded that 60% of the work in the identification and prediction of SARS-CoV-2 has been implemented using convolutional neural network. Only 17% of the work has been executed using LSTM. Next, 13% of the work has been carried using GANs. Lastly, 10% of the work has been performed using autoencoders. As CNNs are capable of extracting features automatically from the images without human interference, these are more appropriate models used in the prediction of the COVID-19. Because of the disadvantages such as LSTM model results in overfitting due to the availability of limited data, GANs require lot of trial and error strategy to train the network, and autoencoders are not efficient in reconstructing the images as

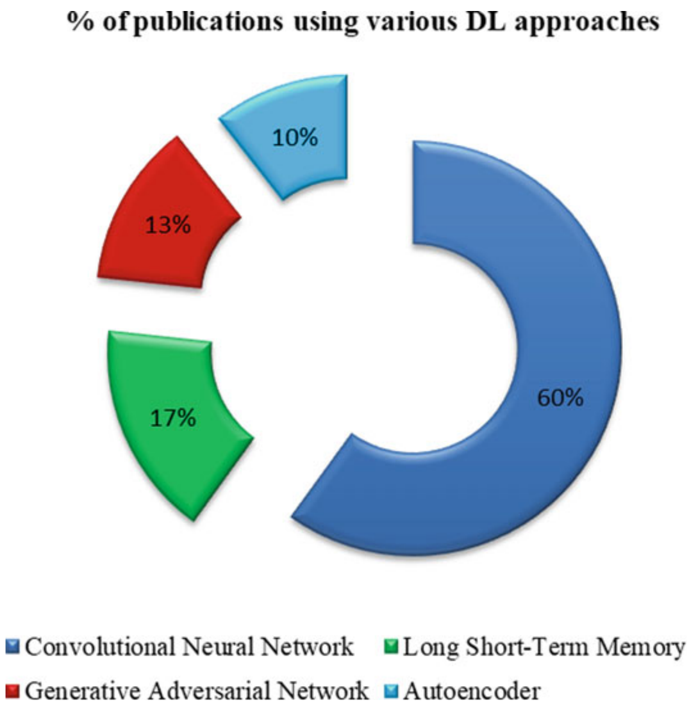

Fig. 3 Articles distribution using different approaches of deep learning

the complexity of image enhances, less work has been carried on LSTM, GANs and autoencoders in the prophecy of nCOVID-19.

4.3 Contribution of Articles on the Prognosis and Interpretation of COVID-19 Using the Techniques of Deep Learning

The analysis of articles in the classification, forecasting, diagnosis and in the development of drugs for COVID-19 using the techniques of deep learning has been depicted in Fig. 4. From Fig. 4, it can be observed that extensive work has been performed in the prophecy of current outbreak using the methods of DL (35%). After diagnosing, 32% of the work has been carried out in the classification of coronavirus-infected images from the bacterial and viral pneumonia-infected images. Next, 17% of the work has been carried out in forecasting the dynamics of COVID-19. Only 16% of work has been published in the drug discovery. As deep learning approaches are widely used in the analysis of medical images and due to the availability of less number of kits for early diagnosis, most of the work has been carried on the identification of COVID-19-infected patients and segmentation of COVID-19 medical images from other pneumonia.

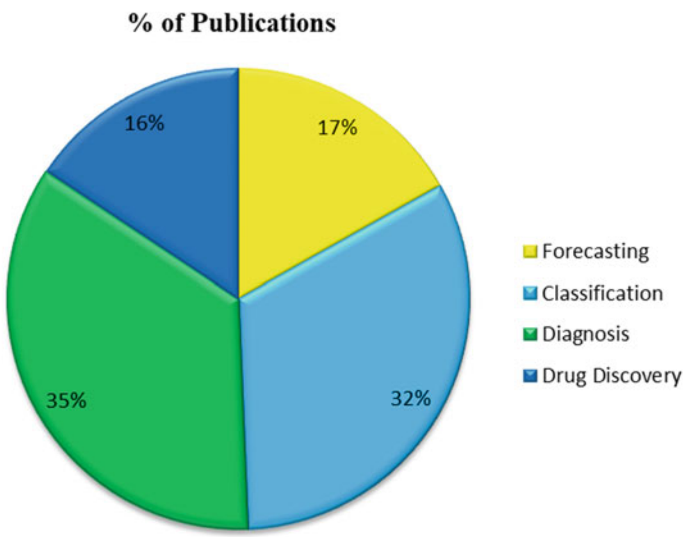

Fig. 4 Articles distribution in the prognosis and diagnosis of COVID-19

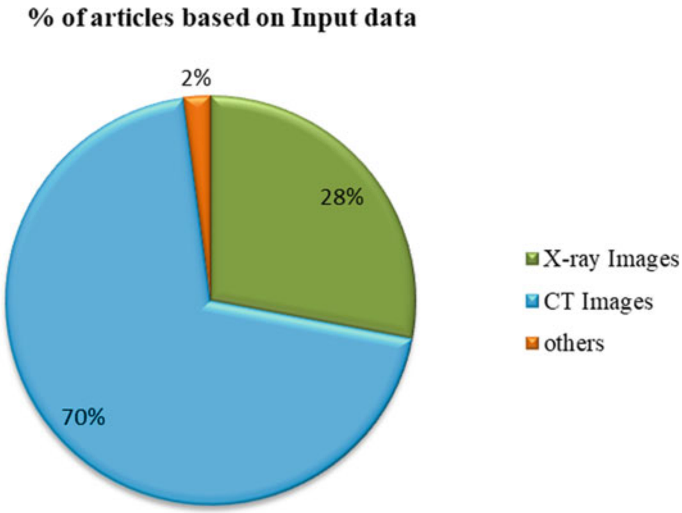

Fig. 5 Analysis of input data using deep learning

4.4 Analysis of Input Data Using Deep Learning

The methods used in DL are representation-learning algorithms that have been widely implemented in the interpretation of radiography images such as detection of abnormalities, classification of radiography images due to its multilayer processing. The analysis of input image using deep learning has been represented in Fig. 5. From Fig. 5 also, it has been concluded that most of the work is done on the analysis of medical dataset when compared to others. It is also identified that 70% of the work has been carried out using CT images and 28% of work has been accomplished using X-ray images. Only 2% of work has been contributed using other dataset as input data. Though chest X-ray images are cheaper than CT images, X-ray images result in false diagnosis. Hence, majority of the work has been carried out using chest CT images.

4.5 Growth in Publication of COVID-19 Articles

The novel coronavirus originated in December 2019 caused thrice the deaths over the combined deaths caused by SARS-CoV and MERS-CoV in the twenty-first century. As the disease is rapidly spreading across the world because of the absence of vaccine or drug and limited number of medical kits, most of the research has been performed on COVID-19 over the other pandemics. Figure 6 represents the analysis of articles published from January 13, 2020 to May 18, 2020. In the first few months of COVID-19, only 4% of articles published on COVID-19 as most of the cases were reported

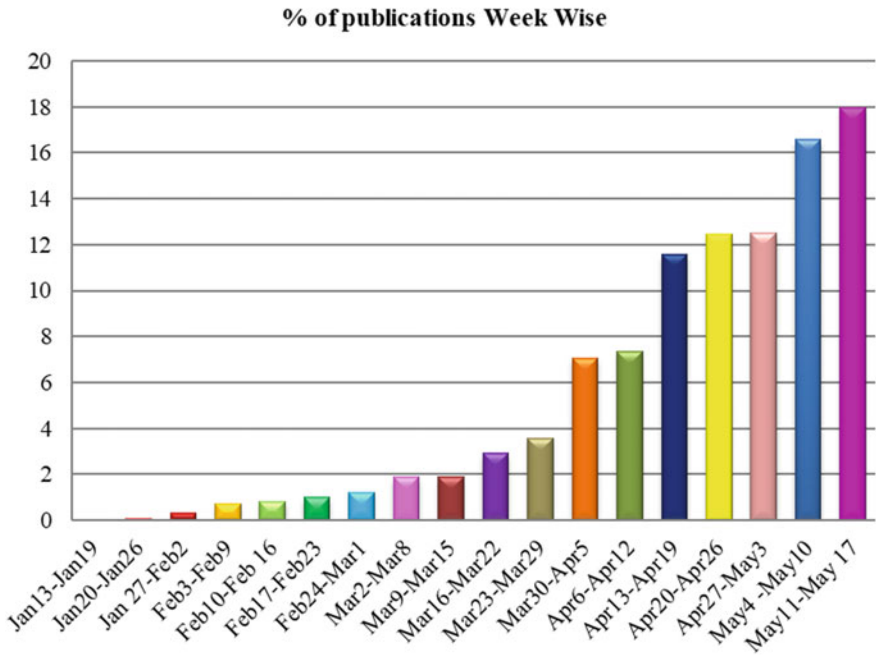

Fig. 6 Growth of publications in COVID-19

in the main land of china. In the month of March 2020, when the COVID cases in other territories are increasing outside the china, the researchers started publishing a greater number of articles on the prediction and analysis of COVID-19 to control the dissemination of disease. 17% of articles were published in March 2020 and 43% of the publications were published in the April 2020. It has been also observed from Fig. 6 that up to May 18, 2020, more number of the articles are published in April 2020.

5 Challenges

From the systematic analysis of this paper, it has been observed that techniques of deep learning have been favorably used in the development of accurate paradigms for the forecasting, classification and estimation of COVID-19 since the start of the outbreak. These prototypes have exhibited a wide scope of discrepancies in the predictions because of the existence of some challenges such as uncertainty of data that needs to be resolved for the expansion of accurate paradigms. As data is segregated in distinct zones of the world, only few datasets for the study of textual and medical images are available. Most of the approaches of deep learning require large datasets to give more accurate results. These regulation of datasets is one of the key challenges that required to be resolved. Most of the forecasting models use online time datasets that results in poor outcomes. To overcome this problem, it is necessary to develop more real-world datasets. The other issues that need to solved are the less involvement of clinical experts while performing the classification of COVID-19 images which may result in poor outcomes.

6 Conclusion

The recent outbreak of COVID-19 in the last weeks of December 2019 has imposed a health emergency all over the world due to the rapid spread of infection across different regions of the world with an estimate of 4,951,752 confirmed cases and 322,948 deaths all over the world as on May 19, 2020. It is apparent that quarantine alone is not adequate to avoid the transmission of COVID-19. Further research is definitely required such as development of appropriate prediction and forecasting models to strengthen the government and health sectors in regulating the escalation of the epidemic. Therefore, in this paper, an overall study of distinct deep learning techniques in the forecasting and interpretation of COVID-19 has been depicted. Form the critical analysis, it has been noticed that majority of the effort has been accomplished in the categorization and prediction of novel COVID infection using CNN and LSTM network schemes. It is also observed that majority of the analysis has been done using CT or X-images rather than text data. The drawbacks such as availability of small datasets, less annotated medical images, less involvement of radiologist in lesion segmentation, not considering some features like GGO, crazy-paving patterns in diagnosis, not dealing with data irregularities require immediate attention for developing more appropriate prediction model in the prophecy and analysis of COVID-19. Also, the research analyst all over the world is facing the scarcity of real-world datasets that needs to be developed immediately for the advancement of precise models. In addition, the usage of progressive schemes such as ensemble methods, optimization methods, application of higher order and artificial neural networks and utilization of ultrasound images in the screening and prognosis of nCOVID-19 pandemic enhances the accuracy of prediction models which might be considered as further scope of research.

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