Deep Learning Methods for the Diagnosis and Treatment of COVID-19 via the Application of Artificial Intelligence

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ABSTRACT

An unparalleled global crisis has ensued as a result of the COVID-19 pandemic, which has killed thousands of people and ground all forms of human civilization to a terrifying standstill. With 5,212,172 confirmed cases and 334,915 fatalities (as of May 22, 2020), COVID-19 continues to pose a serious risk to public health systems worldwide. The virus has now spread to 212 nations and territories. In this study, we propose an AI-based strategy to fight the infection. Several Deep Learning (DL) techniques, such as ELM, Long Short Term Memory (LSTM), and Generative Adversarial Networks (GANs), have been shown to do this. Using a continuum of structured and unstructured data sources, it lays out an integrated bioinformatics method that builds user-friendly platforms for researchers and clinicians. The primary benefit of these AI-powered systems is the speed with which COVID-19 may be identified and treated. In order to choose inputs and network targets that may allow obtaining a trustworthy Artificial Neural Network–based solution for COVID-19 difficulties, the most current relevant papers and medical reports were researched. On top of that, each platform has its own unique set of requirements for data inputs, including clinical data and medical imaging, both of which may help guide the presented methods toward optimal performance in real-world settings.

INDEX TERMS

Machine learning, diagnostics, artificial intelligence, COVID-19, big data, bioinformatics, biomedical informatics, and deep learning.

I. INTRODUCTION

In December 2019, a new coronavirus called SARS-CoV-2 emerged, starting a respiratory ailment pandemic called COVID-19. This illness has shown to be rather complex, with symptoms varying from mild to severe, with even fatal outcomes possible. Symptoms range from moderate, self-limiting respiratory infection to life-threatening, progressive pneumonia accompanied by organ failure [1]-[4]. Concern about the long-term effects of this virus infection is understandably high in light of the increasing number of confirmed cases, the severity of respiratory failure in some patients, and the risk of cardiovascular problems [5]. There has been a lot of focus on finding suitable methods to address the issues linked to COVID-19. While fighting the virus, researchers and decision-makers face additional obstacles from the ever-increasing amount of data, sometimes referred to as big data. As this justice case shows, artificial intelligence (AI) has the potential to play a pivotal role in improving and expanding healthcare systems throughout the world [6]. Many disciplines, including engineering [7]–[9], medicine [10]–[13], economics [14], and psychology [15], have lately focused their research efforts on artificial intelligence (AI) in the hopes of finding solutions to complicated problems. Therefore, in a crisis like this, it is essential to mobilize and conserve medical, logistical, and human resources; AI can do just that while also conserving time, which is crucial since every hour counts when it comes to the Coronavirus pandemic. Artificial intelligence (AI) has recently gained traction in clinical settings, where it has the potential to significantly impact things like lowering the rate of unwanted deletions, increasing the efficiency and productivity of studies involving large samples [16], and achieving more precise predictions and diagnoses [17]. Research on viral activity modeling in any nation may also benefit from big data. Health care officials are able to better prepare their nation for the illness epidemic and make educated choices thanks to the findings analyses [18]. Despite the fact that AI has the ability to aid medical methods in treatment strategies, crisis management, optimization, and improvement, it has not been effectively used to aid health-care systems in their fight against COVID-19. This includes medical imaging and image processing techniques. When it comes to saving lives, one area that may really benefit from AI's helpful contribution is image-based medical diagnostics [19]. This allows for quick and reliable identification of COVID-19. The gap between AI-based methods and medical approaches and therapies may be filled by using AI techniques to address COVID-19-related concerns. Experts in artificial intelligence may speed up procedures to get the best outcomes by using AI platforms to help make connections between different elements. To generalize and provide a range of techniques applicable to high-risk populations, epidemiology, radiography, etc., our team draws on the results of current research concentrating on COVID-19 and its many obstacles in this article. In part 2 of the study, the possibilities of AI techniques to tackle COVID-19 associated difficulties are explored and discussed. Strategies for large data analysis that are based on artificial neural networks are presented in Section 3 of the article. Part 4 gives the body of the conversation, and Part 5 gives the final thoughts.

II. ARTIFICIAL INTELLIGENCE AND COVID-19

The current part is devoted to the presentation of some practical AI-based approaches that may bolster the current conventional ways of addressing COVID-19 in healthcare systems worldwide. The most current published medical updates pertaining to AI and the most recent updates on COVID-19 served as the basis for the development of these methods and procedures, the primary goal of which is to highlight their improved efficacy. Hence, this part offers suggestions that might improve and expedite the acquisition of ANN-based approaches to better treatment methods, health management, identification, and diagnosis. No matter what role humans play, the amount of human input and cooperation determines the best performance of AI technologies during the COVID-19 pandemic. Data scientists serve a crucial role as they code AI systems, therefore they retain knowledge of AI's strengths and limits [19]. The flowchart in Figure 1 shows the many stages used to tackle COVID-19 issues using AI-based approaches. Data comprehension, data preparation, and large data need the first step of preparing the data needed for data mining. In this context, "data" refers to medical records, pictures, clinical reports, and any other kind of information that may be converted into machine-readable data. Gaining familiarity with data qualities and recognizing key features, such data volume and total variables, are goals of data comprehension. Data preparation, or the act of refining and converting raw data, happens before processing and analysis. Data enrichment is the process of reformatting, correcting, and combining data. Data such as consumer, patient, physical, and clinical information is the end result of collecting, analyzing, and using big data. This is when humans step in as part of machine learning approaches; specialists examine and analyze the data to identify features, structures, and nests. Because ML solutions are not yet capable of dealing with enormous datasets, beyond what people could manage or see simultaneously, the input of humans at this point is crucial. In addition, when dealing with very large or complicated datasets, Deep Learning (DL) techniques might be used instead of ML or more conventional approaches. Figure 1 shows that DL approaches do not need human interaction. Deep learning (DL) is a subfield of machine learning that uses many layers of algorithms to draw new conclusions from the input data.

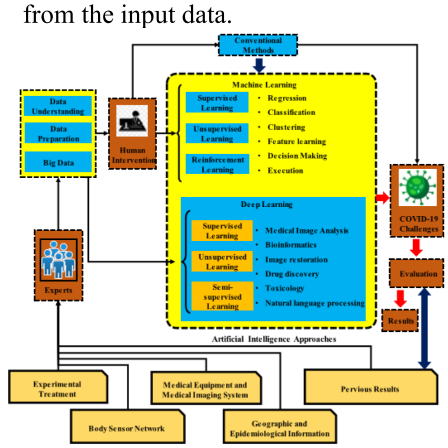

FIGURE 1. The process of application of AI-based methods to conquer challenges associated with COVID-19.

But DL differs from ML primarily in the way it displays system data. In contrast to DL networks, which rely on ANN layers, ML algorithms often rely on structured data. A kind of machine learning that seeks for undetected patterns in a dataset without prior labels, unsupervised learning is characterized by minimal human supervision and differs from supervised learning, which involves learning a function mapping an input to an output from example input-output pairs. The medical doctors, nurses, therapists, and pharmacists who practice conventional medicine—also known as allopathic medicine, biomedicine, mainstream medicine, orthodox medicine, or Western medicine—treat patients by prescribing medications, performing surgeries, or administering radiation to alleviate symptoms. While artificial intelligence (AI) has a lot of potential applications in the fight against COVID-19, our primary goal is to identify the most effective ways to address the problems this pandemic has caused in the healthcare system. Thus, these solutions have been divided into three sections: high-risk populations, outbreak and control, recognition and diagnosis. With five distinct levels, ANNs may be shown in Fig. 2's flowchart illustrating their use in diagnosis and symptom tracking. While the approach has been developed with COVID-19 issues in mind, it might also be used to other types of medical imaging analysis. As the first layer, the input layer is database-related and built to access databases. This layer is coupled to the primary (front-end) computer or computers over a high-speed connection. A database server's connection to the network is loose, whereas a database machine's connection to the main CPU is tight. Database computers are able to transmit massive data packets to the mainframe because they use a multitude of microprocessors in conjunction with database software. The next layer, the selection layer, is created by a smart ANN-based selector and is responsible for using the most effective imaging methods based on the system's previous experiences. The third layer recommends strategies to obtain the necessary photographs if doctors confirm the conclusions made by this layer. As a result, either

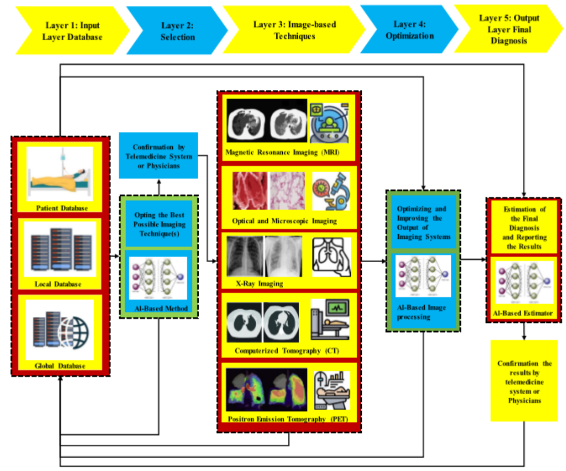

FIGURE 2. Application of AI-based methods in classification, analysis and improvement of the medical imaging approaches.

Depending on the prior findings, other imaging approaches might be proposed. Imaging methods such as X-ray imaging, optical and digital microscopic imaging, computed tomography (CT) scans, positron emission tomography (PET), and magnetic resonance imaging (MRI) may be used for each patient. When it comes to pathology, the conventional optical microscope has become the go-to instrument. One useful imaging test for assessing the quantity and quality of organ and tissue function is the positron emission tomography (PET) scan, which may sometimes identify illness before other imaging tests can detect it [20]-[22]. The PET scan uses a radioactive substance, sometimes called a tracer, to look at this function [23]. The fourth layer is all about making the pictures better and more optimized. Using DL technology for network construction and the conventional ResNet for feature extraction, a classification network was created to help distinguish between COVID-19 and influenza A viral pneumonia [24]. In the fifth layer, which is used for final diagnosis using the system's stored data, an ANN technique should execute learning algorithms. DL technologies, such a CNN, are seen to be the best choice for accomplishing these aims. The rationale for this is because neural networks of this kind are widely used in medical image processing and diagnostics due to their high nonlinear modeling capability [25]-[28].

III. THE POSSIBLE PLATFORM TO ACCELERATE

CONVENTIONAL METHODS

Resolving issues faced by high-risk populations The focus of this article is COVID-19. The primary goal is to get the best possible outcomes, thus we will attempt to show how ANN-based approaches might supplement the traditional ones. It is essential to keep patients involved in the COVID-19 registry, as suggested in [29], which highlights clinical variables and cardiovascular complications. This helps in identifying patterns of these complications, developing a risk model for them, and predicting how different treatment modalities will work.

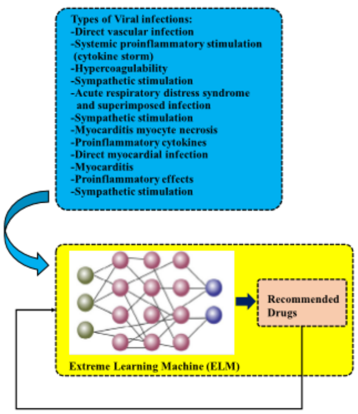

FIGURE 3. An ELM model to predict suitable drugs based on the performed studied in [29]. Fig. 3 presents an Extreme

Figure 3 shows an ELM model that uses the data in [29] to forecast which medicines might be useful for people with these cardiovascular problems. For accurate output prediction, ELM ANN may draw on model instances. This implies that the actual data in the network is used to train the supervised model. Hence, ELM may provide the most effective medications for cardiac problems by taking into account different types of viral infection in prior situations. Learning using ELM is much quicker and yields greater generalization performance than with traditional feedforward network learning algorithms, such as the back-propagation (BP) method [30]. Traditional tuning-based algorithms, on the other hand, sometimes call for many fewer hidden neurons than ELM [31]. Exploring ELM with Fixed Network Architectures has been the subject of several prior research [30], [32]-[34]. Testing or verification follows training and allows for the prediction of fresh data. Coronavirus has been associated with myocarditis, cardiac arrhythmias, and vascular inflammation [29]. In order to forecast the manner in which the Coronavirus affects the cardiovascular system, the proposed model relies on the data that [29]present. As a result, the proposed model may lessen the likelihood of potential cardiovascular problems. In addition, by predicting the pattern of cardiovascular problems, it is possible to anticipate the response to various treatment approaches. Because of its many benefits and characteristics, ELMs are therefore suggested for use with these types of disorders. Heart failure is another complication of COVID-19 in the elderly. Therefore, specialists in heart failure need to be vigilant, create a structured approach for these patients, and involve them in algorithms for their early care. This will be necessary until definitive universal tests for COVID-19 or antiviral clinical trials are available, and our knowledge of the disease's late stages is better understood [35]. Avoid giving older patients more fluids or medications than they need, especially nonsteroidal anti-inflammatory medicines (NSAIDs), which might alter their body's salt-water balance. Use biomarkers and reference [35] with extreme caution in high-risk older individuals who have underlying structural heart disease. Therefore, cardiac specialists have substantial challenges in defining and treating progressive heart failure during the era of hyperinflammation [35].

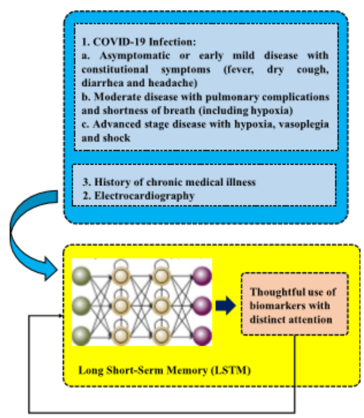

FIGURE 4. Classifying the best treatment method with high precision through LSTM ANN a developed method inspired by [35].

An LSTM network put forwardin model is shown the Fig. 4 [35]. In order to provide an accurate prediction about the optimal therapy, this model depends on well evaluated inputs. Long short-term memory (LSTM) networks are great for learning sequences with longer-term patterns of undetermined duration since they can retain this information [36].

The model training procedure may also benefit from electrocardiograms and a patient's history of chronic diseases. Inputs might be seen of as the mild, moderate, and advanced stages of COVID-19 infection. Using specialized units called "memory cells" and multiplicative gates to provide continuous error flow [36]. The issue of the vanishing gradient in RNNs is resolved by LSTM neural networks [37]. Some others refined and popularized it after Hochreiter and Schmidhuber [37] introduced it. Over the last decade, LSTM NN has shown to be an effective tool for voice recognition [40] and text classification [41], as well as for controlling robots, recognizing speeds, handwriting, and human actions, among other applications [39]. The primary focus of nonlinear systems is failure prediction, as shown in reference [43].

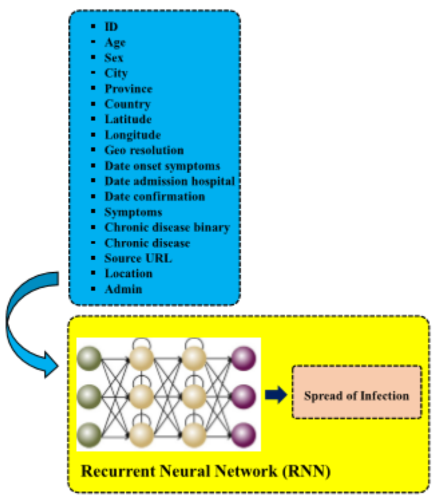

FIGURE 5. Prediction of spreading the infection by Recurrent Neural Network (GRURNN, Clockwork RNN or CW-RNN)) which is a developed approach based on [45].

Another strategy to forecast a COVID-19 epidemic is using ANN-based algorithms. One may get a data dictionary on Github (https:// github.com/beoutbreakprepared/nCoV2019/covid19) that describes the fields in the database, as stated in [45]: One technique to gather geographical information is by referring to individual towns; another is to refer to regions that were administrative entities. Predicting the spread of an illness is now possible with the help of the structured real-time epidemiological data presented in [45]. Figure 5 shows the results of a DL technique that uses RNN to forecast the progression of the COVID-19 infection via big data from the clinical and geographical communities. It is possible to use variants of RNNs to forecast the spread of illness based on geo- and clinical data. The most effective structures for making predictions, however, seem to be LSTM networks[37], Gated Recurrent Unit RNNs (GRURNNs)[46], and Clockwork RNNs (CW-RNNs) [47]. The RNN, also known as an Auto Associative or Feedback Network, is an ANN that uses connections between units to form a directed cycle [48]. Recognized as a highly esteemed DL family, RNNs have shown encouraging outcomes in several computer vision and machine learning assignments [49]. When using this approach, it is crucial to quantify qualitative inputs like nation and location. Real-time data provided by RNNs with real-time learning capabilities makes model updates feasible. Applying the suggested ANN model opens the door to presenting the viral epidemiological model in many places. Utilizing DL-based approaches, the primary purpose of the suggested structure is to enhance the speed and accuracy of virus-related problem detection and categorization. While radiological examinations such as computed tomography (CT) and digital radiography (DR) have proven useful for COVID-19 screening, diagnosis, and progress evaluation, there is a lack of prior experience that could aid radiologists and technologists in their treatment of COVID-19 patients. Rapid detection of the infection is crucial for both the community and clinicians to have a better chance of controlling the spread of the virus. In areas affected by the epidemic, a negative RT-PCR but positive CT feature is a significant sign of COVID-19 [52]. However, there is evidence that many radiologists and technicians have contracted COVID-19 while treating patients, despite the fact that radiological tests, such as computed tomography CT, have shown to be useful procedures for screening and diagnosis [50]. The lung CT scans of COVID-19 show groundglass opacities that are bilateral, subpleural, and accompanied with air bronchograms. The borders of these opacities are not well defined, and there is a small preponderance in the right lower lobe [53]. Distinguishing between various illnesses based on their structure and appearance is made easier by the image classification approach. As an additional metric, the model learns the patch's approximate placement on the lung picture by using relative distance-from-edge [24]. Radiologists are the only experts who can read diagnostic imaging reports and expertly address the context, syntax, structure, and specific terminologies needed to interpret the images. They can extract diagnostic information from images and make them available as structured labels for the machine learning model training, which is a daunting task in and of itself [54]. New human Coronavirus visualization and detection was covered in the first example of this section. But new research shows that when human respiratory secretions pass from the nose to the airway epithelium,

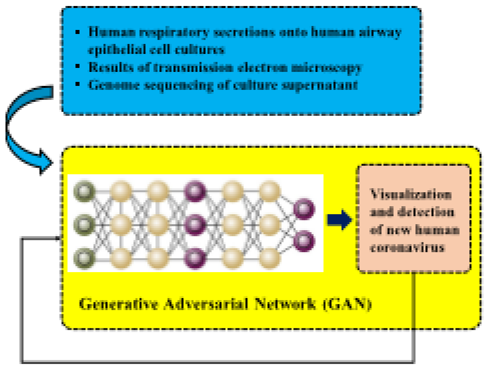

FIGURE 6. Application of Generative Adversarial Network (GAN) for visualization and detection of new human Coronavirus based on the results of [55].

Methods such as whole-genome sequencing of culture supernatant, cell cultures, and transmission electron microscopy may be used to identify novel human coronaviruses that may elude conventional methods of detection [55]. Infection with COVID-19 may harm human airway epithelial cells, as shown in [55]. Additionally, it has been shown that by combining the effects of human respiratory secretions on the airway with transmission electron microscopy and genome sequencing of culture supernatant, novel human coronaviruses may be seen and detected. The suggested neural network architecture and the Generative Adversarial Network (GAN) are shown in Figure 6. It is possible to use feature extraction approach to evaluate electron microscopy pictures. When two networks are trained simultaneously, one focuses on picture generation and the other does discrimination, the result is a specific sort of neural network model called a GAN [56]. These issues may be resolved by using GANs [57] to effectively predict the latent distribution of the training data. Images-to-image translation[58], segmentation[59], and several other areas of medical image computation [60] have all found GANs to be useful. A lot of people have been paying attention to the adversarial training scheme lately due to its success in creating fresh picture samples and its utility in preventing domain shift. For several applications, including text-to-image synthesis [61], superresolution [62], and image-to-image translation [63], this model has attained state-of-the-art performance. All of them have to do with making pictures. The estimation of the level of cardiac involvement is another challenge that may be tackled using ANN-based techniques. Myocarditis may be caused by the COVID-19 virus, according to reference [64]. According to research on cardiac involvement in a COVID-19 infection that can cause severe acute respiratory syndrome, researchers have found that scientists can benefit from closely monitoring patients with acute myocarditis and public health officials can gain a better understanding of these potentially fatal complications if they recognize the association between the two. Thus, an LSTM network is proposed for the assessment of COVID-19 associated cardiac involvement, based on the findings and suggestions of [64]. Although signals in feedforward neural networks can only go in one direction, from input to output, RNNs enable signals to go in both directions, creating loops that allow internal connections among hidden units [65]. An RNN may display dynamic temporal behavior because, unlike a feedforward neural network, it processes sequential inputs via a recurrent hidden state, whose activation at each step is dependent on the preceding one [49]. Model training may make use of the characteristics shown in Fig. 7 from Tesla cardiac magnetic resonance imaging.

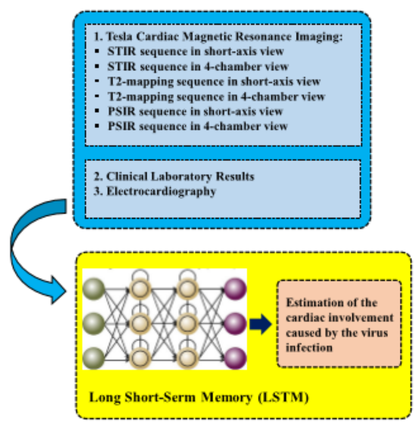

FIGURE 7. Estimation of cardiac involvement caused by the virus infection extracted from The features from Tesla cardiac magnetic resonance imaging and the information given in [64].

Considerations such as age, gender, symptoms, chronic medical disease, and test findings obtained upon hospital admission are taken into account. However, the patient numbers were insufficient for the ELM network. One interesting learning technique for "generalized" single hidden layer feedforward networks (SLFNs) is ELM, which stands for precisely least squares [67]. SLFNs are used for estimating regression problems or categorizing tasks. In ELM, hidden biases and input weights (which connect the input and hidden layers) are chosen at random, while the weights that connect the hidden and output layers are calculated analytically using the Moore-Penrose (MP) generalized inverse [31]. Training the recommended model is therefore possible using the ELM approach. Figure 8 depicts the described ELM model that has been presented.

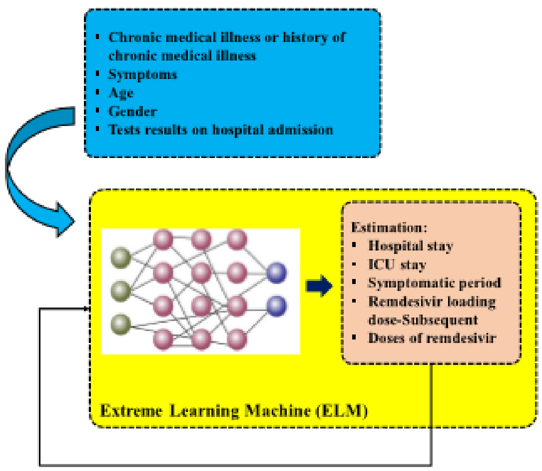

FIGURE 8. Estimation of Remdesivir drug behavior on the patient's treatments, hospital stay, ICU stay and symptomatic period using ELM and the ideas of [66].

In the final step of the diagnostic process, we offer a model that makes use of GAN to estimate the likelihood of a viral gastrointestinal illness. There is evidence of SARS-CoV-2 infection in the gastrointestinal tract and the potential for a faecal-oral transmission pathway in [68]. When it comes to figuring out how viruses travel from infected to healthy cells, virally specified target cells or organs play a major role. Introduction of the virus into a recipient cell by a receptor-mediated process is the initial stage of viral infection [68]. Additionally, glandular epithelial cilia are rich reservoirs for ACE2, despite its low expression in oesophageal epithelium [68]. Nevertheless, twenty percent of SARS-CoV-2 patients still show positive viral RNA in feces, suggesting a viral gastrointestinal infection and the potential for faecal-oral transmission even after viral clearance in the respiratory tract [68]. Consequently, it is strongly advised that patients with SARS-CoV-2 undergo regular RT-PCR testing from their feces. Furthermore, transmission-based measures should be implemented for hospitalized SARS-CoV-2 patients in the event that rRT-PCR testing revealed a positive feces test [68]. The COVID-19 gastrointestinal infection is examined in reference [68]. The study's collection of photos demonstrating histological and immunofluorescent staining of the rectum, duodenum, stomach, and oesophagus provides proof of a COVID-19-related gut infection. The results of laser scanning are these fluorescent staining pictures. confocal microscopy, features may be extracted from these pictures to aid patients in their treatment by training a GAN network to predict the likelihood of a viral gastrointestinal illness. The model's choice to maintain or end transmission-based measures for hospitalized patients is shown in Fig. 9. rRT-PCR testing for SARS-CoV-2 is essential for patients at risk. When compared to other discriminative tasks, such as classification and clustering, GANs' generating process—which applies a conventional distribution to complicated, high-dimensional real-world data distribution—stands out [69]. The use of GANs has expanded beyond picture production to include visual tracking, domain adaptation, hash coding, and feature learning, among other applications [70, 71, 72, 73]. The medical imaging field has two distinct applications for GANs [56]. They assist in learning to produce new pictures and enable exploration and discovery of the underlying structure of training data by focusing on the generative element. Their discriminative nature makes them useful as a regularizer or detector for aberrant pictures [56]. The discriminator D may be seen as a learnt prior for normal images. Results from this study suggest that DL models may efficiently screen COVID-19 patients at an early stage, which could be a useful supplemental diagnostic tool for clinicians who work closely with patients [74].

IV. DISCUSSION

We proposed several AI-based approaches employing RNN, LSTM, GAN, and ELM, with an emphasis on the potential ANN application for assessing COVID-19-related infection concerns including high-risk patients, outbreak control, recognition, and imaging. By integrating and analyzing massive amounts of data pertaining to COVID-19 patients, state-of-the-art machine learning algorithms can help us better understand the pattern of the virus's spread, diagnose cases more quickly and accurately, come up with new and effective treatments, and even identify people who, based on their genetic and physiological characteristics, are most vulnerable to the disease [75]. The tiny number of users who gather, store, manage, and have access to such data has been challenged, despite the accolades that such data has gotten for its role in enhancing efficiency, productivity, and processes across industries [76]. But because Heyman insists AI

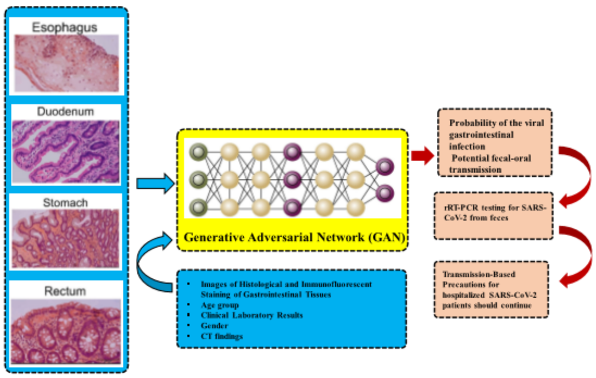

FIGURE 9. The process of viral gastrointestinal infection probability estimation using a combination of GAN and rRT-PCR testing for SARS-CoV-2 from feces to determine the transmission-based precautions for hospitalized SARS-CoV-2 inspired by [68].

allows for the detection of COVID-19-related issues and the initiation of appropriate responses by means of data collected and monitored from various sources, including social media, newsfeeds, and airline booking systems [77]. The methodologies that have been proposed can cover a great deal of ground, including data derived from recent advances and publications in the relevant topic. Despite the fact that several inputs are available, clinical data is still the one that nearly all of the approaches use. In the case of high-risk populations, it is crucial to review the clinical features of COVID-19 patients during the course of their illness or pregnancy. Heart failure patients in the hyper-inflammation phase, as well as those for whom records of clinical characteristics and cardiovascular consequences are available, are the primary focus of the model that is provided here. The same architecture of ML and DL approaches to complicated data estimate and prediction, however, makes these concepts amenable to generalization to additional high-risk cases. The ELM method is recommended for medication suitability prediction because to its strong problem-solving capabilities; nevertheless, feedforward neural networks with several hidden layers benefit from gradient-based learning techniques, such as back-propagation. The current implementation of the ELM algorithm holds true for SLFNs. For the second scenario, which involves the classification of the optimal treatment approach, we suggested a model that is equipped with LSTM. Since significant events in a time series may occur at intervals of undetermined duration, LSTM networks appear to be viable choices for classification, processing, and prediction based on time series data. Because a word's meaning in a sequence depends on the word before it, LSTMs are a useful tool for dealing with the exploding and vanishing gradient difficulties that might arise while training regular RNNs. Another topic covered in this study was the use of AI for epidemiology and epidemic prediction. Our proposed model relies on RNN and requires a full complement of inputs, which the database described in[45] can provide. The ability to display temporal dynamic behavior is made possible by RNNs, a kind of ANNs, which create a directed graph along a temporal sequence by connecting nodes. Since RNNs operate in a loop, their ability to recall previous occurrences influences their future predictions. This is because, in order to access the hidden layers, RNNs must first understand the underlying relationships of the data. With the hope that imaging workflows will lead to better machine learning techniques that can aid radiologists in analyzing large amounts of complex imaging and text data, we detailed models that can examine medical imaging to identify COVID-19 infections [54]. We discussed how COVID-19 may be a case in areas where both negative RT-PCR and positive CT results are present. The argument has important clinical and societal ramifications, such as the need for faster virus identification, which can significantly aid in controlling the spread of the virus more effectively [52]. We spoke about how radiological exams, such computed tomography (CT), may screen for and identify infections. Someone else brought up the fact that a large

The examination of COVID-19 patients has resulted in the infection of radiologists and technicians [50]. Radiographs of the lungs taken using a computed tomography (CT) scanner typically reveal bilateral subpleural groundglass opacities with air bronchograms, poorly defined borders, and a small right lower lobe predominance in cases with COVID-19 pneumonia [53]. Data from transmission electron microscopy, the impact of respiratory secretions on the airway, and genome sequencing of culture supernatant make up the inputs of the proposed GAN in the first instance of identifying, visualizing, and detecting novel human coronavirus. Patients' present health is no assurance that they are unaffected by the disease, and safety net recommendations must be seriously considered, since COVID-19 is infamous for the quick decline of respiratory system function that frequently occurs in the second week of the illness [78]. This emphasizes the need for a reliable ANN-based approach for visualizing and identifying novel human coronaviruses. Given a training set, this approach can learn to produce fresh data using the same statistics. Additionally, GANs have shown their worth in reinforcement learning [81], fully supervised learning [80], and semi-supervised learning [79]. Different from GANs, which learn to map latent spaces to data distributions of interest, discriminative networks separate the generator's created candidates from the actual data distributions. In the second scenario, an LSTM method is employed to determine the extent to which the viral infection has affected the heart. There are several architectures that LSTM units come with. A typical layout for LSTM units includes an input gate, an output gate, and a forget gate, which are all known as "regulators" or information flow gates. It is the responsibility of the cell to record the interdependencies among the items in the input sequence. The input gate is in charge of how much new data flows into the cell, the forget gate of how much old data stays in the cell, and the output gate of how much data is utilized to calculate the activation of the LSTM unit. However, in the third instance of recognition, the ELM network should estimate Remdesivir's behavior in the patient's therapies, hospital stay, intensive care unit stay, and symptomatic duration. Whenever it comes to use in dangerous automation jobs, engineers typically worry about neural networks and ELM networks due to their black-box nature. Nevertheless, there are a number of methods that may be used to tackle this specific problem, such as decreasing reliance on random input [82], [83]. Last but not least, a GAN might foretell the likelihood of a viral gastrointestinal illness. It is the job of the discriminative network to finish evaluating candidates once the generative network has generated them [57]. Data distributions are the basis for the contest's operations. An approximate viral gastrointestinal infection can be achieved by utilizing this characteristic of the discriminative network, which separates the candidates created by the generator from the true data distribution, while the generative network learns to map from a latent space to the distribution of interest. There are several medical reports and reliable sources of information on the efficacy and accuracy of these approaches in preventing various types of comparable diseases, even if these procedures have not yet been tested to determine their efficiency. The ability to generalize such robust approaches based on COVID-19 traits is the most significant outcome of our work.

V. CONCLUSION

This article examined the theoretical frameworks and research platforms in the area of artificial intelligence (AI)-based approaches that are appropriate for addressing COVID-19 concerns. Various methods have been created, utilizing the diagnostic systems of COVID-19, including RNN, LSTM, GAN, and ELM. Studies and discussions in this study have focused on the geographical issues, high-risk individuals, and identifying and radiography as the primary challenges with COVID-19. Additionally, we demonstrated a method for picking the right models for estimating and predicting the target parameters from a variety of clinical and non-clinical datasets. If doctors take these platforms into account, AI specialists may examine massive datasets and then use that information to train robots, create algorithms, or enhance how the infection is dealt with. We spoke about how appealing they are because of the possibility of a shared office space where doctors and AI specialists might collaborate. While AI can certainly expedite the methods to conquer COVID-19, it is imperative that real experiments be conducted in order to fully understand the benefits and drawbacks of AI-based approaches. This level of complexity necessitates the development of novel approaches. In order to save more lives and succeed in the fight against COVID-19, we need a toolbox full of platforms, methods, approaches, and technologies that work together to accomplish our aims.

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