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ARTIFICIAL INTELLIGENCE IN TACKLING CORONAVIRUS AND FUTURE PANDEMICS

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ABSTRACT

SARS-COV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) was initially tested in Wuhan City, China, in December 2019 and had a devastating impact worldwide, exterminating more than 6 million people as of September 2022. It became the biggest worldwide health crisis since the 1918 influenza outbreak. Viruses generally mutate randomly, so predicting how SARS-CoV-2 will transform over the next few months or years and which forms will predominate is impossible. The possibilities for virus mutation, in theory, are practically endless. Enabling researchers to determine which antibodies have the potential to be most effective against existing and future variations could help machine learning to assist in drug discovery. In the COVID-19 pandemic, AI has benefited four key areas: diagnosis, clinical decision-making for public health, virtual assistance, and therapeutic research. This study conducted a discourse analysis and textual evaluation of AI (deep learning and machine learning) concerning the COVID-19 outbreak. Further, this study also discusses the latest inventions that can be very helpful in future pandemic detection. COVID-19 has already changed our lives, and in the future, we might be able to deal with pandemics like this with the help of AI. This review has also emphasized the legal implications of AI in the battle against COVID-19.

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1 Introduction

The COVID-19 pandemic greatly impacted global politics and economy (Naudé 2020). It had a severe impact on people's lives all around the world and caused many deaths. Despite enormous vaccine advancements, outbreaks still occur in more than 200 nations. People in different countries must adopt new ways to combat COVID-19. It is critical to develop antiviral medications and treatment methods to manage COVID-19. After passing through the human respiratory system, the unique coronavirus severely damages the patient's lungs, leading to illnesses more severe than the commonly recognized case of pneumonia. Inflammation and swelling of the lungs resulted in regions of ground-glass opacity (GGO). We need to devise alternate ways to diagnose the condition because its symptoms are challenging to spot, and not many diagnostic instruments are available. Numerous researchers around the world are looking for solutions to these problems. Researchers are actively identifying several possible barriers and offering ways to stop the transmission of the virus in one of the study domains known as machine learning (ML) (Albalawi and Mustafa 2022). In this pandemic, AI has assisted with socioeconomics, clinical diagnosis and therapy, scientific research and drug discovery, demography, and other aspects of the crisis. A way to learn more about a novel viral strain's biology and control epidemics may be made possible by artificial intelligence (AI) with its growing capabilities (Davenport and Kalakota 2019).

Both doctors and hospitals have struggled during this major outbreak, resulting in increasing workloads that make it more difficult for them to identify and admit suspected patients to hospitals. According to previous reports, some patients with an early coronavirus infection tested negative on computed tomography, making it more challenging for radiologists to check out the infection conclusively. Due to inadequate resources to isolate COVID-positive patients from all the suspected cases, the infected individuals may transfer the virus to their close contacts while waiting for RT-PCR detection of the SARS-COV-2 virus. Even this can happen while waiting 48 hours for COVID-positive confirmation (Khera et al. 2021). In the initial phase, SARS-CoV-2 underwent very little genetic change, except for the globally dominant variant D614G, which showed comparable severity but enhanced transmissibility. Since then, many other SARS-CoV-2 variations have been identified, and, as a result of their potential harm to public health, these are now referred to as variations of concern (VOCs). Five VOCs of SARS-CoV-2 have been reported till now: Alpha (B.1.1.7), Beta (B.1.351), Gamma (P.1), Delta (B.1.617.2), and Omicron (B.1.1.529). There is a greater affinity of the spike protein of the Delta variant towards ACE2 receptors in human cells, which boosts viral attachment to the cell and its subsequent attachment (Aleem et al. 2023). According to Davenport and Kalakota (2019) hospitals were responsible for approximately 40% of cases. It is critical to swiftly validate patients' COVID-19 status because early false negative reports could raise the likelihood of viral transmission. AI can recognize patterns in big data sets, potentially among the most important tools for resolving this dilemma. AI uses speech recognition, advanced learning, ML, Natural Language Processing, and data evaluation to track contacts, create vaccinations, and improve biometric technology. The main objective of applications of AI in the health field is to examine relationships between patient care and clinical methods. The primary applications of AI systems include medicine, research, clinical decision-making for public health, virtual assistance, and diagnostics.

'Figure 1' depicts AI and its application in COVID-19 detection. There are three main categories for coronavirus diagnosis with the help of AI, and these include binary detection (whether the individual is coronavirus positive or negative), assessment of aberrant regions in lungs caused by COVID-19, and differentiation among the individuals who are COVID-19 positive, negative and pneumonia. The most thoroughly researched category was binary detection (Presence or absence of COVID-19). The most restricted research fields involve prognosis of acute respiratory illness, infectivity to patients from foreign countries, incorporation of imaging (Magnetic Resonance Imaging, Computed Tomography, X-rays) and medical reports, customizing chemotherapy, and fatality prognosis. Radiological scans are incorporated into machine learning exemplars to anticipate critical care unit hospitalization requirements by employing natural language processing for medical data (Summers 2021). This review article collected a discourse analysis and textual evaluation of AI (ML and Deep Learning) about the COVID-19 pandemic from NCBI, PubMed, PMC, Science Direct and ResearchGate. This was followed by summarising significant contributions and the latest AI technology advancements during the COVID-19 pandemic. While collecting personal data about people is necessary for disease control, breaching privacy remains a major challenge. Blockchain may be helpful in this situation to safeguard data integrity and protect consumers from online fraud. Nevertheless, hackers are still attacking individuals with malware, and the privacy of individuals is still being shared. With the growing advancements, there will be a time when the era of hackers will be over, and our information will stay private.

2 Application of AI in Combating COVID-19

AI can be used more frequently in the health sector due to the intricacy and expansion of data. Funders, healthcare providers, and biomedical research organizations use various AI technologies. The primary application areas are diagnosis, clinical decision-making for public safety, virtual assistance, therapeutics, and research.

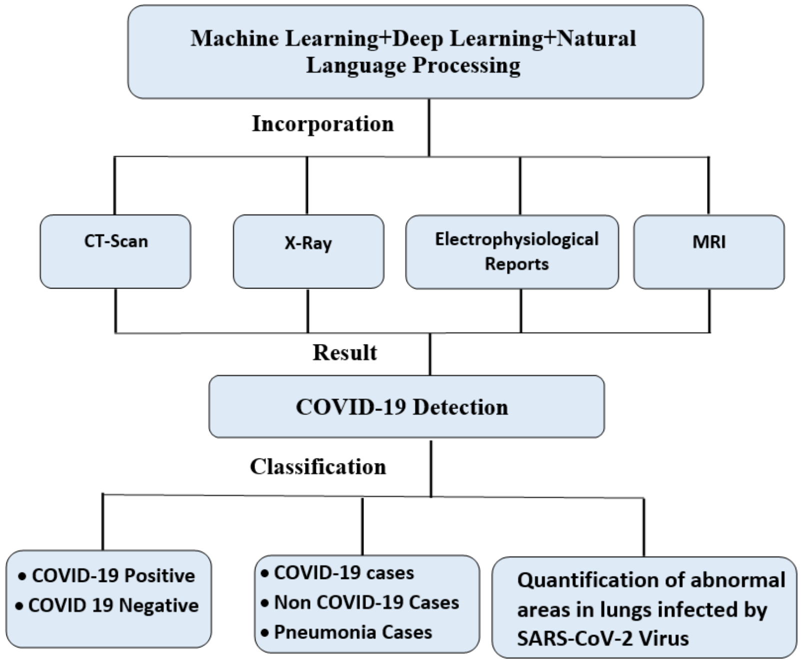

Figure 1 Schematic of AI application in COVID-19 management

2.1 Diagnosis

During the pandemic, AI algorithms are vital for quickly detecting patients who are COVID-19-positive. Most articles discuss using chest CT scans and AI algorithms to detect COVID-19. As a consequence, applications of AI in the early detection of COVID-19 using various medical research and their challenges and promises in COVID-19 have been analyzed in this study. In treating COVID-19 during the pandemic, medical imaging methods, including computed tomography (CT) scans and X-rays, are essential. These imaging tools are becoming more potent to recently created artificial intelligence (AI) technologies, which are also helping medical practitioners. When used by qualified radiologists, chest image analysis, mainly CT, shows early lung abnormalities and attains greater precision. Additionally, chest radiography, particularly chest X-ray (CXR), is affordable and widely accessible. Radiologists must make a visual diagnosis to diagnose chest CT with certain issues. For instance, diagnosing a chest CT requires a lot of time due to the large quantity of sections. Moreover, COVID-19, a recently identified lung condition, has symptoms similar to those of several pneumonias. For radiotherapists to function at a good detection level, particularly when distinguishing comparable diseases, they must acquire a significant amount of CT diagnostic expertise (Vaishya et al. 2020; Jin et al. 2020). Unlike other respiratory conditions, such as lesion detection, lung cancer diagnosis, and tuberculosis screening, distinguishing COVID-19 from other cases of pneumonia is challenging due to the high degree of similarity between different types of pneumonia and the vast differences in different phases of the same kind. Therefore, an AI detection technique tailored to COVID-19 is required. Additional advantages of AI diagnostic methods are improved performance, high repeatability, and broad implementation (Jin et al. 2020). Panwar et al. (2020) discussed nCOVnet, which can identify a patient who is COVID-19 positive in less than 5 seconds with 97.62% accuracy with the limited available data. Similarly, Butt et al. (2020) demonstrated ResNet-18 and ResNet-23, which uses CT scans to build the model and show 86.7% efficiency. In this context, Apostolopoulos and Mpesiana (2020) described about VGG19 (Visual Geometric Group), which shows 98.75% accuracy. Singh and Gupta (2019) published an article regarding a deep learning technique based on Rectified Linear Units (ReLU), which can detect malignant lung cancer with an accuracy of 85.55%. Chen et al. (2020a) also described RF (Random Forest) with more than 95% accuracy in predicting COVID-19 severity. In a detailed study, Alqudah et al. (2020) demonstrated a “Support Vector Machine” (SVM), “K-Nearest Neighbor” (KNN), and “Random Forest” (RF) with the CNN using soft-maxcan to diagnose SARS-Cov-2 virus and found their accuracy is about 98% (Alqudah et al. 2020). Li et al. (2020) demonstrated XGBoost and reported that it can distinguish COVID-19 patients from influenza patients with more than 92% accuracy (Li et al. 2020). Guhathakurata et al. (2021) also described the Support vector machine (SVM), which can classify COVID cases into “Mildly infected”, “Severely infected”, and “Non-infected” with 87% accuracy (Table 1).

Table 1 AI Applications in Healthcare System and COVID-19 Management

AI Techniques	Role	Reference
Decision tree algorithm	Clinical decision making	Azar and El-Metwally 2013
DRUGSURV	Drug Repurposing	Amelio et al. 2014
Rectified Linear Unit (ReLU) based deep learning method	Diagnosis (85.55% accuracy)	Singh and Gupta 2019
MARIA and NetMHCPan4	Vaccine formulation	Fast and Chen 2019
"K-Nearest Neighbor" (KNN), "Random Forest" (RF), and "Support Vector Machine" (SVM) with the CNN using soft-max	Diagnosis (98% accuracy)	Alqudah et al. 2020
Visual Geometric Group (VGG19)	Diagnosis (98.75% accuracy)	Apostolopoulos and Mpesiana 2020; Panwar et al. 2020
ResNet-23 and ResNet-18	Diagnostic purpose (86.7% accuracy)	Butt et al. 2020
Random Forest (RF)	Diagnostic purpose (>95%accuracy)	Chen et al. 2020a
DrugBank using a gradient-boosted decision tree (GBDT) model	Drug Repurposing	Gao et al. 2020
XGBoost	Diagnosis (>92% accuracy)	Li et al. 2020
Vaxign reverse vaccinology platform	Vaccine formulation	Ong et al. 2020
nCOVnet	Diagnosis (97.62% accuracy)	Panwar et al. 2020
multi-layer neural network	Vaccine formulation	Prachar et al. 2020
3D protein exemplar of 3CLpro	Drug Repurposing	Zhang et al. 2020
AlphaFold created by Google DeepMind	Vaccine formulation	Zhavoronkov et al. 2020
Convolutional Neural Networks utilizing Tensorflow (CNN-TF)	Virtual Assistants	Alodat 2021
Support vector machine (SVM)	Diagnosis (87% accuracy)	Guhathakurata et al. 2021

2.2 Clinical Decision-Making for Public Safety

Supervised learning (SL), deep learning (DL) and Machine learning (ML) are three types of AI technologies that are particularly well adapted for use with healthcare data and impending problems. The difficult task of risk-classifying patients for medicines, identifying those at risk of imminent symptoms, and monitoring a variety of minor outcomes to optimize overall health outcomes can be made more accessible for clinicians with the aid of AI. Since there are many advanced AI methodologies, the ease with which doctors can understand and interpret the results will vary; the next paradigm shift in medical training will include integrating practitioners in model creation and teaching them this. Doctors frequently employ decision tree algorithms. However, they are fundamentally tied to the initial tree layout, making them less useful (Azar and El-Metwally 2013). Big data techniques are widely used in healthcare services to support scientific proof for clinical decision-making amid technological, sociological, and ethical challenges. The medical information is updated regularly with changing statistics and growing observations and includes numerous patient groups and a range of results (Santosh 2020). Theories and models of decompensation, mortality risk, or therapeutic approach developed for SARS-Cov-2 negative cohorts are not expected to uphold previous reports' effectiveness since COVID-19 has a different phenotype as compared to the typical Acute Respiratory Distress Syndrome (ARDS) (Zampieri et al. 2019; Mousavizadeh and Ghasemi 2020). Few clinical algorithms have been implemented to identify COVID-19 infection in symptomatic patients or prioritized specific predictors, missing important data and thus restricting performance in extensive screens. Patients who move between different therapeutic environments (Emergency departments, outpatient departments, floor units, and Intensive care units) produce distinct individual data that represents their phenotypes, demand various therapeutic tools, and take part in a variety of choices that might be minor or possibly serious. Clinical staff, patients, and their family members can benefit from the fast performance of all existing data in such configurations and throughout each transformation. This will enable them to make well-informed, scientific-proof guidelines and participate in collective decision-making to decide on the most appropriate action (Debnath et al. 2020).

2.3 Virtual Assistance

AI employs natural language processing to respond to COVID-19-related questions, offer accurate information, provide straightforward suggestions, and deliver multi-lingual consultative services. It can also monitor symptoms and make recommendations about whether or not a person should be admitted to the hospital or place themselves in self-isolation at home (Cury et al. 2021). It has been estimated that people worldwide are consulting doctors virtually since it is a better option than personal advice when the pandemic emerged in Wuhan (Webster 2020). The term "telemedicine," which was coined in 1970, means "healing from afar" and relates to the application of technology for communication and information to enhance societal well-being by facilitating access to medical data (WHO 2019). By implementing chatbots to answer patients' COVID-19 inquiries and providing virtual consultations and evaluations, telemedicine intends to keep patients at home while treating mild COVID-19 symptoms. As a result, fewer people will be exposed to COVID-19. This decreases the use of resources and the burden on the care system. Efficiency and strategic planning tools can produce initiatives based on regional infection counts to evaluate the number of patients requiring hospitalization, beds for intensive care, medicines and mechanical ventilation (Moore et al. 2020). To reduce the chances of transmission in clinical and non-clinical personnel caring for COVID-19 patients, research on the interactive telemedicine approach and computed tomography (CT) strategy was implemented (Miyake et al. 2021). Alodat (2021) used several deep learning-based technologies to power real-time telemedicine to respond to and manage the COVID-19 situation. According to research, the “Convolutional Neural Networks Using Tensorflow” (CNN-TF) system could differentiate between positive and negative COVID-19 situations. An Internet of Things (IoT) based wearable tracking device was created by Al Bassam et al. (2021) to evaluate several crucial parameters of COVID-19. By tracking the individuals' real-time geolocation data, the technology would immediately notify the appropriate medical officials regarding quarantine infringement for potentially infectious patients. This system uses three layers: an Android web layer for smartphones, a cloud layer with an application peripheral interface, and wearable IoT sensor layers (Al Bassam et al. 2021). New research suggests a computer-aided decision-making framework as a telemedicine component to aid practitioners in making the best choice. The design combines ML models that were designed using information from both clinical queries and patient symptoms. With an accuracy of 84.9%, the combination's outcome demonstrated enticing predictability, suggesting the model's ability to forebode the medical assessment of a potential patient's status based on the reported symptoms and potentially assisting clinicians in making the best choices (Faris et al. 2021)

2.4 Therapeutics and Research

Virus identification, mutation evaluation, recurrence prediction, biological assessment, tracking and isolation, vaccine research, and processes for controlling the virus are among the main SARS-CoV-2 concerns where AI can play a crucial role. Researchers have been motivated by the SARS-CoV-2 pandemic to create cutting-edge, rapid antiviral treatments. Innate immunological responses to disease pathogenesis or host physiological machinery required for viral infections are targeted by host-based antiviral medicines. Utilizing proven methods for drug development might enhance it. A medicine or vaccine typically takes a long time to produce using conventional approaches, but multiple research has used AI techniques to find possible treatments and build efficient and secure vaccinations for COVID-19 to speed up the whole process (Regla-Nava et al. 2015). Molecular dynamics and molecular docking are two computational techniques widely used to find potential artificial and natural therapeutic options for SARS-CoV-2 target protein. The capacity of natural or artificial molecules to attach to the proper pharmacophore sited of the target protein may be examined using extensive chemical libraries of chemicals (Pinzi and Rastelli, 2019). Drug repurposing, defined as adapting current medications for novel treatment purposes, has been an effective drug development method for lowering expenses and streamlining drug authorization. It is possible to teach AI systems to search through the current pharmacological market for potential COVID-19 treatments (Amelio et al. 2014). Thirteen medicines with anti-feline infectious peritonitis (FIP) coronavirus activity were identified using AI. Additional research showed these medications inhibit SARS-CoV-2 (Ke et al. 2020). Forty-one drug candidates were analyzed with a high degree of certainty and a high “Area Under the Receiver Operating Characteristic” (AUROC) of 0.85 (Zeng et al. 2020). After screening 8,565 medications, DrugBank has been using a gradient-boosted decision tree (GBDT) model. Gao et al. (2020) discovered 20 FDA-approved treatments and 20 preclinical medicines that could be beneficial against SARS-CoV-2 (Gao et al. 2020). Zhang et al. (2020) found protein-ligand interaction pairings and constructed a 3D protein exemplar of 3CLpro. Then, they offered probable molecule and tripeptide lists for 3CLpro (Zhang et al. 2020). Batra et al. (2020) used accurate ensemble docking and machine learning to extract 75 FDA-approved and 100 additional ligands as possible COVID-19 chemotherapeutic drugs from data sets.

Researchers have identified several correlations between the SARS COV (2002) virus and SARS COV-2 (2019) virus, and based on the data already available, it is conceivable to create AI learning models that could help in predicting drug structures that could cure COVID-19 (Gns et al. 2019). During situations, the safest and genuinely required approach is to request this specific information about medicine so that the AI professionals can utilize their measurements to evaluate relevant attributes of the drug. To achieve this, governments and legislators throughout the world must take action to compel large pharmaceutical corporations and research facilities to collaborate with smaller test partnerships and share their knowledge. The repurposed medicine will reach the advanced testing phase without the first research and safety evaluations (Mohanty et al. 2020). Any of the most promising work is based on identifying virus mutation before there is even a new virus. Software developed by the Salama community can determine nucleotide substitution of the Avian pneumoencephalitis (Newcastle virus) in primary RNA sequences using a “rough-set gene evolution theory” (Salama et al. 2016). “Rough set theory” is a data analysis theory that is considered a significant method for accessing incoherent and ambiguous information, particularly in the applications of AI (Zhang et al. 2016). Training data were made, with one-generation RNA sequences as inputs and next-generation RNA sequences as outputs. The system was introduced to estimate successive generations of RNA sequences, and after that, the results are applied to real sequences of RNA. They applied the algorithm to Avian pneumoencephalitis virus databases in China and South Korea and detected that the mutant nucleotides were approximately 70% accurate (Khan et al. 2020).

3 AI AND ML in Vaccine Preparation

The White House has appealed to AI researchers worldwide to deliver cutting-edge text and data mining tools to support COVID-19-related studies in partnership with academic institutions and tech enterprises. Scholarly reports based on COVID-19 have been updated weekly, and the Allen Institute for AI has published this data as open-source in partnership with top research institutions. This data is crucial for launching new research projects (Alimadadi et al. 2020). The taxonomic classification of COVID-19 genomes, the CRISPR (“Clustered Regularly Interspaced Short Palindromic Repeats”) based COVID-19 identification test, the safety assessment of serious COVID-19 patients, and the revelation of possible drug candidates against COVID-19 are all accomplished through the use of highly advanced machine learning techniques. A component of bacterial immune systems that cut DNA called CRISPR has been developed into a gene-editing tool. It is a precise tool for a restriction enzyme that can cut the DNA sequence by following a predefined track (Metsky et al. 2020; Ge et al. 2020; Yan et al. 2020; Randhawa et al. 2020). The previous finding, in which senior citizens are at a higher risk for COVID-19, is contradicted by a new report that the number of young adults suffers from serious COVID-19 symptoms, suggesting an immediate need for a systematic risk assessment focused on individual physiological and genetic properties. Biochemistry (expression degree of ACE2) and clinical details (respiratory history, ability to survive, virus load and age) of COVID-19 patients with implicit health issues may, therefore, be evaluated using machine learning methods to classify not just certain attributes (e.g. ACE2) for risk factors, but, existing portfolio and predictive analytics for the structured preparation of ongoing therapeutic strategies and COVID-19 defensive measures are also performed. It's been shown that ACE2 genetic polymorphism, expressed by various gene mutations in the human genome, affects the virus-binding process, indicating a potential genetic vulnerability to COVID-19 (Cao et al. 2020). By studying genetic variations that are symptomless, moderate, or severe using COVID-19 patient data, it is now possible to determine and predict individuals based on their susceptibility or tolerance to contracting COVID-19 infections with the help of ML techniques. As a result, the ML algorithm can return specific target gene mutations, such as the ACE2 polymorphism, as important components for pragmatic and rationalistic analysis in its decision-making process. For instance, great sensitivity and efficiency have been proven for machine learning-driven testing of SARS-CoV-2 assay models utilizing a viral detection approach powered by CRISPR. Based on their unique breathing patterns, neural network classification techniques for the widespread screening of COVID-19 patients were developed (Wang et al. 2020). To identify and follow COVID-19 patients automatically over time, a deep learning-based categorization approach of thoracic CT scans was created (Gozes et al. 2020). A deep learning framework for drug development was used to create and manufacture novel drug-like substances targeting SARSCoV-2. AlphaFold, a deep learning technology created by Google DeepMind, has published expected COVID-19-related protein structures that can take months with conventional experimental methods and serve as useful knowledge for COVID-19 vaccine formulation (Zhavoronkov et al. 2020). Prachar et al. (2020) found 174 SARS-CoV-2 biomarkers with better prognostic molecular docking and the ability to stably connect to 11 HLA allotypes using a multi-layer neural network. The fact that the authors assessed the peptide-HLA prediction model currently being utilized to identify SARS-CoV-2-related biomarkers is important. Fast and Chen (2019) used the MARIA and NetMHCPan4 artificial neural network approaches to identify SARS-CoV-2 T-cell and B-cell epitopes. The method found 2 putative neutralizing B-cell epitopes on the S protein and 405 T-cell epitopes with excellent presentation scores for both MHC-I and MHC-II. These findings will assist in the creation of effective COVID-19 vaccines and neutralizing antibodies. When compared to the S protein, they discovered that the largest non-structural protein, nsp3 (Coronaviridae family), which earned the highest protective immunogenicity score, emerged as the most promising vaccine option for COVID-19 (Fast and Chen 2019). In addition, Ong et al. (2020) designed a Vaxign reverse vaccinology platform combined with ML has been introduced for COVID-19 vaccine candidates. The overabundance of COVID-19 treatment reports in hospitals around the world also necessitates more developed AI methods to evaluate the tailored therapeutic potential for analyzing fresh patients, such as predicting the chances of hospitalization, that not only provide each patient with high-quality care but also helps the local hospital system set up and operation. The availability of COVID-19 clinical findings that can be regulated and maintained in conveniently accessible databases is a significant potential problem. Therefore, it is crucial to develop cyberinfrastructure that will support global cooperation. The incorporation of COVID-19-related clinical findings with current biobanks, such as the UK Biobank, along with information already known about those patients, like physiological and genotypic attributes, can help us in the direction of a more expedient and practical approach by bioinformaticians and computational scientists for meaningful data analysis.

4 The Application of AI and Blockchain in the Covid-19 Pandemic

Point-of-care (POC) testing is carried out near the patient's location and provides fast results that enhance patient care. POC screening was developed and implemented in response to the COVID-19 pandemic to minimize the spread of the virus and relieve the strain on the health system. Emerging medical breakthroughs like blockchain and AI technology can be combined with POC diagnostics to enable patients to self-test during quarantine (Mashamba-Thompson and Crayton 2020). A sophisticated blockchain technology database system allows unrestricted data sharing inside a company's server. Blockchain technology can improve the procedures for clinical trials for vaccines and pharmaceuticals, publicly track donations and fundraising events, increase public awareness, and serve as a trustworthy data-tracking system (Agbo et al. 2019). The World Economic Forum brought attention to the fact that hackers are distributing malware through coronavirus map data. These hackers pretend to be real interactive maps that show the disease's distribution. By doing this, fraudsters deceive people into disclosing their private data, including Passwords, card details and usernames. The attackers then trade this confidential information on the dark web or use it to defraud individuals. The issues with centralized data systems can be solved by blockchain technology. It eliminates any failure in the system while introducing permanence and data integrity. Anyone with an internet connection can use a blockchain data tracking system to quickly and securely obtain updated data about the SARSCoV-2-virus (Marbouh et al. 2020). In resource-limited environments, Smartphone-linked POC diagnoses and self-testing are effectively applied (Makhudu et al. 2019; Bervell and Al-Samarraie 2019). However, there isn't enough proof to support the use of blockchain technology for disease detection. All experiments are reported to the disease control authority by the blockchain and AI system, along with the proportion of positive and negative test reports (Braun et al. 2013). This will ensure appropriate patients are admitted to quarantine centres for treatment and analysis. The AI feature would allow powerful data collection (patient knowledge, patient geographic position, and medical reports), authentication, review, and blockchain systems to quickly extract modified data from fragmented medical data sources with high trust. Local manufacture of these remedies might assist in overcoming supply chain challenges (Kuupiel et al. 2017).

5 Cross Population Test Models in COVID-19 and the Role of Active Learning

AI is a new model for health care, offering alternatives to conventional practices and therapies. The core tenet of AI-driven products is that they require a lot of data on all known combinations for preparation. Traditional machine learning also promotes a positive collection of compiled data, making classifiers well-qualified within the supervised learning domain. Unfortunately, researchers failed to quantify the number of training sets that should be developed for a successful classifier and whether it is still acceptable to wait for reasonably large amounts of data to be collected. For instance, deep learning (DL) requires enormous training data (Guo et al. 2019; Chen et al. 2020b). Most AI-driven solutions can only create concrete evidence models for coronavirus cases. The severity of the coronavirus epidemic will spread restricted data, according to AI specialists. According to The Wall Street Journal, coronavirus exhibits flaws in AI health software. Given the paucity of current coronavirus data and the shortcomings of health services delivered as AI in the face of emergent, rapidly spreading illnesses, several testing app suppliers are avoiding equipment upgrades (Santosh 2020). In particular, online platforms, newspaper articles, healthcare articles, and conventional AI-driven tools may not provide the desired outcomes for real-world scenarios with less data.

Active learning is used in contrast to passive learning (standard ML classifiers) to solve a learning conundrum where the learner has some control over selecting the data to be learned (Sammut and Webb 2017). Exploiting real-time data is required since manual annotation and analysis cannot be done in real-time. It implies that rather than having a traditional collection of training, verification and testing sets, AI-driven resources are needed, and these can be trained over time without requiring full knowledge of the results, this is known as Active Learning (AL). Using Anomaly Detection (AD) techniques, the variations in data over time may be measured when studying. AD aids in locating and identifying unusual objects, incidents, or findings that give rise to concerns by varying dramatically from the rest of the data or a collection of standard data for that unique occurrence (Bouguelia et al. 2018).

Since there is a dearth of sufficient data from the essential regions, cross-population test models are further necessary in these situations. Parallel to this, the data collected over time can be used to train models depending on the choices. RNA sequences are the most common data type AI-driven tools utilized for coronaviruses (Ai et al. 2020). In addition, it considers and checks Data from chest X-rays, computerized tomography (CT) scans, electronic health records (EHRs), and other sources. Alibaba unveiled a brand-new AI-based tool that can accurately diagnose coronavirus illness using up to 96% of the time using CT scans. It may be applied to various data types, including multidimensional data, vector data (1D array, signal, or pattern), and 2D matrices (images). Thus, it makes sense for AI researchers to use longitudinal and multimodal data to examine whether different types of data can help to give an accurate judgement over time regarding COVID-19 outbreaks rather than using machine learning models with one type of data and looking for clustering methods to incorporate outcomes (Fong et al. 2019).

6 Latest Inventions in the Use of AI in COVID-19

Prognostic computational techniques are being employed more often and have proven effective in delivering information that helps improve clinical management and policies. Such innovations are currently in their early phases; therefore, acceptance for meaningful policy evaluation at the national and global levels is only slowly progressing. Nevertheless, a recent instance shows that AI-powered computers are becoming more precise (Allam et al. 2020). COVID-19 induces a decrease in oxygen levels, which is challenging to diagnose because the patients do not show perceptible respiratory problems, which leads to a state of silent hypoxia. Therefore, it is essential to identify this silent version of hypoxia in COVID-19 individuals before they start to suffer from breathing difficulties (Teo 2020). This silent hypoxia can be detected via mobile phones acquired with medical-graded pulse oximeters to record the oxygen saturation values easily. Tayfur and Afacan (2019) evaluated pulse oximetry measurements against two diagnostic instruments often seen in emergency rooms with a Samsung Galaxy S8 mobile, which showed 96% to 99% similarity compared to standard procedure. The gadget's accuracy is very high when the users' oxygen saturation levels are over 90%. Healthy individuals have oxygen saturation levels between 95 and 100%, might use their cellphones to effortlessly measure their oxygen level on a routine basis at home and get in touch with their doctor right once if they see a noticeable drop below 95% (Tayfur and Afacan 2019).

A viable strategy for COVID-19 surveillance, identification, and prognosis is wearable Internet of Things (IoT) devices. Even for asymptomatic people, the sensor readings from wearable technology can warn patients of a possible COVID-19 disease as symptoms develop (Seshadri et al. 2020). A technique to detect coronavirus-affected patient from their breathing patterns via smartphone has been developed by Alkhodari and Khandoker (2022). To test this technique, 480 breathing sounds of people were acquired from the Coswara database (open data), out of which 240 voices were shallow and 240 voices were deep. Using a cellphone microphone and a web application, 120 COVID-19 patients' and 120 healthy individuals' voices were recorded with “Mel-frequency Cepstral Coefficients” (MFCC) attribute extraction from the voice data, and in-depth attributes were acquired using a mixture of “Convolutional Neural Network” (CNN) and “Bi-directional Long Short-Term Memory units” (BiLSTM) to make up the deep learning tool. As a result, it showed 94.58% accuracy in differentiating between COVID-19-positive cases and normal cases. It also suggests using deep learning as a prior examination technique for such conditions before doing industry-standard RT-PCR analyses (Alkhodari and Khandoker 2022).

Wearable technology (Activity trackers and smartwatches) has generated significant attention due to its ability to measure our health. The focus of the pandemic has shifted to whether these wearable technologies may identify physiological abnormalities which might point to a COVID-19 infection. It might then assist with early testing and quarantine, halting the spread of the virus (Mishra et al. 2020). The effects of COVID have been mapped out on a larger scale using smartwatches. Fitbit is a smartwatch brand that showed variations in sleeping pattern data collected from thousands of customers during the outbreak. According to the data, people slept longer on average compared to the initial phase of the pandemic (Rezaei and Grandner 2021).

Wurzer et al. (2021) established a telemonitoring technique in which respiratory rate, temperature, oxygen saturation level and pulse rate can be monitored every 15 minutes via phone calls. With the help of the web or cellular phone, the Telecovid centre receives the information, and an experienced crew keeps track of it around the clock. The National Early Warning Score was adjusted to determine each person's specific risk. 153 (76 men and 77 women) patients older than 60 years of age or who fulfilled any one criteria like pregnancy, cancer, high blood pressure, diabetes, cardiovascular or lung diseases were included. The Telecovid crew recommended 20 COVID-19 individuals to the hospital. All patients acknowledged the ease of use of the gadget. Approximately 90% of the recommended patients were grateful for the research since they were admitted and treated at the right time.

In 2020, Dubai Police deployed AI-based smart helmets incorporated with IR (Infrared radiation) cameras, facial detection technology, and automobile plate number readers to quickly observe individuals and identify potential coronavirus cases using thermal scanning. The United Arab Emirates is the first country to employ this technique. These 'smart helmets' instantaneously obtain additional personal information about the home address and detect the body temperature of individuals on public transportation. In the meantime, a Chinese company, Hanwang Technology Ltd, claimed that they had created the nation's first facial detection system to detect people wearing or without masks (Ahlawat and Krishnamurthi 2022).

7 Overcoming Challenges

AI has several applications in the healthcare sector due to the development of sophisticated technology, but there are also substantial disadvantages in this field that hinder AI from being fully absorbed into the current healthcare sector. To create good results, AI exemplars are getting increasingly complex. Due to its complexity, AI operates in a "black box," making it more challenging to understand how the model truly works (Wadden 2021). Healthcare professionals must understand how precisely AI produces specific discoveries to respond correctly. Lack of justification creates trustworthiness issues for both healthcare organizations and patients. Explainable AI (XAI) approaches can be used to tackle this issue and promote trust between humans and machines. Medical experts can apply complex but intelligible algorithms as more study is done in this area (Linardatos et al. 2020).

Finding high-quality medical data is a significant barrier to implementing AI in healthcare. Getting information about a patient's health is always challenging due to its sensitivity and moral obligations. Even automated processing is time-consuming and expensive because interpreting a particular model might take up to ten thousand pictures. By obtaining additional sets of data from a single image and drastically lowering the quantity of data required to train a system, new methods of diagnostic image interpretations are assisting in overcoming this obstacle (Kotter and Ranschaert 2021).

The medical error made by diagnostic tools is 60%, which causes 40,000–80,000 fatalities annually in US hospitals. Thus, the application of AI in various medical sectors can aid in minimizing judgment mistakes caused by humans. Organizations are hesitating to embrace AI in diagnostics, even though it can provide more precise results by reducing the chances of human error. To make sure the machine learning exemplar is applicable, it must be examined and confirmed, and the model must generalize effectively, avoiding overfitting or underfitting over the training set (Lee and Yoon 2021). A legal basis must be established for exchanging data and accessibility for AI technologies. To improve AI effectiveness in the healthcare sector, relevant data exchange and intelligence gathering are necessary. The accuracy of the information is crucial since the more confident users generate the output, the lower the danger of undesirable results (Moreno 2020).

8 Legal Implications of AI in Combating COVID-19

AI rapidly changes how we work and live and is viewed as the fourth industrial revolution ("Ministry of Electronics & Information Technology, Government of India, 2023"). To tackle global challenges like COVID-19, AI and ML are potent tools that may promote science and research and increase access to healthcare (Report of Committee – D on cyber security, safety, Legal and ethical issues, Ministry of Electronics & Information Technology, Government of India, 2018). Recently, to combat COVID-19, the world has witnessed AI's vital role. However, it has also attracted concerns like privacy and anti-discrimination. 'The right to Privacy is a fundamental right' (Justice KS Puttaswamy (Retd.) & Anr. vs. UOI and Ors, 2017). AI can suffer from *"algorithmic bias,"* which has striking implications for health care. Thus, the algorithms must be developed to not exacerbate social inequities in health care (Atherine 2021). Unfortunately, AI remains largely unregulated. The "Information Technology Act 2000" and the rules and regulations framed are India's primary statutes governing AI. In 2018, the "Ministry of Electronics and Information Technology" (MEITY) established the following four committees to advance AI initiatives and create a regulatory framework: (i) Committee on Platforms and Data for AI, (ii) Committee on Leveraging AI for Identifying National Missions in Key Sectors, (iii) Committee on Mapping Technological capabilities, Key Policy enablers required across sectors. Skilling and Re-skilling R & D, and (iv) Committee on Cyber Security, Safety, Legal and Ethical Issues. These Committees have provided various recommendations. It's high time to frame comprehensive guidelines based on these recommendations in consultation with all the stakeholders, including civil society.

9 Conclusion and Future Prospects

In recent times, Artificial intelligence has steadily moved beyond the laboratory into public and clinical concerns, including the early detection of outbreaks and the insightful analysis of vast healthcare records. AI has significantly raised our degree of diagnosis, prediction, and therapy in the COVID-19 battle. Through significant clinical data, AI was able to examine the epidemiological, medical, and pharmacological impacts of COVID-19. Diagnostic analysis, genetic analysis, patient hospitalization, healthcare, pharmaceutical research, and related medical and health services have been impacted by AI. "Table 1" depicts numerous AI, ML and DL applications in the healthcare system. In drug research, a cutting-edge approach to finding cures for illnesses rapidly and safely involves repurposing already-approved medications and finding new applications for AI. AI is beneficial in predicting virus propagation, relieving the pressure on medical professionals and the rush to develop a treatment for COVID-19. However, contemporary research has shown AI's flaws and drawbacks. Simple AI strategies have dominated research in COVID-19, and only a small amount of study is focused on creating novel AI technologies. The limitations are: a) minimal success in AI research toward creating medications and vaccinations against SARS-CoV-2 has been achieved. b) AI has not yet impacted COVID-19 since it is challenging to utilize due to a lack of data and an overflow of data. Thorough human-AI interaction and careful data privacy and public health balance would be required to overcome these limitations. Furthermore, there hasn't been any cross-disciplinary AI study on COVID-19. AI has not yet impacted COVID-19. The disease outbreak and possible solutions may speed up the advancement of the economic system, including the automation of human workers, the outsourcing of manufacturing operations, and market dominance by a small number of new digital companies, even though the use of AI is limited. It can be concluded that AI scientists don't necessarily hesitate to prepare, validate and analyze the prototypes for the complete datasets; instead, AI-driven devices must be incorporated from the start of data gathering. Experts are concerned about AI because they believe that AI and ML technologies will replace workers in their current positions in the upcoming years. Even though such technologies are replacing humans in various work roles across industries, including marketing, banking, telecommunications, and more, this is not diminishing job chances. AI is creating a variety of new career openings that were not even possible a few decades ago. It is essential to the healthcare industry, which we have already discussed. There doesn't seem to be a direct link between exposure to AI and employment. However, more engagement with AI is associated with faster employment rates in jobs with substantial technology use.

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