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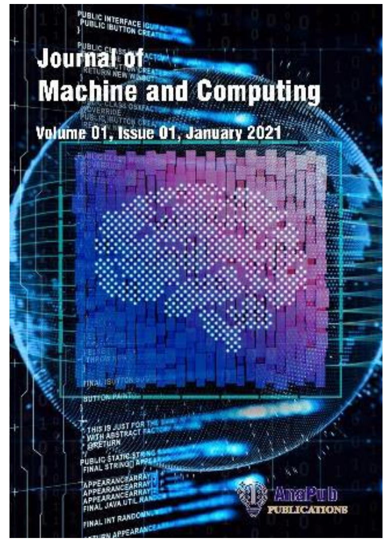

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An Innovative Artificial Intelligence Based Decision Making System for Public Health Crisis Virtual Reality Rehabilitation

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Abstract

On 23rd April 2020, the COVID-19 disease caused by the SARS-CoV-2 virus was declared by the World Health Organization (WHO) as a spreadable viral disease. During the COVID pandemic, there was difficulty in notifying the Decision-Making System (DMS) about the rapid and precise triage of patients admitted to the emergency wards. As a method to achieve the aim and develop digital healthcare revolutions in data and analytics, digital healthcare information was established. Artificial Intelligence (AI) is a robust automation tool for sustainability in the context of the COVID-19 health crisis on big datasets. Besides, the gap between AI investment and commercial real-time application, which are the initial digital technology development curves, has been identified. It was discovered that AI's new applications are grounded in Digital Transformation Mapping (DTM) for the DMS of Health Crises. The fast inventions in AI and Machine Learning (ML) have implications for amazingly preventive and clinical healthcare, and for the association, ML was developed as a predictable attention. Billions of smartphones, massive online datasets, linked wireless wearable devices, comparatively cost-effective computing resources and improved ML and Nural Language Processing (NLP) are leveraged by these rapid responses, with the trained dataset of 65% and evaluated in the other 35%, the renowned ML models for structured data like Support Vector Machine (SVM), Multinomial Naive Bayes (MNB), Logistic Regressive Tree (LRT), Decision Tree (DT), Stochastic Gradient Booster (SGB), and

Random Forest (RF) are used for simulating new unidentified data. AI-DTM challenges DMS of Health Crises (COVID-19) and the drawbacks of critically contributing risk factors to healthcare diseases. Meanwhile, a comprehensive collection of healthcare datasets over what is spreadable would be required to save human lives, train AI, and limit cost-effective health risks.

Keywords: Artificial Intelligence, Data Science, Machine Learning, Digital Transformation Mapping, Health Crises, Decision Making Systems.

1 Introduction

The new Coronavirus 2 (COVID-19) bacterial pneumonia syndrome has become risky [1]. During rapid transmission, Containment and prevention was the core of pandemic management that maintained the need for an Innovative Artificial Intelligence (AI) Assisted Decision-Making System (DMS) in case the mortality rate is more than 1% with an absence of an effective antiviral therapy/vaccine. In December 2019, the first case of COVID-19 was identified in China, and on 11th March 2020, the World Health Organization (WHO) [2] announced a global pandemic. COVID-19 is related to viruses such as SARS and ARDS. WHO also confirmed this virus as an epidemic. When a healthy and a diseased person is in close connection, the virus spreads into the human respiratory system. The virus is spread throughout other virtually uncertain origins among humans [3]. Despite relying on proven principles of public health, world countries have had varying degrees of success in handling COVID-19 crises.

AI-assisted DMS supports numerous time-series analytics for analyzing data, making implementing DMS related to emerging situations in Health Crises much easier. The AI systems of Machine Learning (ML) with Digital Transformation Mapping (DTM) constantly enhance analytical skills by using past experiences of data behavior to predict future mechanisms of particular health diseases. The COVID-19 pandemic created unique tests for the world of medical and clinical diagnosis. Digital health AI can accelerate planning and response to the pandemic under challenging ways to accomplish manually. This view proposes a context for AI-based digital technology implementation in pandemic management and response, demonstrating how effectively countries have implemented AI-supported digital pandemic preparation technologies [4]. The panel offers a short supplement on some of these terms. The main focus of many researchers is on quantitative studies in which AI was used to get certain healthcare services in the healthcare sector by obtaining results from publications like Oxford University Press, PubMed, Food and Drug Administration, Nature Biomedical Engineering, Accenture, and PWC's reports. This generates numerous comparative analyses of the effectiveness of AI along with other normal services.

The cost-effective tool attempted to address the COVID-19 pandemic is AI. The COVID-19 pandemic presents the AI Community with a range of challenges. These challenges include: "Will AI help to monitor and forecast the spread of infection?”, "Is it possible to assist with producing diagnoses and predictions?” [5], “Will the medication and vaccine quest be used?" and "Should social monitoring be used?”. This paper explores how AI has contributed to this problem early and mentions DTM's limitations and pitfalls. There is too much (noisy and outlier) information, a shortage of data, and friction between data protection concerns and public health issues. To use computers for large data models for designing recognition, description, and forecast, AI could be useful for the present purpose, like ML, Natural Language Processes (NLP), and Computer Vision (CV) applications [6]. These functions can help to identify COVID-19 infections and predict, treat, and manage socioeconomic significance. The use of AI data analytics tools to digitize COVID-19 diseases has spread over the years since the pandemic health crises [7-8].

1.1. Impact of DMT Set-up

The regards now rely on standard devices (sensors) and computational methods in the place of flesh and blood spooks. Many governments have adopted these new monitoring techniques in the fight against COVID-19. World maps demonstrate that the decline in human transport has dramatically decreased carbon emissions across various countries, but what about digital technology emissions? Can the use of digital tools by the number of people who work at home or in quarantine raise pollution from other sources? What are the major cloud service providers doing to solve the capacity problem?

Because of COVID-19, social health and economic performance are based on AI-digital technologies [9]. A COVID-19 digital response has significant value and can take multiple forms. New AI and ML technologies for patient screening and risk assessment have been significant fields in which rapid progress has been made in the past few weeks. The population screening to classify those who are likely ill is necessary for COVID-19 intake. Traditional infrared image scanners and handheld thermometers have been introduced at many public places in China, where they hit first. Chinese AI champions have implemented advanced AI-powered temperature control systems [10]. These systems screen people remotely and can monitor hundreds of people with fever within minutes. The binary classifier of Support Vector Machine (SVM), which maps original data, improves the performance of information processing features by AI-assisted DMS. The feature of higher-level data is considered and extracted to learn large infectious data to predict from many unlabeled data (Figure 1).

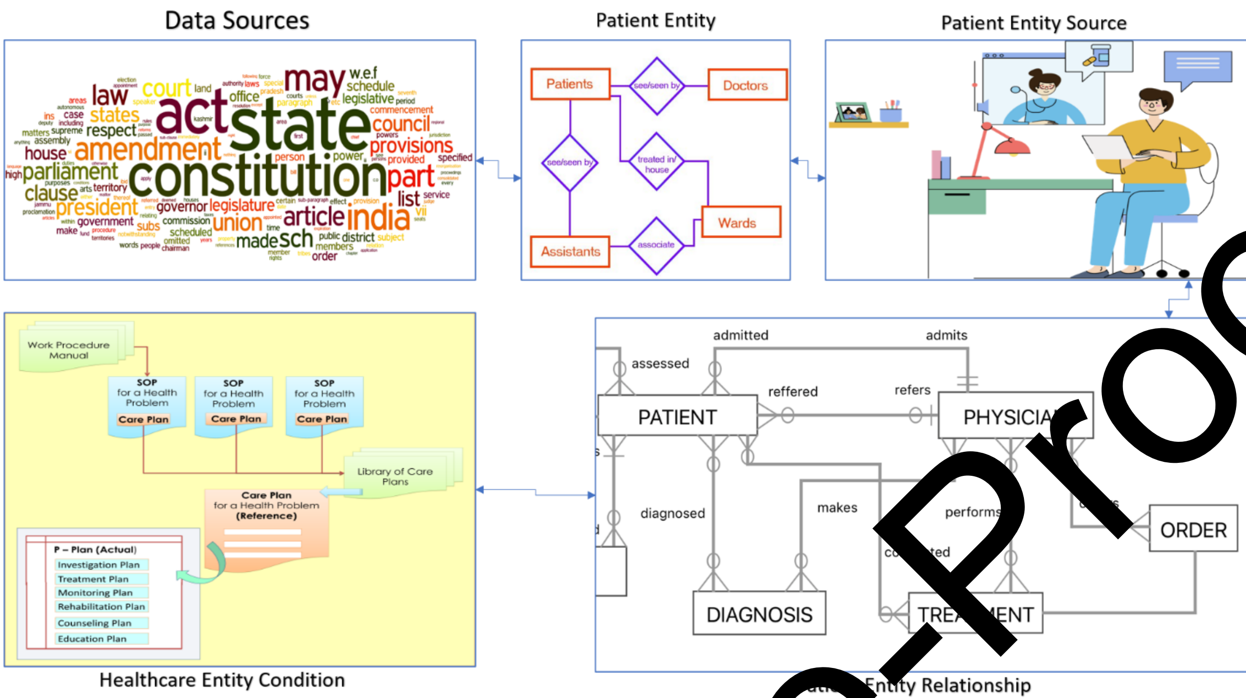


Figure 1. Healthcare Source of Big Data Analysis using AI

Globalizing the wellbeing of people and monitoring the global spread of the virus are enabled by modern AI-powered smartphone applications. These apps aim to predict groups and populations most vulnerable to the negative impacts of COVID-19 epidemics. They would allow patients to obtain information from their medical providers in real-time, provide medical advice and alerts without attending a hospital, and notify them of the risk of infection. Since this research work takes on a particular context in ML and COVID-19's essence, our readers are encouraged to explore more ML potential for scientific study and additional knowledge on virology, clinical features, and COVID-19 epidemiology [11].

The following comments were based on this paper:

(a) The future applications of the COVID-19 pandemic cover a broad spectrum of medical and societal challenges, but currently, very few of them are necessarily developed to demonstrate operational effects through DTM on AI.

(b) AI will help with COVID-19 diagnoses in medical imaging through DTM, from the clinical vision and proposal of alternate methods of monitoring disease progression DMS using non-invasive instruments and patient recovery prediction based on numerous data inputs like digital health records.

(c) Research translations into modern global solutions that can be adapted to local contexts must be significantly enhanced through International AI Collaboration on Science, DTM, and Open Science.

(d) This paper accurately divides the text into multiple categories of diseases to prevent COVID-19 from additional clinical symptoms [12].

The organization of this research article is as follows: Section 2 reviews the fundamental and probability contributions of AI to healthcare. Section 3 presents the Impact of AI-based DMS in medical sectors to prevent health crises. Visualizations of data related to COVID-19 are presented in Section 4. The research challenge of the AI dataset on health crises is described in Section 5. The performance of the training dataset on AI with DTM is projected in Section 6. At the end of Section 7, the research work and scope for future improvement are concluded.

2. Background of Real and Probability Contributions of AI on Health Care

2.1. AI-Supported Detection and Prevention of DMS of Health Crises

The epidemic of unknown pneumonia in the communist party of China was observed by AI systems within China long before the world became aware of the risks caused by COVID-19. The epidemic that has become a global pandemic has made AI devices and techniques to help policymakers, the local clinical community and society deal with all economic recession phases and their implications: identify, prevent, react, recover, and accelerate science. Frequently washing hands with soap for 20 *Sec.* and maintaining a distance of roughly 1 *Min*. to prevent close contact with other humans can reduce the possibility of groups affected by the virus. Reusable tissues covering the nose and mouth can help stop nose, ear, and mouth communication, preventing it [13].

AI can also identify, diagnose, and prevent virus spread, as shown in Figure 2 [14]. ML Algorithms that recognize trends and abnormalities already detect and predict Health Crise's distribution while imaging DMS to accelerate the medical diagnosis system. For instance (Table 1):

(1) Early-warning systems powered by AI can be used to identify epidemiologic patterns by mining mass media, web content, and other data sources to provide early alerts, complementing syndrome tracking, and other medical networks and data flows (*e.g.,* WHO Early Warning System) in many LMP. In many cases, AI technologies have shown that they can infer epidemiologic data more efficiently than conventional health data reporting.

(2) The large-scale impact of virus spread chains is detected and tracked with the assistance of AI. Institutional organizations, including the Johns Hopkins University and OECD [15], have also got interactive dashboards for tracking the virus' spread in live and real-time data on reported outbreaks, recoveries, and deaths of COVID-19. The AI can assist in diagnosing COVID-19 cases promptly with images and symptom data.

(3) Quick diagnoses are essential for reducing contagion and recognizing the spread of the disease. The responsibility to collect the data representing the whole population is taken to ensure scalability and accuracy.

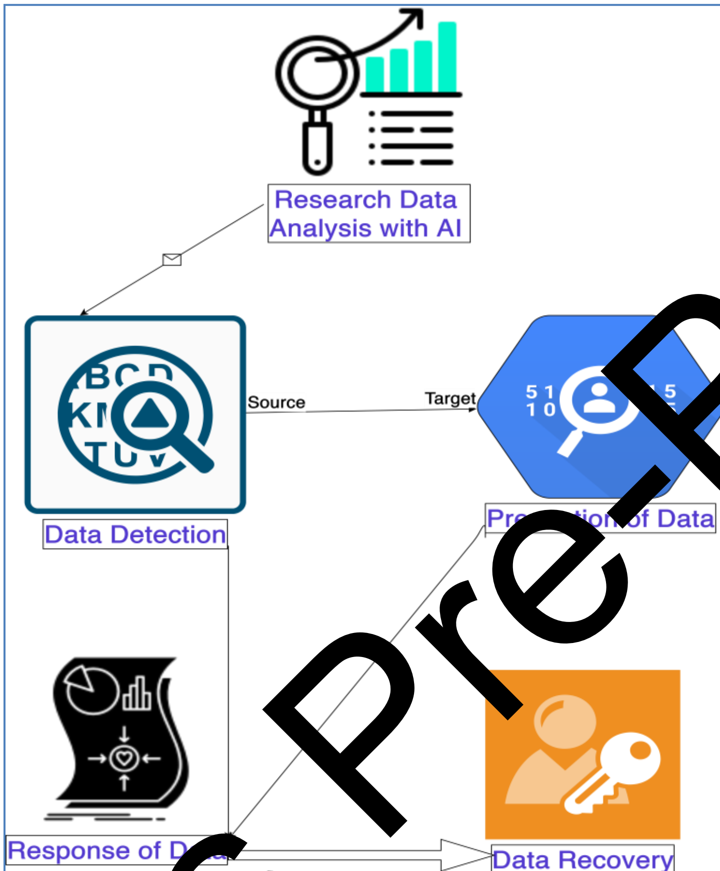


Figure 2. AI Knowledge in BPM Phases of the Economic Recession of Health Crises

Table 1: Instances of AI applications for a grouping of participants

Test Case	Class	Real-Time Applications	AI/ML Methodology
Patients	Benefits of Healthcare Monitoring/Assessment of Risk Methodologies	Wi-Fi Wearables Devices, Apps Specific for Smart devices	ML, NLP, Speech Recognition System (SRS), Chat- Bots
	Prevention and Management of Health Disease	Control and Management of Obesity and Diabetes, Emotional and Moral Support	SRS, NLP, and Conversational AI.
	Healthcare System Management	Medicine Adherence	Smart Home Tele Healthcare System
	Disease Treatment	Treatment for Stroke through Apps and Robots	Automation

Clinician Care Management Experts	Automation Tools for Rapid Detection and Prediction of Disease	Detection of Cardiac Arrhythmias using Imaging, Retinopathy, Early Detection of Cancer (e.g., Melanoma)	ML
	Robotics Surgical Treatments	Robotic Surgery Controlled by Remote-Surgical Roadmaps Assisted by AI	Automation and ML
	Automation and ML	Modified Chemotherapy Treatment	ML/DL
	Patient Security System	Detection of Sepsis at Early Stage	SVM and RF, ML

2.2 Containment in all regions of the world is a priority in DTM, and AI applications help Healthcare Crises

ML techniques are used to predict where the following new cases were registered.

(a) A variety of countries use population tracking (e.g., geo-location data, surveillance camera video, credit card records in ML algorithms to track patients with COVID-19), for example, to monitor COVID-19 cases. Each person who indicates the risk of infection with smartphone software is assigned a risk level [16].

(b) Several countries, such as Austria, China, Israel, Poland, Singapore, and Korea, have developed contact monitoring systems to identify potential infection pathways. Geo-location data in Israel [16], for example, were used to classify people in close ties with established carriers for viruses, and the immediate isolation is done by sending them text messages.

(c) Semi-autonomous robots and robotics are deployed to supply food and medicine, clean and sterilize, assist doctors and nurses, and distribute equipment for hospitals' urgent needs.

The results are collected from various viewpoints of the healthcare sector, which contain improved health and financial care. In addition, proposals and crucial elements for executing AI methods in healthcare detection with AI-assisted DTM and ML support are provided (Table 2). It is stated that implementing AI in healthcare can minimize costs and simultaneously give better results than the commonwealth effect.

Table 2: Application and advancement of AI tools in clinical settings and its practical DTM challenges in Healthcare

Challenge	Challenge

Integration of workflow	Recognize the social, political, cognitive, and technical elements and incentives that affect the incorporation of AI into healthcare systems.
Improved ability and interpretability	To upgrade the incorporation of AI into healthcare systems, consider what is to be explained and the techniques to guarantee all members' understanding of the healthcare professional.
Educational workforce	Promulgate education-related programs to let clinicians know about AI/ML techniques and enhance the excess workforce.
Omission and regulation	Techniques to evaluate algorithms and their influence by considering the accurate regulatory mechanism for AI/ML approaches.
Identification of problem and prioritization	List health care and public health's various domains where AI/ML could be modified, highlighting intervention-driven AI.
Clinician and patient's involvement	Make the patients and clinicians involved in prioritizing, enhancing, and incorporating AI/MI by understanding the accurate techniques and the AI/MI algorithm's potential influence on the patient-provider relationship.
Quality of data and access	Besides structured and unstructured data, it promulges data quality, access, sharing, and the complications involved in incorporating non-clinical data to implement AI tools effectively.

3. Impact of AI-based DMS in Medical Sectors to Prevent Health Crises

Partner's healthcare contributed live responses to patients, clinicians, and everyone else who had questions and concerns about COVID-19 on 9th March 2020 due to increased patient demand in Boston. The aims are to recognize and encourage the public without medical treatment and provide the most effective services, including test sites and newly-created clinics; the average waiting time was 30 *Minutes* as the hotline became overwhelmed. In order to get the patient to the precise care atmosphere in good time, we lacked resources for pre-hospital treatment [17]. The input from various zones of health crises is predicted by grouping each area into clusters, and entity condition is incorporated within the Govt. database. This DTM produces accuracy towards real-time training dataset fetching that is up-to-date in big data analytics of DMS.

Given the familiar scenario, efforts were made to refill our oxygen tiers after the second wave, but we could not get clinical admission with the scientific control protocol. While the fake human feedback drops in oxygen tiers, the professionals say that the oxygen requirement is five liters a minute, and they caution that using a concentrator without scientific steerage may be very harmful. This helps to test several patients and easily distinguish those who are affected by COVID-19 from those who may be less susceptible. We expect the AI-DTM tools to minimize patient traffic to the hotline and expand and stratify the system's management until recently inconceivable. Transferring patients with symptoms to the most suitable medical environments, including virtual emergency care, primary healthcare providers, respiratory health disease clinics, and healthcare emergency services, is underway. The Chabot will significantly help our broad suppliers as we have seen the need for regular change by using AI-DTM in our clinical triage algorithms based on an evolving environment [18].

3.1. Health Crises: Challenges of AI-DTM Real-Time Applications

AI-powered applications allow people to test the latest COVID-19, reduce the burden on health institutions, and alert people at high risk of infection worldwide and in India. Globally, the algorithms are unsuccessful in being progressed by the medical chat startups to test people and decide whether the person is affected by the disease. However, applications that make risk evaluations at home within a few minutes are also available in India. AI then uses an algorithm to analyze their details quickly, submit the assessment of risk: Zero, low, and high, and notify the closest facility where healthcare tests are possibly required. This ensures that the person must complete a comprehensive form. The main issue with epidemics is the massive incompatibility of supply and demand—an incredible demand that is short to satisfy healthcare institutions. Medius Health created Quro, and a COVID-19 risk assessment method was tested on over 70 infected Indians [19].

"Within 24 hours, we have had over 4000 hits, and the AI device was introduced in India, considering its population size and the unexpected pandemic of COVID-19. Our AI system also continuously collects these data to enable the Department of Health to understand the extent of panic among people and to direct possibly high-risk cases to early detection and prompt medical intrusion to avoid more spread," the researcher said. The risk assessment smartphone app had 64,8[illegible] visits until Thursday. There have been 28,750 hits in India.

The number of risk evaluations has risen by 32.19% daily. The recent interaction with a person suspected of having a coronavirus was inquired about their place of stay and other information such as sex, age, and race. The researchers frequently question users about the places they have been commuting to. The app examines repeated signs and duration of infections, including fever, cough, shortness of breath, nausea, sputum, headaches, diarrheal diseases, and lung inflammation [20-21].

3.2. AI: Find Drugs and Treatments on COVID-19

Though COVID-19 is still spreading worldwide, businesses and scientists are pursuing artificial intelligence to meet the virus' challenges. A variety of research projects use AI to classify medicines that have been developed to combat other diseases but now have been repeatedly attacked by COVID-19. By researching the molecular structure of existing AI medicines, companies look at those that can interfere with COVID-19 activity. In late January, the British company Benevolent AI started highlighting COVID-19-related problems. The knowledge diagram of AI will digest vast amounts of scientific and biomedical literature to start connections between diseases' genetic and biological characteristics and drug structure and behavior. Previously, the company concentrated not on viruses but on chronic diseases. However, it has upgraded to COVID-19 by presenting the latest virus study. 'We have been able to consider the more applicable ideas in biological and the current updates regarding COVID-19 themselves due to the large amount of data we have about COVID-19,' said Olly Oechsle Benevol, a software engineer [23]. Although a broad spectrum of biomedical research has been conventional over the decades to deal with chronic diseases, COVID-19 only covers several months of studies. However, scientists will use knowledge to monitor other viruses with familiar qualities, monitor their function, and then figure out which medications can control the spread of the virus.

On the cell surface known as ACE2, the COVID-19 infection was found to bind with a specific protein. It was observed that it is relatively quick. With this DTM, we can investigate something unique to COVID-19. Introducing the virus and its reproduction. This helps us look closer at the literature about various coronaviruses, including SARS [24], and any form of biology used in taking viruses in cells, said Oechsle. The device indicated various drugs, along with the most successful drug, Baricitinib, that might impact COVID-19. Rheumatoid arthritis is now approved for use. With the characteristics of Baricitinib, the process of taking the virus into the cells will theoretically slow down, and its capacity to infect the lung cells reduces.

Benevolent AI has announced the development of the investigation of Baricitinib's safety and efficacy in COVID-19 as part of the month's healing process trials by Ely Lilly and the United States National Institute for Allergies and Infectious Diseases (NIAID). Further analysis and clinical testing are done to decide whether the medication predicts the results of AI. In the next two months, the outcome of the tests is expected [25].

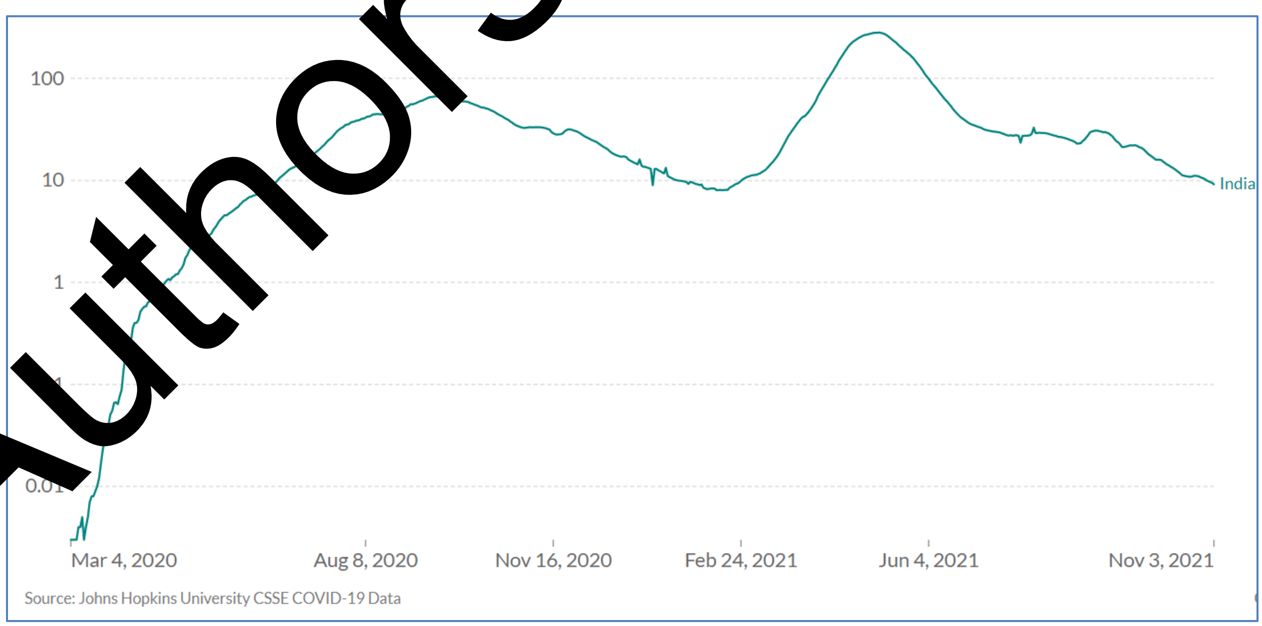
3.3. AI: Detection of Pandemic and Increase of Novel Diseases

When it was still located in Wuhan's Chinese town, one of the first to identify the coronavirus epidemic that could be seen as a comprehensive global pandemic was artificial intelligence systems. It was assumed that AI-DTM had driven HealthMap [26], associated with the Boston Children's Hospital, shortly before human researchers took up the mysterious pneumonia, but it was only classifying an outbreak as "low" in severity.

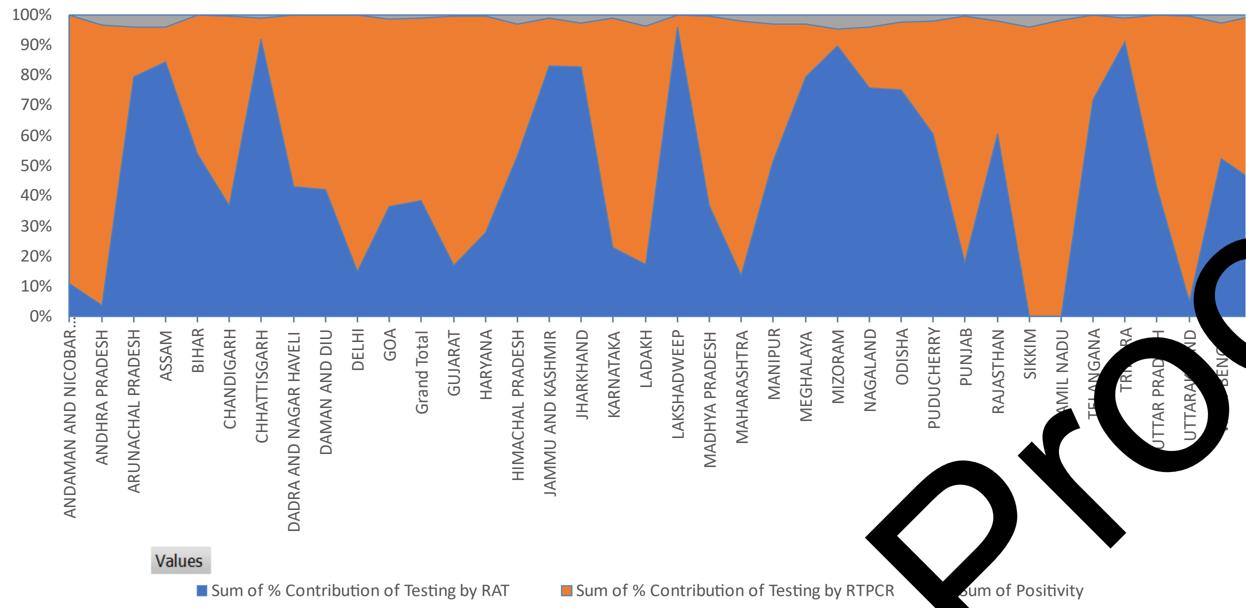
Only 30 minutes after HealthMap, Human epidemiologists at ProMed, a monitoring organization for infectious diseases, issued their warning, and Brownstein recognized the significance of human virologists for studying the virus's progression. *"We soon learned that it is easier to scrap the Internet and generate a comprehensive list of cases worldwide than taking it from a crowd. It is not just ML and web scraping that can be achieved,"* he said. HealthMap has used *"formal and informal sources"* to feed into the list of university researchers worldwide. HealthMap data have been made available, which scientists and researchers will use in their quest for relations between this disease and specific populations, including the containment phases. Data on body motions collected from the researcher have already been combined to see how people's migration and control laws have influenced China's transmission of the infection. HealthMap has managed to monitor COVID-19's transmission worldwide.

4. Visualizations of Data Related to COVID-19

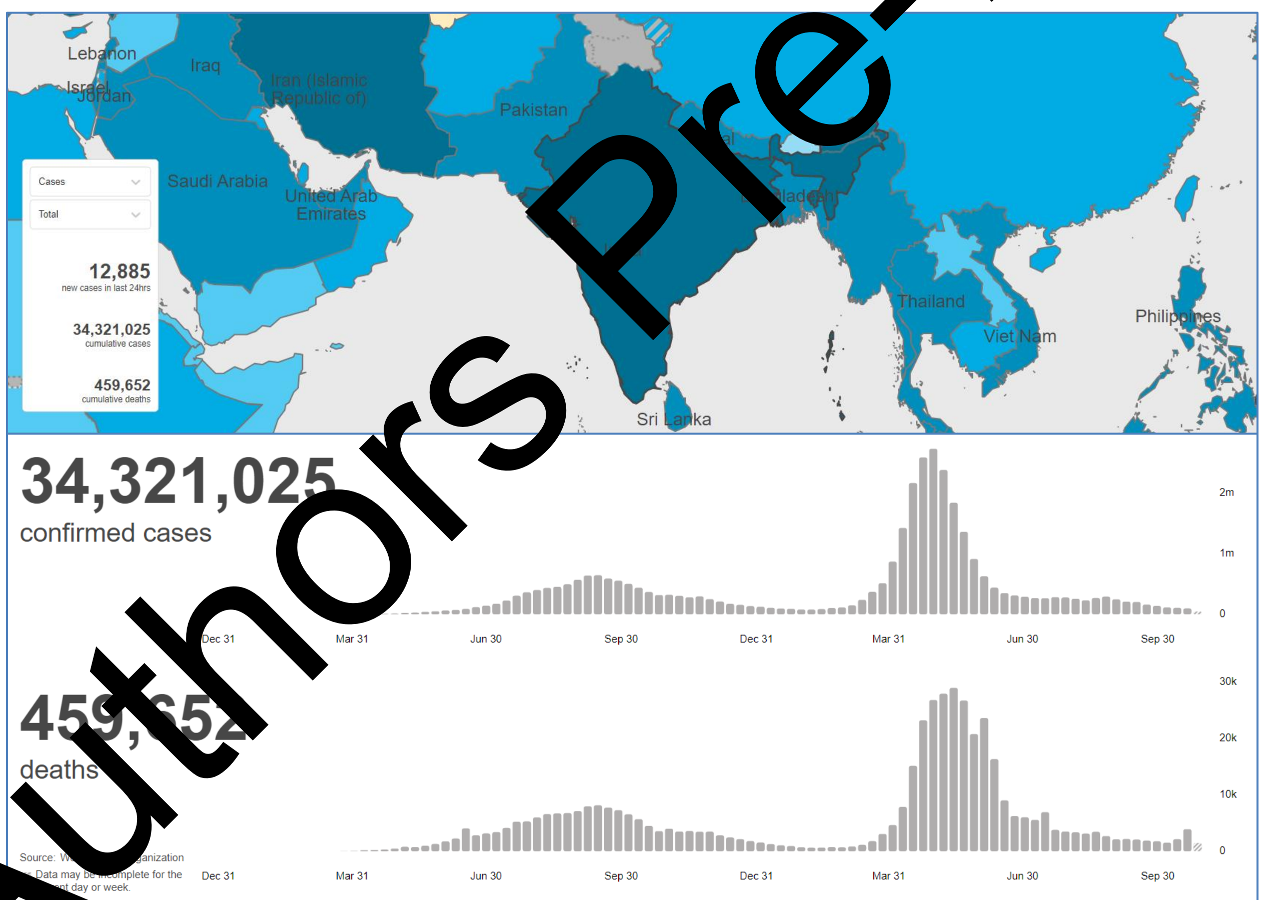
The monitoring and forecasting of COVID-19 led to a console industry to show the current and anticipated distribution. The test case analysis dashboards for COVID-19 are in Figure 3 (a), (b), and (c) [27].



(a) Day-to-Day Analysis [28]



(b) State-Wise Analysis [29]



(c) National Wise Data Analysis [30]

Figure 3: Dashboard Real-time Tracking and Prediction of COVID-19

4.1. AI-based Clinical Scale using DTM

The COVID-19 response that uses most AI diagnostic test applications has concentrated on medical analysis-based diagnosis. In relevant research, many AI-enhanced Computer Tomography (CT) and X-ray scanning diagnoses that forecast the disease's progression using patients' medical data have been used in many works. CT information is used for DTM verification purposes, and it initially takes non-invasive diagnostic measures [31].

Diagnostic medical imaging, such as Reverse Transcription-Polymerase Chain Reaction (RT-PCR) testing, constitutes the primary method for diagnosing COVID-19, but they are constrained in resources, specimen collecting, analytical time, and results. Therefore, more interest is shown in numerous other diagnostic techniques that apply medical imagery to test and diagnose COVID-19 cases. This is mainly because COVID-19 has radiology and image patterns identified in medical imaging, but it remains time-consuming to identify these patterns, even for professional radiologists. As a result, the candidates for lung CT and X-ray scans in COVID-19 patients are key for ML that may improve these human body scans' study, even if they would use the imagery to confirm the diagnosis (Figure 4).

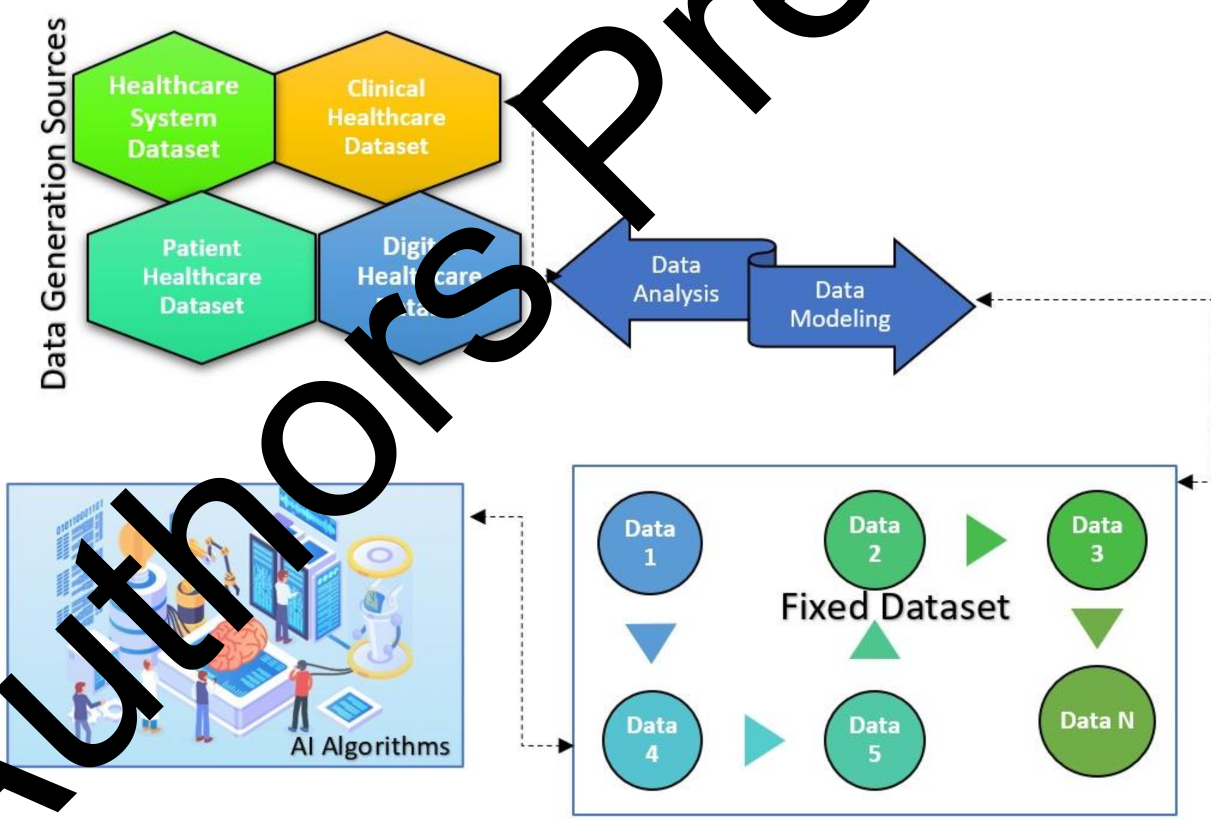


Figure 4: The Process Flow of Data in an AI-based DTM Empowered Healthcare System on Health crises

4.2. Non-Invasive Imaging for AI-based COVID-19 Detection Procedure

Some original methods in which redundant advanced medical imaging instruments to diagnose and monitor COVID-19 are also available. One research has been used, for example, a GRU neural network in Kinect's profound cameras for classifying the respiratory patterns of patients qualified in the footage, based on new observations that lung patterns illustrate COVID-19 by mapping, particularly tachypnea. Although these irregular breathing habits are not generally associated with the actual COVID-19 diagnosis globally, tachypnea identification may be a significant diagnostic function in a first-order way to detect potential patients in a broad-scale manner. Inventive studies attempted to recognize the support of wearable device data rendered to COVID-19 monitoring, which is performed based on clinical trials showing the importance of additional heart rate signals from intelligent virus surveillance watches. The primary motive of cloud providers in the healthcare sector is to provide hybrid servers to balance the data set of the ever-changing world. The risk has been initiated in the healthcare sector, and cloud providers are appropriately in danger for balancing risk factors in the present condition.

4.3. Patient Outcome Prediction by AI

Predicting future health outcomes during the COVID-19 pandemic is overly extended health systems that are essential for the preparation, planning, and implementation. The factors that facilitate people who require hospitalization, Acute Respiratory Distress Syndrome (ARDS) outbreaks, and deaths caused by shortage of breath are essential to be recognized. Several recent papers suggest triage diagnosis and high-risk patients' management, and later, they take the risk of further developing ARDS based on the characteristics of patients' healthcare information and blood tests reported in this vein. These methods seek to define the key observable features to prevent death, which can be checked in the Hospital after receiving the medication and during hospitalization; there are various procedures, including the XG-Boost algorithm and SVM. Lactic (LDH), lymphocytes and high-sensitivity C-Reactive Protein (CRP), Alanine Aminotransferase (ALT), myalgias, and hemoglobin are clinical indicators associated with these ML-driven methods, but further study is necessary to identify certain thresholds and ranges of such indicators like Interleuchin-6, Systolic blood pressure, and the Monocyte ratio.

4.4. Potential to Contribute to AI -Treatments and Cures

AI was praised for its capability to contribute to the latest discovery even before the COVID-19 epidemic. In COVID-19, many research laboratories and data centers have already reported the deployment of AIs for diagnosis and a COVID-19 vaccine. The hope is for AI to speed up the development of new medicines and renovate existing ones. For instance, Google's DeepMind, a well-known game-playing algorithm for AlphaGo, utilized AI Technology to improve the design of virus proteins that could help to develop new medicines. Furthermore, this study stresses that the observations of these processes are not experimentally tested or that the precision of test techniques is not assured, as DeepMind said on its web page. AI, with DMS assistance and ML, provides various healthcare supports to address the challenges and healthcare crises along with the disruption of DTM in every healthcare industry. This increases healthcare organizations' demands for earlier detection and provides more precision and personalized care for necessary treatments.

4.5. AI Support for Social Organization

AI has maintained the pandemic by implementing thermal imagery to avoid physical contact and lockdown metrics, which are used to inspect public areas and persons possibly contaminated. In the South China Morning Post, infrared cameras check people's gatherings for high temperatures at transport hubs and railway stations throughout China. Typically, they are used in a face detection system to determine whether they wear an operating face mask at high temperatures.

4.6. DTM-AI on Recent COVID 19 Study

COVID-19's propagation extends organizational systems in and beyond healthcare. There has been a massive shortage of face masks, hand gloves, ventilators, and hospital emergency care capacity in ICU beds. The point is obvious and disturbing: our financial and healthcare systems tackle steady sequential demands while COVID-19 is dramatically growing. Our national healthcare system can never maintain this potentially toxic demand without any of the new business model's rapid and wide-ranging roles. We can significantly improve our effective responses by DTM by taking as many steps as possible to mitigate the infection's transmission. That's because the death rates at which we train people, arrange, and employ human resources are limited by traditional processes — that depend on people working on the critical signal processing route. Also, traditional methods produce declining returns on a scale. DTM, on the other hand, can be expanded at almost endless rates without such constraints. Computer power and storage capacities are highly theoretical bottlenecks — and we have many of these. Exponential growth can continue at the pace of AI systems. More crucially, public healthcare AI must be compensated with an ideal age for the final decision-making to ensure the best possible patient care. In the majority of cases, the substitution for AI can never be human clinical reasoning and DMS; instead, the improvement of human efficiency and effectiveness can be made by AI, which is a DMS aid [27]. Other manufacturing industries have been lagging behind the DTM in healthcare.

The untapped opportunities for personalizing rapid growth in maintaining patient healthcare records required transparency, reports without replicability, and consideration for potential ethical concerns with clear demonstrations of practical outcomes, which are the best guidance in this real-world research investigation. Today, our public reaction to COVID has accelerated the adoption and scaling of virtual and AI devices. The quick and decisive digital modifications are used to address the growing threat of COVID-19, from Providence's AI bots and public healthcare partner organizations to hospitals. We hope and expect that in the future following the settlement of COVID-19, we will have improved healthcare DMS.

5. AI Research Challenge of Dataset on Health Crises

5.1. Data Access and Control by Big Data

The wrong models will result from big data, remembering the old proverb “garbage in, garbage out.” Hyping AI as something magical, capable of learning without bothering about the inputs, is a tendency. Practically, the choice of the model’s particular mathematical formulation is always trumped by the choice of data.

The resulting interest (for example, the death rate of inpatients) and the extraction process are to be explained in a replicated way while selecting the data for any model ML practices. There should be a truthful definition of the time taken for the observation and recording of the result vs the time it ought to be anticipated in case of the involvement of any time-series data (Figure 5). The learning of the ML model, i.e., the observation window and the time required from the anticipation, will be added using the data window.

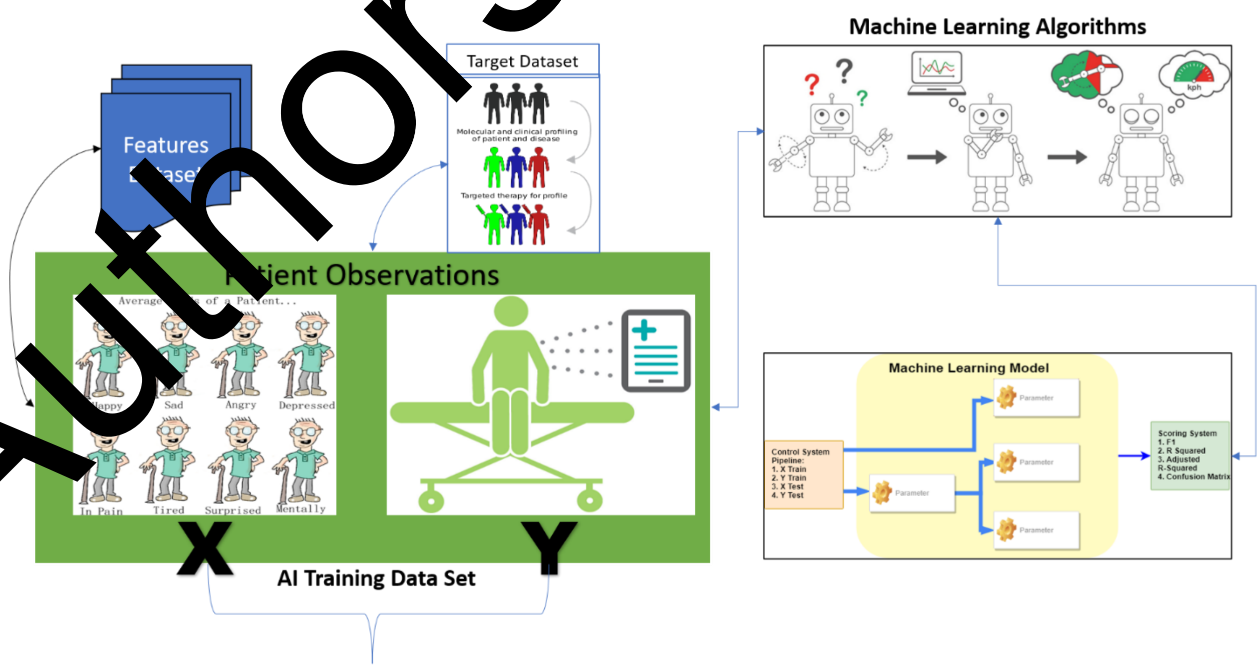


Figure 5: AI-based ML Model for DTM

A map from input (X) to output (y) is a model, which is a mathematical function. The accurate data generation function $f(x)$ is anonymous, and that being tried at different fidelity levels is assumed to exist.

In general, such technologies require access to mobile data, including GPS. It is vital to develop a framework that is as effective as possible in regular practice during the instrumental development. Close coordination among the authorities, telecommunications operators, high-tech industry, and research institutions is necessary. High-tech companies can provide the tools, leading universities and telecom companies can provide access to personal data, and the authorities must ensure that data sharing complies with privacy laws and that there is no risk of misuse of individual data. PubMed Central, bioRxiv, medRxiv preprint servers, and the WHO COVID-19 database are published in the collection. CORD-19 is free to download, and it is updated daily or weekly. It is available free of charge. The group now includes over 128,000 publications on the disease, COVID-19 and SARS-CoV-2 virus, and re-related coronaviruses (with more than 59,000 full texts as of 26th May 2020). It appeals to the AI community to develop AI techniques to provide new insights to support the combat against COVID-19. A series of tasks, such as some questions in research questionnaires, have informed us of this call for action.

5.1.1. Research Questioner (RQ)

RQ 1: What is meant by propagation, hatching, and biodegradability?

RQ 2: Are we aware of the risks of COVID-19?

RQ 3: Are we aware of viruses' genesis, origin, and development?

RQ 4: What do we know about therapeutic agents and new drugs?

RQ 5: Which medical care was published?

RQ 6: Are we aware of non-pharmaceuticals?

RQ 7: What did we understand about monitoring and diagnostic testing?

RQ 8: What was reviewed on factors of social and ethical sciences?

RQ 9: What has already been a shred of complete evidence for optimization and flow of information?

5.2. AI-Powered Search Tools

While evaluating the massive quantities of COVID-19 data, many of them have been collected (*e.g.*, CORD-19 Dataset, COVID-19 cases, hospital data, and case statistics) to represent an enormous challenge of how AI-based search tools like WellAI and Allen Institute for AI

(SciSight) can be supplied with this big data problem. Compared with conventional search engines, there are many advantages of IA-powered tools that utilize NLP (Table 3).

Table 3: Assessment of ML based on NLP and a usual search engine

Assessments	Powered Search Tools NLP
Common Objective of AI	Networks synthesize, generalize, and predict relationships
Correlated Concepts of AI	For instance, it compromises acronyms and associated ideas that "high blood pressure" is synonymous with "hypertension"
Outcome of AI	Conceptual focus and exploration of relationships not only between concepts but among concept clusters (*e.g.*, COVID-19+diagnostic, Clinical + Diagnostic Tests, and Radiology)
DTM Example	Starting the concept "COVID-19," "Review Articles" for the "Diagnosis Clinical" selection provides a list of articles in which ML models with DTM have identified an association between COVID-19 and medical treatment rather than just the list of publications that refer to the COVID-19 as well as the therapeutic diagnosis.

5.3. Clinical DMS

Many gamut applications designed to make clinicians vigilant to crucial details are aided by CDMSS, and proposals help with different clinical activities that include a prediction. CDMSS has been sufficiently used as rule-driven alerts for more than twenty years, such as cues for vaccination or warnings using comparatively easy Boolean logic based on the publication of risk indices, which frequently change in time, for example, the Framingham risk index. The much-established knowledge-based applications that manage enduring situations like hypertension are the basis of more extravagant systems. Again, with advances in computer science, including NLP, ML, and AI programming tools like case management, notation, business process modeling notation, and correlated situations, modeling and monitoring complicated clinical processes become feasible. The systems devise appropriate advice for decisions and treatment recommendations with significant information about providers and patients. The enhanced search and analytical skills, which could furnish information like the previous patient's outcomes, who are the same as those getting several treatments, may be included in other applications. AI/ML analyzes EHR data from approximately 250 million patients to determine the most successful second-line hypoglycemic agents.

5.4. AI-based Digital Navigator of COVID-19

The COVID-19-related DMS is used in our citizens' professional and personal lives without justification. The go-to-market method in the new drug was also interrupted. Interactions in individuals have stopped and are now "digital-first." Worldwide, the COVID-19 epidemic presents unparalleled difficulties and uncertainty. A digital transformation army has been mobilizing at Startup Health to tackle this international health crisis. COVID-19 Navigator was established to centralize remedies, resources, news, and articles, quickly bringing businesses, shareholders, and partner organizations together in Figure 6. The market model shows digital data retrieved from various government sectors to analyze how many persons are affected and how many are affected by time.

Figure 6. Go-To-Market Model in Health Care [31]

5.5. Effectiveness of AI + DTM for Healthcare

The techniques include an AI video-oriented, spoken autonomous robot and an AI assistant with DTM used on any COVID-19 staff Smartphone to enhance and simplify healthcare professionals' duties within COVID-19 divisions. It also involves new technologies that provide physicians with periodic and non-contracted patient access to vital heart rate, respiration rate, and ongoing patient control. A Continuous Protection Disinfectant (CPD), a 12-hour active and persistent disinfectant, is essential to secure the surface from new contamination attacks. It seems to have a non-intrusive remote monitoring system that helps screen suspected COVID-19 patients' pulmonary measures preliminarily and retrieve patients. Ultrasound AI-based software with digital mapping has been explicitly built to combat COVID-19, according to the release of the All India Institute of Medical Science (AIIMS).

5.6. AI Classification

ML and NLP use Deep Learning (DL) frameworks for method recognition, justification, and predictive analytics. Recently, NLP has become more concerned with classifying the source context, particularly in text processing and four types of viruses. The four virus classes are COVID, SARS, ARDS, and COVID/ARDS. The text is labeled in these categories by different ML Algorithms. The ML algorithms have been used, including the SVM, MNB, LRT, DT, SGB, and RF (Table 4).

Table 4: Comparison of AI algorithm for Data Classification Support for Health Crises

Type of ML	Algorithms	Performance of Data Collection
Classic	SVM	• SVM in multiple categories for classifying text data. • The hyperplane serves the purpose of the classification.
	MNB	• Using the Bayes rule, MNB predicts the target class of a particular text.
	LRT	• This method computes the class of statistic variables based on their relationship to the label. • In general, the algorithm estimates the probability of membership.
	DT	• An additional classification technique converts the input space into regions and autonomously classifies each continent. • The area is divided recursively by the input data and labeled at the base of a tree. • The text is classified into four categories by the leaf nodes. • A vital feature known as the distance measure is needed when building an RF. • The schematic structure on how to address gaps for the maximum capacity.
Ensemble	RF	• The bootstrap aggregation technique was used to train the RF. • The aggregate forecast may be decided by assessing the evaluations of all specific RTs. • A public vote shall be considered in the case of a DT. • This model utilizes an amended method to obtain and divide a subset of random features into each training practice.

SGB	• This method allows for greedy trees from training dataset sample data to be produced. • It mitigates the gradient boosting cause and effect relationship between the tree branches.

6. Performance of Training Dataset on AI with DTM

6.1 Descriptive Data

The clinical features of the patients that require descriptive statistics are shown in Table 5. Men (50.1%) were the prominent participants in the study sample (2000 patients with COVID-19) with an age of approximately 55 years, and (49.9%) of the majority of patients were white. Figure 7 presents the comprehensive descriptive statistics for all variables.

Table 5: Descriptive data of the Clinical Features of the Test Cases

Parameters	ICU	Ventilation	Death
Age Group (Years)	64.10	66.18	75.18
BMI	29.19	[illegible]	28.15
Height (cm)	145.19	[illegible]	154.26
Male (%)	55.10	[illegible]	50.44
Female (%)	44.90	35.10	49.56

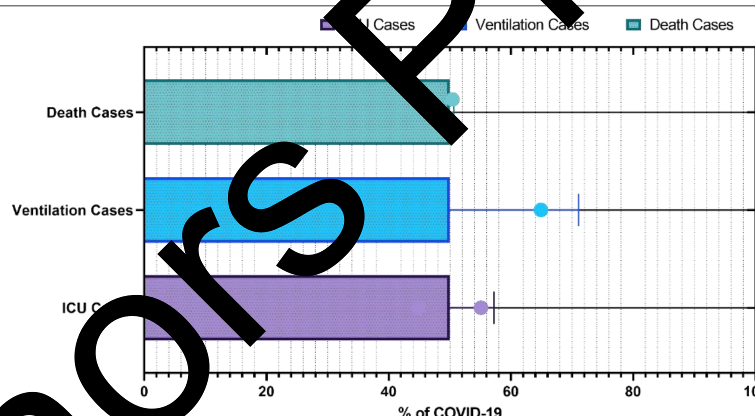


Figure 7: Graphical view of Test Cases

6.2. ML Algorithm's Performance with DTM

For three negative prognostic outcomes, the predictive performance of the ML algorithms was assessed: ICU (T=1000, 55.5%), Ventilation (T=400, 10.5%), and Death Ratio (T=600, 34%).

First, the baseline for comparison is attained for an exclusive individual outcome like death cases by evaluating the ML with DTM predictive performance. The aggregated model is trained using patient observations with the other two outcomes: ICU, Ventilation, and Death

Cases. The performance is tested in the aggregated model when the acute result not consistent in training (*e.g.*, Death Cases) is predicted. Under the receiver operating characteristic curve, the performance of the two strategies is compared, for example, individual as against aggregated models, by applying the 96.19% confidence interval of the area.

The models trained with the aggregated outcomes and single output ML models are shown in Table 4. Invariably, the test set with an AUC over 0.91 of each predictive performance is presented with ML in the DTM model for even those trained with distinct outcomes. With AUC over 0.961, 0.951, and 0.981, respectively, predicting the ICU, Ventilation, and Death Cases, the individual models performed better Area Under Curve (AUC) than the aggregated models. Within the 96.17% confidence intervals, there is a difference in the aggregated and individual ML models.

The ML had high sensitivity and specificity in many cases, above 0.89 with 0.93 average sensitivity and 0.84 specificity. When the Ventilation and ICU cases are predicted to attain 0.418 and 0.747, respectively, the aggregated models' accurate values were more than the individual models. In comparison, there was a dip of 0.31[illegible] in Death. This indicates that while predicting the patients, it is found that they are the victims of acute ailments and need hospitalization than the individual ML. For each ML, the ultimate hyperparameters are presented in Table 6.

Table [illegible]: Predictive Analysis of ML

ML Algorithms	Cases	AUC	Sensitivity	Specificity	Precision	F1-Score
SVM	ICU	0.93[illegible]	0.901	0.809	0.935	0.831
	Ventilation	0.961	0.951	0.783	0.950	0.858
	Death	0.911	0.914	0.792	0.931	0.891
MNB	ICU	0.915	0.911	0.878	0.917	0.821
	Ventilation	0.941	0.941	0.751	0.935	0.813
	Death	0.921	0.978	0.778	0.967	0.871
L[illegible]	ICU	0.944	0.913	0.819	0.981	0.801
	Ventilation	0.931	0.941	0.741	0.962	0.873
	Death	0.914	0.967	0.775	0.971	0.841
DT	ICU	0.935	0.914	0.819	0.981	0.821
	Ventilation	0.914	0.945	0.724	0.961	0.831
	Death	0.927	0.951	0.751	0.974	0.858
SGB	ICU	0.961	0.911	0.878	0.985	0.891
	Ventilation	0.941	0.931	0.756	0.962	0.857
	Death	0.947	0.951	0.764	0.991	0.878

	ICU	0.951	0.901	0.891	0.991	0.819
RF	Ventilation	0.924	0.928	0.731	0.973	0.849
	Death	0.931	0.961	0.745	0.981	0.861

The ML classification tool supports a few libraries, such as NLTK STOPWORD, to enhance the complete ML pipeline's precision. Better results were collected after data analysis. We have 1000 clinicians' spread of infection findings labelled in four classes. The classification was experimented with ML by presenting training data collected during the dimensionality reduction step. The result is a comparative study of all standard ML methods and evolutionary algorithms to classify the clinical text into four classes. We can conclude that there are enhanced performance possibilities if more data are made available for ML algorithms. This study experiences a significant challenge in identifying the viral disease, and our research will benefit society by reviewing the clinical findings and taking measures.

6.3. Machine Learning

With the trained data of 65% and evaluated in the other 35%, the well-known ML models for structured data like SVM, MNB, LRT, DT, SGD and RF are used for simulating new anonymous data. This study consists of all the results attained from the test set. The hyperparameters with Bayesian optimization (HyperOpt) were adjusted using the K-fold cross-validation with ten folds. The random selection of examples from the predominant class performs the random under-sampling in the training data set for exclusion because of the unstable nature of the outcomes (Figure [illegible]). There is a rejection of variables with a correlation of more than 0.90, and the missing values are attributed to the median. Measures like Specificity, Sensitivity, AUC, F1-score, and Precision were investigated to evaluate the ML's performance. The best model is selected using the AUC value. The respective Shapley values of each variable were calculated to understand the contribution of each variable to the predictive models. The Python Tool was used to perform all the analyses with the Sci-Kit-learn library.

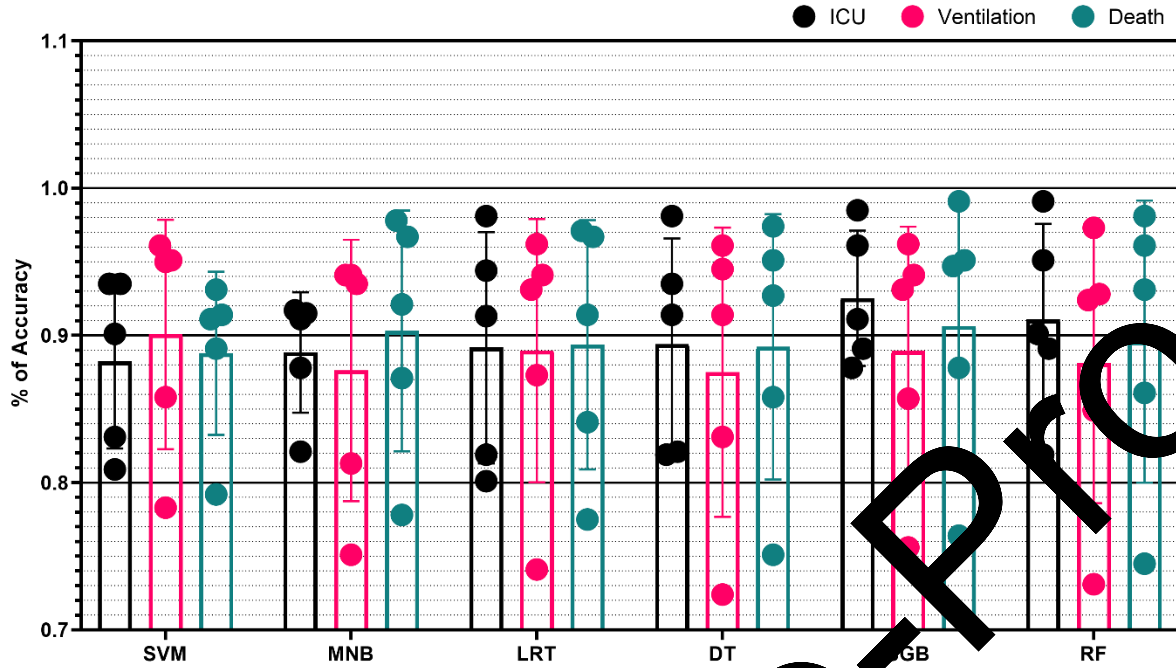


Figure 8: Performance Analysis of Various ML Models

7. Conclusion and Future Work

The world has been surprised by the lack of readily accessible COVID-19 vaccines/drugs. Consequently, the above quick scan of the current *state-of-the-art* shows that "AI systems with Digital Transformation Mapping are still in the beginning stages, and it is time before the outcomes of such AI actions can be seen." This paper demonstrates that AI-Assisted Decision-Making Systems can support the Health Crisis (COVID-19) reaction in many areas. Researchers have reflected on emerging pharmaceutical research and development applications, diagnosis and prediction of clinical outcomes, Epidemiology, and Infodemiology. We have selected 500 clinical reviews in the four classes: COVID, SARS, ARDS, and COVID/ARDS. It provides training information to enable AI/ML models to operate better and manage the pandemic-threatening human life and the economy. The complete and accurate quarantine and mitigated countries' responses could provide an overview of other countries still confronting a massive increase in specific cases.

To achieve better performance, more feature selection is expected, and a Deep Learning framework is adopted.

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Availability of Data and Material-Not applicable

Code Availability-Not Applicable

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