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THE ROLE OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE: APPLICATIONS AND CHALLENGES AFTER COVID-19

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Abstract- The COVID-19 outbreak served as a stark reminder that the global community is not fully prepared for pandemics. In order to effectively deal with potential future health risks, such as diseases that might be more lethal and widespread than COVID-19, strong and adaptable health systems will need to be built. The provision of relief by the government in the form of aid for healthcare and contingency planning becomes a source of delight in light of the insights gained from the present predicament. The advancement of general healthcare as well as the identification and control of epidemics might benefit significantly from the use of AI. The use of artificial intelligence (AI) in healthcare has expanded more rapidly in recent years as a direct result of the pandemic; yet, there are still a great number of challenging issues that need to be handled before the approaches can be used in real-world contexts. It is imperative that the World Health Organization's Department of Health Research and Technology, which is in charge of digitizing COVID-19, be established in order to provide assistance to nations whose levels of digital development differ greatly. The World Health Organization (WHO) is dedicated to assisting nations in the use of these cutting-edge technologies in order to improve the ability of health systems to respond to outbreaks and prevent future ones.

Keywords: artificial intelligence, healthcare, COVID-19.

1. INTRODUCTION

The broad COVID-19 epidemic presented new challenges for healthcare institutions and practitioners. The government was forced to make challenging judgments about how to distribute its limited resources as the epidemic quickly spread and personnel became scarce [1]. Machine learning, often known as artificial intelligence (AI), has swiftly gained ground as a major player in the fight to modifyexisting healthcare systems to comply with COVID-19 criteria. The most efficient options for patients' treatment requirements have been available thanks to a number of unique models, from diagnostics to medications to logistics. Sadly, just a few of these ideas were put into action, and nobody really appeared to give a damn about any of them. [2][3].We argue that key institutional, technical, and ethical issues must be resolved if AI is to meaningfully improve clinical care. These weaknesses have been made apparent by the COVID- 19 pandemic. Similar to how intelligent individuals extract meaning from data and methods, artificial intelligence (AI) does the same, turning information into useful insights and results. In the realm of medicine, artificial intelligence (AI) has started to be used infields like drug discovery and the modeling of complex biological systems. Despite the apparent ease of the issue, efforts to integrate AI into routine clinical care have mostly failed. Enhancing patient itineraries, making the most use of available resources, and choosing when and how to allocate funds are all included in this.

We think that the initial data's characteristics, how easily they appear, and the social context in which they occur are what causes the interpretation gaps, which were made worse by the COVID-19 epidemic. It's critical to comprehend how these factors affect the effectiveness of AI in order to properly prepare healthcare systems for catastrophes.

2. ISSUES WITH DEVELOPMENT

An AI model requires a large number of slightly elevated data points in order to detect patterns from observations and convert them into an analytics model for prediction. The COVID-19 pandemic revealed significant gaps in institutions' ability to provide data using standardized methods that can be quickly used in AI model development. Strange events, such as the outbreak of a pandemic, might prevent vital data from being readily accessible inside a single institution. If researchers are working across organizational, regional, or national borders, they may be forced to choose between vast datasets containing fundamental data and smaller datasets with considerably more targeted data, compounding already challenging decision-making processes. It might be difficult or even dangerous to develop an AI model without collecting the right sort and amount of data. If the phenomenon under study is uncommon, coordination among institutions may berequired to facilitate the application of AI models. For example, at the outset of the pandemic, there were so few COVID-19 patients at so few institutions that it was impossible to collect reliable data about particular routesand outcomes. [4] [5] Traditional medical research methods, which include pooling patient data from several facilities in order to create larger databases, are impractical owing to substantial ethical and regulatory difficulties. There are a

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number of novel approaches offered by AI that may help with this problem. Few-shot learning is a method for formulating predictions based on a small number of samples in order to generalize about unobserved phenomena using easily available data (e.g., historical knowledge).
For instance, a COVID-19 detection model may be developed with a very minimal set of training instances. However, federated intelligence [6] takes a different tack, emphasizing the free flow of ideas across companies rather than data. Using this strategy, information may be sent securely without compromising any private details. [7] Different operations, such as data harmonization, must be technologically prepared to be put into action during a health emergency.
To achieve effective generalization, it is not sufficient to simply ensure that AI models have been trained on a large enough sample of high-quality training data. Some institutions may use the term "urgent" to refer to a different kind of treatment than others, for example hospitals. Modern studies have focused on trying to build models that can take these differences into consideration. [8]These problems are exacerbated by the need to translate ideas across languages and by the fact that patient demographics and technological capabilities vary among regions. In certain cases, low- income nations may not be able to benefit from AI, while in others; they may need specialized knowledge transfer tacticsdue to disparities in available resources. Since federatedlearning allows for local training of a model's components, it may enhance the generalization of models. Some rather general AI approaches should be compared to institution- specific tactics in terms of performance trade-offs. Undoubtedly, the overarching solution to the issues discussed above will be more cooperation and information exchange among academics building models for treating patients. In August 2021, 27 models for the onset of illness were found by a live, systematic investigation of artificial intelligence systems for COVID-19. [9] In March 2021, researchers used chest computed tomography and active magnetic resonance imaging to reexamine 62 previously published studies in an effort to predict the course of the COVID-19 illness. [10] Both investigations found methodological flaws and concerns about bias in almost every inquiry, and they linked this at least in part to a failureto collaborate.

3. ADOPTION AND DEPLOYMENT REQUIREMENTS

If AI researchers really want to have an impact, they need togo beyond just building models and start looking at how their work might be implemented immediately at the bedside in a helpful and ethical manner. To be effective, this method requires a more holistic perspective that ensures communication with healthcare practitioners, adherence to ethical norms designed to safeguard patients, and the adaptation of current methods in light of and in deference to expert knowledge. Without applying their results to real- world clinical settings, researchers run the danger of creating systems that are hazardous, difficult to use, or ineffective. One difficulty is modernizing healthcare systems to allow for trained AI models. It may be necessary, for instance, to couple diagnostic models with picture storage and dictation systems in order to identify long illness at an early stage.
Artificial intelligence must be held to the same rigorous ethical standards as any other technological advancement.[11] For example, researchers have discovered unintentional racism in US care recommendation systems [12][13].Accelerating the development of AI models may lead to greater inequity both within and between countries. The CONSORT-AI expansion for clinical trials [14] and the continuous development of TRIPOD-AI for making recommendations have greatly aided the progress of guidelines for AI techniques. [15] Introducing new criteria like these will increase reproducibility and openness.
There has to be a two-way flow of useful information between researchers and doctors before this technology may be used in therapeutic settings. The potential impact of AI inhealthcare is growing, so medical schools may want to include data science and machine learning in their curriculum. [16] In the meanwhile, researchers may gain a deeper understanding of healthcare needs and steer clear of "black box" solutions wherever feasible. This calls for a shift in strategy, one that includes creating AI models that are easier to comprehend [17][18][19].In order to increase the acceptance and usage of AI models, it is important to collaborate with clinicians to develop models that supplement clinical judgment rather than try to replace it. It is important for academics working on AI to include new techniques in healthcare decision-making when it is warranted. Gaining the trust of patients is crucial at every stage of the research and rollout of AI in healthcare. This requires focusing artificial intelligence (AI) research on patient needs and addressing legitimate worries that AI would only serve to exacerbate existing inequalities in healthcare. [13] One important step toward this goal is taking part in inter- and multidisciplinary research to learn about patients' experiences across demographic boundaries such as age, socioeconomic position, race/ethnicity, and health. Developing legislation that may regulate the development, production, deployment, maintenance, and oversight of AI in dealing with patients would need consideration of several perspectives.

4. ENABLING ROBUST, ADAPTABLE, AND ETHICAL AI AT THE BEDSIDE

Due to issues with research, technical challenges, and the surrounding regulatory framework, artificial intelligence hasnot yet developed a single widely used solution for the bedside treatment of patients on COVID-19. This is not an example of a catastrophic industrial disaster. There is still a lot of work to be done before solid groundwork can be laid for AI implementation in hospitals [20]. By thinking about the research of other academics and the whole technical and decision-making context in which their ideas will be deployed, AI

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experts may obtain a more complete understanding of the problems they are trying to tackle [21]. For this reason, it may be beneficial to network with other researchers in addition to physicians, nurses, hospital staff, and patients in order to determine the best areas to concentrate research efforts. During a pandemic, these aids may hasten research and serve as a quality control measure [22].
Accurate criteria are essential for the development and use of AI. Establishing clear regulations for the use of AI in healthcare requires a thorough understanding of the requirements and values of all parties involved, including patients, caregivers, and hospital managers [23]. Thus, it is crucial to develop binding criteria that account for the different stages of AI model evaluation. After these principles are established, modeling approaches may be developed and implemented [24]. This intellectual, technical, andpolicy basis will require a long time and a great deal of effort to build, but progress has already started in this direction [25]. Researchers in the field of artificial intelligence are well aware of the need to develop new instruments that may facilitate the application of their results in clinical practice and have begun to shift their focus away from individual studies [26].

5. AI SYSTEMS THAT CAN BE USED IN HEALTHCARE

Intelligence enhancement relies on a number of distinct technologies rather than a single one. Despite the wide rangeof healthcare-related pursuits that these innovations facilitate, their importance cannot be overstated. The following sections provide an overview and more information on certain AI developments that are particularly relevant to the healthcare industry.

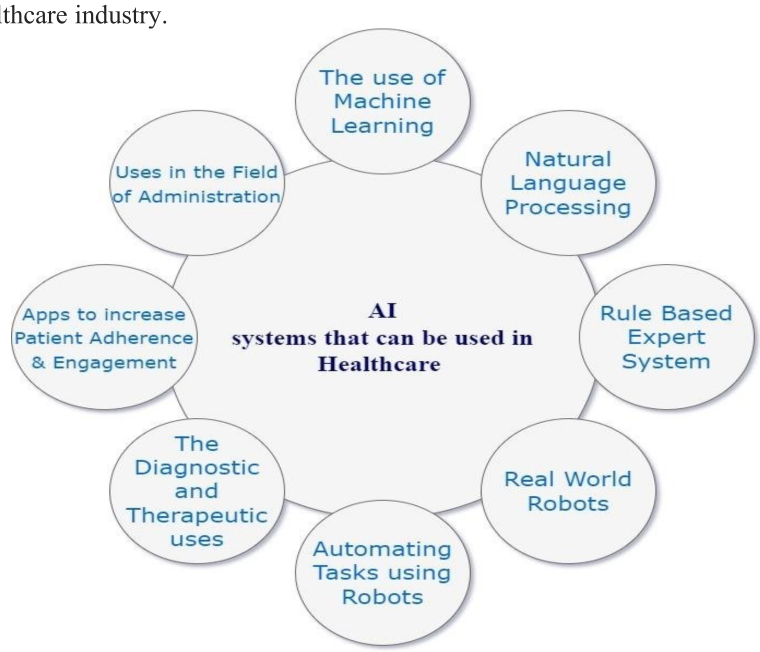

Fig. 5.1 Cycle of AI Systems for Healthcare

5.1 The use of Machine Learning

The most common use of traditional machine learning in healthcare is precision medicine, which determines which proven therapies are also most likely to benefit a patient based on a variety of patient traits and the therapeutic environment. The bulk of future machine learning and individualized medicine applications are expected to use reinforcement learning, which requires a training dataset with a well-specified goal variable (e.g., illness onset). When trying to predict outcomes, deep learning (the most advanced kind of machine learning) employs neural network models with several layers of inputs or variables. The detection of radiographic tumors that may be malignant commonly necessitates the application of deep learning. Deep learning is increasingly being used in computer-aided diagnostics, which is the study of patterns in visual information that are clinically meaningful but unseen to the human eye. Deep learning and technological frontier arewidely used methods for oncology image analysis. In conjunction with other machine learning analysis tools, they seem to improve diagnostic precision.
Natural language processing (which will be addressed in further depth below) is becoming increasingly popular as a method for automatic voice recognition. When compared to standard statistical studies, human observers often find the features of a deep learning model to be of little use. Therefore, it may be difficult or even impossible to interpret the model's predictions.

5.2 The Processing of Natural Language

Since the 1950s, understanding human language has been a primary focus of artificial intelligence study. Natural language processing (NLP) is used for many purposes, such as text analysis, voice recognition, translation, and behaviour analysis. Semantic natural language processing and statistical analysis are the two

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approaches. Improved recognition accuracy has resulted from recent developments in supervised learning neural networks and natural language processing. One must learn a wide variety of words and phrases.
For the healthcare industry, natural language processing is most often used in data production, analysis, and categorization tasks related to patients and medical literature.
Friendly AI conversation and Natural language processing systems are capable of transcribing conversations, creating reports (for instance, on radiological tests), and analysing extensive patient medical records.

5.3 Rule-Based Expert Systems

In the 1980s, knowledge-based systems dominated artificial intelligence research and found broad usage in industry. These systems were constructed using lists of "if-then" rules. In the last several decades, they've played a crucial role as "healthcare decision support" variables. Electronic health record (EHR) vendors often bundle some kind of guideline with their products these days.
Experts and information researchers in a certain field must define a set of criteria for expert systems in that field. You can get a good grasp on them quickly, and they do their job (up to a point). However, problems arise when there are a great number of rules (often over a hundred) and the standards begin to vary. Keeping up with the pace of technological development may make it challenging and time- consuming to update the legislation. More and more healthcare operations are depending on machine learning algorithms that use data analytics.

5.4 Real-World Robots

More than 200,000 physical robots are manufactured annually throughout the globe; therefore, they are now rather popular. Professionals assign them duties like lifting, carrying, welding, and putting things together, and these workers complete the jobs by delivering commodities to locations like hospitals and clinics. The ability of robots to work in tandem with humans after being taught a job makes them easier to train. In the same way that their "brains" are becoming smarter as more AI capabilities are added to them, so too are they. The intellectual progress made in several branches of AI may find its way into future physical robots.
To better view their patients, make accurate, minimally invasive incisions, suture wounds, and do other duties, surgical robots provide surgeons with "superpowers." The United States is where they first received approval. Human surgeons, however, continue making life-or-death decisions. Procedures involving the prostate, the neck, and the head are common areas for robotic surgery.

5.6 Automating Tasks Using Robots

Automated digital administrative duties, such as those requiring systems, are carried out by this technology as if they were being performed by a human following a plan of action or a set of instructions. They are easier to understand, cheaper, and less time-consuming to develop than other AI methods. Robotic process automation (RPA) uses computer programmes hosted on a server rather than physical robots to do tasks. It uses a combination of human intervention, business requirements, and a connection to the "presentation layer" in order to make data systems behave in part like intelligent controllers. They provide administrative duties in the healthcare business, including billing, prior authorization, insurance claims, acceptance, and revisions to patient data. It might be used to enter data that has been retrieved from fax photographs using other techniques, such as image recognition.
As robots develop "brains" with intelligence, RPA and image identification are becoming more intertwined, challenging long-held assumptions about the differences between the two methods. It's possible that in the future, various techniques could become so intertwined that hybrid solutions will be the most efficient.

5.7 The Diagnostic and Therapeutic Uses

Since Stanford University's MYCIN was created in the 1970s to detect blood-borne bacterial infections, researchers have focused most of their AI efforts on improving the efficiency and accuracy of both of these processes. Although there was some hope that these and other early rule-based procedures would improve the accuracy with which medical conditions were diagnosed and treated, they were not widely adopted in clinical practice. Regarding efficiency in making diagnoses and maintaining patient files, they are not vastly superior to human doctors.
Watson, IBM's supercomputer, has been getting a lot of press as of late due to its potential applications in precision medicine, notably in the detection and treatment of cancer at an early stage. Watson employs two very different forms of machine learning and natural language processing. Customers' initial excitement about this technology's application waned as they learned how difficult it is to integrate Watson into care systems and teach Watson to handle particular types of cancer. Watson is a suite of application-accessible graphical user interfaces for "machine learning and artificial intelligence" tasks such as voice and speech, images, and data analysis (APIs). Experts believe that, in principle, Watson APIs may work, but that their initial focus on cancer medications was unrealistic.
Many healthcare organizations are impacted by difficulties in using AI. Rule-based electronic health record systems are usually less accurate than more complicated machine learning-based solutions [26], despite their widespread usage, notably in the NHS. Healthcare systems based on rules often struggle to keep up with the

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wealth of information and data generated by "omics-based" approaches to treatment, such as genomics, proteomics, metabolism, and others. As our knowledge of medicine expands, they become more difficult to uphold.

While this is still more common at IT companies and research centres, this is starting to change. Practically every week, a new study emerges from a lab claiming to have found a way to use big data or AI to diagnose and cure ailments with the same level of accuracy as medical personnel. Radiological image analysis, retinal imaging, and individualized medication based on genetic data are all used to back up these conclusions. These results, backed by statistically significant machine learning algorithms, herald the facts of the present case and potential future medicine, which is generally accepted to be beneficial but raises various ethical difficulties and affects how patients and physicians interact.

Many companies have developed expertise in the use of genetic profiles for the diagnosis and treatment of certain malignancies. Since many malignancies have a genetic basis, it has become more challenging for doctors to understand all the genetic variations of cancer and related responses to cutting-edge therapies and regimens. Foundation Medicine and Flatiron Health, both of which are presently owned by Roche, are two companies that specialize in this approach.

5.8 Apps to Increase Patient Adherence and Engagement

It has long been acknowledged that the greatest barrier between bad and effective healthcare outcomes is patient involvement and adherence, the "last mile" challenge in healthcare. Participation in one's own health and treatment improves outcomes, costs, and satisfaction for both the provider and the member. More and more, organizations are turning to big data and AI to solve these problems.

Seventy-plus percent of healthcare providers in a study of more than 300 said less than half of their patients showed substantial involvement, and 42 percent said the same thing. [19]

Can AI-based skills adequately adjust and contextualize treatment if more patient engagement leads to abetter health outcome? Complex treatments are increasingly being driven by organizational intelligence and machine learning technology throughout the medical continuum. Alert messages and time- sensitive, personalized material may be the subject of an investigation.

5.9 Uses in the Field of Administration

A wide variety of administrative programmes serve the healthcare sector. While the transformative power of AI in this industry is lower than in healthcare, significant cost savings may still be realized. These are crucial in the healthcare industry since, on average, US doctors spend 25% of their working time on regulatory and administrative chores. RPA is the most likely tool to achieve this objective. It may be used for many healthcare-related tasks, such as billing, clinical documentation, claims processing, and record keeping.

6. AI IMPLEMENTATION CHALLENGES IN HEALTHCARE

By the year 2025, it is expected that AI will have a considerable impact on medical supplies. This essential skill enables the development of focused therapy, which is often recognized as a critical achievement in therapy. While early efforts at diagnosis and treatment recommendations have failed, we are confident that AI will eventually become adept in this field as well. Recent advances in artificial intelligence (AI) for image processing suggest that, in the near future, mainly radiology and pathology images will be reviewed automatically. Sound and written IDs are likely to be utilized more often in healthcare records, such as for noting patient relationships and medical histories.

Regardless of how useful the technologies themselves may be, adoption into conventional clinical practice remains the biggest roadblock for AI in a number of healthcare domains. Artificial intelligence systems need to be approved by regulators before they can be widely used. They also need to be integrated with EHR systems, organized so that comparable products operate efficiently, taught to physicians, supported by public or private payer-funded groups, and improved over time in the field.We will succeed in overcoming these obstacles, but this will take a lot longer than the technical progress itself. Therefore, we expect AI will be used sparingly in clinical practice during the next five years and then extensively over the next decade.

CONCLUSIONS

Artificial intelligence (AI) has already proven useful in several areas of healthcare, and its widespread use is inevitable. Every major player has some responsibility for making sure healthcare resources are used effectively and updated often to keep up with the industry's changing demands. Insights from current research may be used to better understand future studies on AI in healthcare, which might facilitate both study identification and response. Several AI technologies with potential medical applications have been highlighted in the academic literature, along with a research direction that has not been extensively explored. Some key areas where artificial intelligence initiatives might benefit from access to professionals with the relevant skill set are statistical analytics and knowledge-based management. Each individual patient may greatly benefit from the application of AI and machine learning to the healthcare industry. Although there may be risks associated with this invention, it might enhance medical care by facilitating quicker responses, more precise diagnoses, and trend tracking via data analysis.

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REFERENCES

[1] Khemasuwan D, Colt HG Applications and challenges of AI-based algorithms in the COVID-19 pandemic BMJ Innovations 2021; **7:387**-398.

[2] Mohta, N. S., Prewitt, E., Gordon, L., & Lee, T. H. (2021). How Covid-19 and Care Inequities Have Changed Health Care. NEJM Catalyst, 2(7). https://doi.org/10.1056/cat.21.0219.

[3] Chang, Z., Zhan, Z., Zhao, Z., You, Z., Liu, Y., Yan, Z., . . . Zhao, L. (2021). Application of artificial intelligence in COVID-19 medical area: a systematic review. Journal of Thoracic Disease, 13(12), 7034–7053. https://doi.org/10.21037/jtd-21-747.

[4] Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial Intelligence (AI) applications for the COVID-19 pandemic. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(4), 337–339. https://doi.org/10.1016/j.dsx.2020.04.012.

[5] Haleem A., Javaid M., Vaishya Effects of COVID-19 pandemic in daily life. Curr Med Res Pract. 2020 doi: 10.1016/j.cmrp.2020.03.011.

[6] Bai H.X., Hsieh B., Xiong Z., Halsey K., Choi J.W., Tran T.M., Pan I., Shi L.B., Wang D.C., Mei J., Jiang X.L. Performance of radiologists in differentiating COVID-19 from viral pneumonia on chest CT. Radiology. 2020 doi: 10.1148/radiol.2020200823.

[7] Hu Z, Ge Q, Jin L, Xiong M. Artificial intelligence forecasting of COVID-19 in China. arXiv preprint arXiv:2002.07112. 2020 Feb 17.

[8] Ai T., Yang Z., Hou H., Zhan C., Chen C., Lv W., Tao Q., Sun Z., Xia L. Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. Radiology. 2020 doi: 10.1148/radiol.2020200642.

[9] 5. Luo H., Tang Q.L., Shang Y.X., Liang S.B., Yang M., Robinson N., Liu J.P. Can Chinese medicine be used for prevention of coronavirus disease 2019 (COVID-19)? A review of historical classics, research evidence and current prevention programs. Chin J Integr Med. 2020 doi: 10.1007/s11655-020-3192-6.

[10] 6. Haleem A., Vaishya R., Javaid M., Khan I.H. Artificial Intelligence (AI) applications in orthopedics: an innovative technology to embrace. J Clin Orthop Trauma. 2019 doi: 10.1016/j.jcot.2019.06.012.

[11] 7. Biswas K, Sen P. Space-time dependence of coronavirus (COVID-19) outbreak. arXiv preprint arXiv:2003.03149. 2020 Mar 6.

[12] 8. Stebbing J., Phelan A., Griffin I., Tucker C., Oechsle O., Smith D., Richardson P. COVID-19: combining antiviral and anti-inflammatory treatments. Lancet Infect Dis. 2020 Feb 27.

[13] 9. Sohrabi C., Alsafi Z., O'Neill N., Khan M., Kerwan A., Al-Jabir A., Iosifidis C., Agha R. World Health Organization declares global emergency: a review of the 2019 novel coronavirus (COVID-19) Int J Surg. 2020 Feb 26.

[14] 10. Chen S., Yang J., Yang W., Wang C., Bärnighausen T. COVID-19 control in China during mass population movements at New Year. Lancet. 2020 doi: 10.1016/S0140-6736(20)30421-9.

[15] 11. Bobdey S., Ray S. Going viral–COVID-19 impact assessment: a perspective beyond clinical practice. J Mar Med Soc. 2020 Jan 1;22(1):9.

[16] 12. Gozes O, Frid-Adar M, Greenspan H, Browning PD, Zhang H, Ji W, Bernheim A, Siegel E. Rapid ai development cycle for the Coronavirus (COVID-19) pandemic: initial results for automated detection & patient monitoring using deep learning ct image analysis. arXiv preprint arXiv:2003.05037. 2020 Mar 10.

[17] 13. Pirouz B., ShaffieeHaghshenas S., ShaffieeHaghshenas S., Piro P. Investigating a serious challenge in the sustainable development process: analysis of confirmed cases of COVID-19 (new type of coronavirus) through a binary classification using artificial intelligence and regression analysis. Sustainability. 2020 Jan;12(6):2427.

[18] 14. Ting D.S., Carin L., Dzau V., Wong T.Y. Digital technology and COVID-19. Nat Med. 2020 Mar 27:1–3.

[19] Akash Rawat, Rajkumar Kaushik and Arpita Tiwari, "An Overview of MIMO OFDM System for Wireless Communication", International Journal of Technical Research & Science, vol. VI, no. X, pp. 1-4, October 2021.

[20] R. Kaushik, O. P. Mahela and P. K. Bhatt, "Events Recognition and Power Quality Estimation in Distribution Network in the Presence of Solar PV Generation," 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2021, pp. 305-311, doi: 10.1109/CSNT51715.2021.9509681.

[21] Rajkumar Kaushik, Akash Rawat, Arpita Tiwari, "An Overview on Robotics and Control Systems" International Journal of Technical Research & Science (IJTRS), Volume 6, Issue 10, pg. 13-17, October 2021.

[22] Simiran Kuwera, Sunil Agarwal, Rajkumar Kaushik, "Application of Optimization Techniques for Optimal Capacitor Placement and Sizing in Distribution System: A Review" International Journal of Engineering Trends and Application.

[23] G. Kumar and R. Sharma, "Analysis of software reliability growth model under two types of fault and warranty cost," 2017 2nd International Conference on System Reliability and Safety (ICSRS), Milan, Italy, 2017, pp. 465-468, doi: 10.1109/ICSRS.2017.8272866.

@2017, IJTRS All Right Reserved

[24] Kumar G., Kaushik M. and Purohit R. (2018) "Reliability Analysis of Software with Three Types of Errors and Imperfect Debugging using Markov Model" , Published in International Journal of Computer Applications in Technology, Vol 58, No. 3, pp. 241- 249.
[25] Lamba, M., Mittal, N., Singh, K., & Chaudhary, H. (2020). Design analysis of polysilicon piezoresistors PDMS (Polydimethylsiloxane) microcantilever-based MEMS Force sensor. International Journal of Modern Physics B, 34(09), 2050072.
[26] Lamba, M., Chaudhary, H., Singh, K., Keshyep, P., & Kumar, V. (2022). Graphene piezoresistive flexible MEMS force sensor for bi-axial micromanipulation applications. Microsystem Technologies, 28(7), 1687-1699.

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