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Generation AI's View on Digital Healthcare: Property Rights vs. Realities

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Abstract—

This article explores the issues of data ownership and the actual application of integrating artificial intelligence (AI) into digital healthcare. It recommends seeing each patient as a complicated data structure in order to make tailored therapy more accessible. But this raises ethical questions about marketing and privacy. The paper highlights how AI may improve healthcare by analyzing large datasets to improve diagnosis and treatment. Nevertheless, challenges remain related to prejudice, openness, and human supervision. It demonstrates the value of AI by converting MRI data to CT scans using generative adversarial networks. However, more effort is needed to ensure that AI promotes health equity. The report concludes that in order to find a middle ground between technical progress and patient rights, ongoing research and stakeholder participation are necessary. As the healthcare business embraces digital transformation, more investigation into safeguarding privacy, enhancing human-AI interaction, and reducing prejudice is vital. Medical Technology, Generation AI, Data Ownership, Patient as an Organization, and Data Security are some of the index terms.

I. INTRODUCTION

The medical field has been profoundly impacted by the advent of digital healthcare. Electronic health record (EHR) systems and other digital health solutions have led to a meteoric rise in the volume and sophistication of patient records. Every patient is seen as more than just a person; they are a complex "structure" made up of various information, and this change in perspective encourages new ways of thinking. An all-encompassing understanding of health profiles, which include genetic information, medical histories, and medications, may be attained from such a vantage point. However, it poses complications that need careful analysis, as do other complex systems. There is a fundamental tension in the current digital health revolution between the many possible benefits and the many impending problems. Personalized healthcare, which takes into account the unique qualities of each patient, has the potential to improve treatment outcomes and make proactive management of healthcare easier. By seeing the patient as an organization, healthcare professionals might potentially improve their risk assessment, intervention personalization, and decision-making abilities [1]. Keeping the patient at the center of healthcare decisions is essential for seeing the person behind the numbers.

Figure 1. Secure Medical Record on Tablet with Aadhaar Card and Anonymized Data (created with DALL·E 3 system card [2])

Data security and patient privacy are at the center of the digital health conversation. Protecting patients' personal information is crucial in this day of rampant data breaches. Some solutions have been suggested, such as linking data to national identity systems like India's Aadhaar or making the data anonymous [3]. There are certain challenges with these approaches, despite the fact that they provide strong access and security. Concerns about privacy and a loss of faith in the healthcare system are just two of the far-reaching consequences that may arise from abuse or breaches of these systems [4].

These developments have come hand in hand with the advent of AI in healthcare, which has added a new layer of complexity. Advanced AI systems are able to sift through mountains of data, which opens up exciting new possibilities in healthcare diagnosis, health insights, and the creation of individualised treatment plans. The potential for biases to originate in the training data is one of the concerns surrounding AI. By looking to mathematics and philosophy for guidance, one may find common ground with Russell's dilemma [5], a central issue in set theory that highlights the complexities and paradoxes of classification. With the growing reliance on data in

healthcare, it is essential to be vigilant about possible logical and categorical traps, especially when incorporating AI into the patient care system.
Ownership and control are at the center of the last movement of this complex symphony. More specific legislative frameworks are sought for in response to growing concerns about the commercialization of patient data and the ethical consequences of artificial intelligence. The increasing need for transparency about data ownership and use rights, as well as the concerns voiced by writers in the field of literature about AI training on copyrighted content, are striking similarities to the expectations of patients and advocacy organizations. Building legal frameworks that protect rights without stifling technological advancement is the challenge at hand. While we go further into this complex topic of digital health, it is essential to have a level head. Being alert, empathetic, and visionary are necessary for successfully navigating the complicated and exciting junction of healthcare and technology.

II. BACKGROUND

The article "Patient as an Organization" discusses how healthcare may profit from digital technologies. The significance of people actively participating in their own healthcare management is further highlighted. Compare and contrast conventional organizations with the idea of patients as organizations, and have a discussion about it. Medical personnel make judgments and patients obey orders in traditional healthcare systems, which follow a top-down model. Patients as organizations, on the other hand, stress the need of teamwork in healthcare, with patients given the tools they need to become equal stakeholders in their own treatment and decision-making. By putting patients in the driver's seat, this change encourages better health outcomes, greater patient agency, and a healthcare system that caters to each person's unique tastes and requirements.
Seeing Patients as Organizations Has Many Benefits a) The "Patient as an Organization" concept places an emphasis on patients' agency and participation in their own healthcare decision-making. Care that is patient-centered places an emphasis on tailoring services to each individual. b) Patients gain agency over their health care choices when they are seen as an organization. Promoting self-advocacy, research, and doctor-patient communication, it helps patients feel more empowered. c) Being proactive about one's health is encouraged by this. This reduces the burden on the healthcare system by encouraging early illness identification and preventative treatment. d) The importance of mental health and resilience to overall wellness is becoming more and more recognized. Patients may get assistance and learn to cope with stress via digital tools. f) Better health literacy is achieved by seeing patients as organizations. Patients are able to make more informed healthcare choices because to the widespread availability of trustworthy health information made possible by digital technology. This document is designed to be printed on standard US letter size paper.

Figure 2. Patient-Centric Health Network: Connections to Consultations, Digital Records, Monitoring, Pharmacy, and Community Groups (created with DALL·E 3 system card [2])

What Artificial Intelligence Is Doing and How It Will Change Healthcare The increasing application of AI in healthcare has been both made easier and more difficult by the rapid pace of technological advancement. The following is an overview of the key points of AI in healthcare. Enhanced Diagnosis Artificial intelligence is capable of accurate analysis of large medical imaging datasets, such as X-rays [6], MRIs [7], and CT scans [8]. This has the potential to aid early detection, leading to more accurate diagnoses in cases of cancer and fractured bones [8, 9]. AI has the ability to analyze many types of patient data, including as genetic information, medical records, and lifestyle decisions, in order to create personalized treatment plans. Potential benefits of this approach include more efficient and effective treatment. Using AI algorithms that predict how certain compounds would interact with biological targets can speed up the development of new drugs. Patients may be monitored continuously by AI-powered wearables and smartphone apps, resulting in faster medical treatment and fewer hospitalizations. Important to note when discussing long-term health conditions. C. The Pros and Cons of Artificial Intelligence in Medicine Artificial intelligence's remarkable speed and endurance in processing massive amounts of data allows it to provide more precise treatment recommendations. Healthcare staff will be able to concentrate on more complex, patient-centered tasks because to AI's capacity to automate

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repetitive tasks. The effect of healthcare staff shortages will be mitigated if this occurs. Over time, artificial intelligence has the potential to lower healthcare costs by improving efficiency and reducing diagnostic errors. By streamlining teleconsultations and enabling remote patient monitoring, artificial intelligence (AI) has the potential to enhance telemedicine and increase patients' access to healthcare. It's possible that AI systems' prejudice derives from the data they were trained on, leading to healthcare disparities. In order to achieve health equity, it is crucial to eradicate these biases. A number of issues arise when considering the application of AI in healthcare, including data protection, consent, and governmental regulation. Healthcare organizations have a special responsibility to protect patients' personal information and act ethically at all times [10]. For the time being, many AI applications remain in their early stages and need substantial clinical validation to ensure their efficacy and safety. When collaborating, AI and human healthcare providers may have trouble finding areas of agreement. There are dangers to patient safety in healthcare settings caused by both the under- and abuse of AI. Artificial intelligence systems must secure and safeguard the massive amounts of sensitive health data they use. The Marketing Use of Data (D) Concerns about the use of patient data for marketing reasons are substantial in the healthcare industry [11]. All patients want is for their medical records to be used for their care and treatment. A violation of privacy and a breach of trust may result from the improper or unauthorized use of medical records for promotional purposes. Strict laws, including the EU's General Data Protection Regulation (GDPR) and the US's Health Insurance Portability and Accountability Act (HIPAA), are in place to safeguard patient information and control its use in response to this threat [12]. Because AI may improve patient care in many areas, including diagnosis and treatment, it can cause a major shift in the healthcare system. Prejudice, concerns about regulation, and ethical dilemmas are only a few of the numerous challenges that must be surmounted. Prioritizing patient privacy and data security is essential in overcoming these challenges and fully realizing AI in healthcare.

III. PROPOSED METHODOLOGY

Medical imaging is one area where artificial intelligence (AI) has had a significant impact on the healthcare industry. While both MRI and CT scans have many useful applications, the different picture formats provided by the two technologies make diagnosis more difficult. An important step forward in artificial intelligence has been the incorporation of Generative Adversarial Networks (GANs), a branch of generative artificial intelligence (GAI). The discrepancy between MRI and CT images may be resolved by using Generative Adversarial Networks (GANs), which have a dual-network design. To improve the quality and depth of insights, GANs generate synthetic pictures that help clinicians grasp the patient's anatomy better. This integration makes it easier for medical professionals to avoid making mistakes and speed up the diagnosing process by doing away with the need for mental translation across various modalities.

Key medical imaging modalities that provide non-invasive organ pictures include ultrasound, magnetic resonance imaging (MRI), positron emission tomography (PET MRI), and X-ray-based invasives (radiation enters the body). Segmentation becomes more challenging when there are variations in topology, morphology, spatial orientation, imaging plane, and anatomical plane. It is challenging to locate border components that are connected to the same tissue structures. The region of interest might be severely limited by foggy, low-quality results caused by artifacts, sampling, noise, and image capture. It is possible for the generative model GAN to produce data points that closely resemble the originals. Two components, a "generator" and a "discriminator," are used. Send the discriminator data that is both noisy and randomly generated. At first, it was marked as fake by the discriminator, a binary classifier that had been trained on actual data. After each cycle, the generator improves the subsequent data set using discriminator input. Keep going until you reach the saturation you want. Because the false information seems and feels real, the discriminator is unable to tell the difference. Medical image processing tasks, such as image segmentation using CNN models, have been radically altered by deep learning. Decisions involving complex medical images are best handled by deep neural networks. The groundbreaking GAN model of deep neural networks is well-liked because of the many medical imaging tasks it can do. In contrast to the usual deep neural networks, GANs train not one but two networks all at once.

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Algorithm 1: MRI to CT Image Conversion using U-Net

Input: Set of MRI Images, $M = \{M_1, M_2, ..., M_n\}$
Output: Set of CT Images, $C = \{C_1, C_2, ..., C_n\}$

Initialisation:
1: Import necessary libraries (e.g., TensorFlow, imageio).
2: Define paths to the directories containing MRI and CT images.
3: Normalize MRI images:
For each image M_i in M:
$M_i\_normalized = (M_i / 127.5) - 1.0$

4: Resize MRI images to *(64, 64, 1)* and reshape them for de learning.
Model Building:
5: Define Instance Normalization layer.
$InstanceNorm\ (x) = \gamma*(x - \mu)/(\sigma + \varepsilon) + \beta$
Where x is the input, μ and σ are the mean and standa deviation of x, respectively. γ and β are learnable paramete and ε is a small constant for numerical stability.
6: Define Downsampling layers using Conv2D.
$Conv2D\ (x;\ W,\ b,\ s) = Activation\ (W*x + b)$
Where x is the input, W is the filter weights, b is the bias, *s* the stride and *Activation* is an activation function (e.g., *ReLU*
7: Define Upsampling layers using Conv2DTranspose.
$Conv2DTranspose\ (x;\ W,\ b,\ s) = Activation\ (W*x + b)$
8: Combine downsampling and upsampling layers to form t U-Net model architecture.
Training Process:
9: for each epoch *e* in range(epochs) do
10: for each batch of MRI images B_m and corresponding (images B_c do
11: Forward pass the MRI images through the U-Net mod
$Y_{pred} = U\_Net(B_m)$
12: Compute the loss between the model's output and t actual CT images.
$L = Loss(Y_{pred},\ B_c)$
13: Backpropagate the error and update the model's weigh
$\nabla L = \partial L/\partial W$ *(Compute the gradient of L with respect weights W)*
$W = W - \eta * \nabla L$ *(Update weights using learning rate η)*
14: end for
15: Optionally, validate the model on a separate set of MRI and CT images.
16: end for
Prediction:
17: for each new MRI image M_i do
18: Pass the MRI image through the trained U-Net model.
$Ci = U\_Net(Mi)$
19: Obtain and save the corresponding CT Image as output.
20: end for

The goal of the U-Net algorithm-based MRI to CT Image Conversion is to get a matching set of CT images C from a collection of MRI pictures M. In order to guarantee that the data scale is consistent, the procedure starts by normalizing each picture Mi in M using the following formula: Mi_normalized = (Mi / 127.5) - 1.0. After that, the pictures are transformed in terms of size and shape so that they may be fed into the deep learning model. As part of the model's design, an Instance Normalization layer is established, using the symbol InstanceNorm(x), to modify image characteristics. There are downsampling and upsampling layers in the U-Net model. Using convolution techniques, the downsampling layers (Conv2D (x; W, b, s)) extract and decrease picture information. Whereas the learnt features are preserved by the upsampling layers, which are represented by Conv2DTranspose(x; W, b, s), the image's spatial dimensions are restored. The model is trained by iterating across epochs that have been specified. The processing of MRI image batches Bm and CT image batches Bc occurs at the beginning and end of each epoch. Ypred are the projected CT outputs obtained by sending Bm via the U-Net in the forward direction. Loss L is the difference between Ypred and the real Bc. In order to maximize the model's weights, gradient descent optimization methods use the gradient ∇ L and a learning rate η to backpropagate this loss. Lastly, in order to make predictions, the trained U-Net model is applied to each fresh MRI image Mi, resulting in a CT image Ci. As a last step, this CT picture is stored. This technique uses the robust U-Net deep learning architecture to capture the full process of converting MRI to CT pictures in an elegant way. This study's methodology develops a non-invasive way to generate CT scans from MRI data by using the U-Net architecture and comprehensive preprocessing procedures. pportunities for better medical diagnosis and research breakthroughs are created by connecting these two

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imaging modalities utilizing mathematical transformations and deep learning approaches.

IV. DATASET DETAILS

The Unpaired MR-CT Brain Dataset for Unsupervised Image Translation contains 179 two-dimensional axial image slices from 20 patient volumes, including 90 MRI and 89 CT slices [13]. The preprocessing techniques used to create these slices are detailed in Table I. The dataset was developed in accordance with the following: the Declaration of Helsinki, the Code of Ethics of the World Medical Association, and the permission of the Institutional Review Board (IRB). Accurate 2D slice extraction was necessary for image extraction using the RadiAnt DICOM reader program and converting to DICOM format. Images were standardized to be 256 by 256 pixels. T2-weighted imaging, three fat sat pulses, a TR ranging from 2500 to 4000, a TE ranging from 20 to 30, and a 90/180 degree flip angle were some of the specific parameters used to capture MRI pictures using a Siemens Verio 3T machine. The images had a resolution of 0.7x0.6x5 mm^3. CT images were captured using a Siemens Somatom scanner, which had the following settings: a dose length of 2.46 mGY.cm, a voltage of 130KV, a tube current ranging from 113 to 327 mAs, a slice thickness of 7.0 mm, filters that were both smooth and sharp, and a resolution of 0.6x0.6x7 mm^3. Thanks to these meticulous preparation processes, the dataset is now more reliable and consistent, which opens up new possibilities for medical imaging and machine learning research.

TABLE I. PREPROCESSING AND HANDLING STRATEGIES FOR BRAIN TUMOR MRI AND CT SCAN DATASET

Attribute	Description
Dataset Name	Unpaired MR-CT Brain Dataset for Unsupervised Image Translation [13]
Size	179 2D axial image slices referring to 20 patient volumes (90 MR and 89 CT 2D axial image slices)
Ethical Compliance and Consent	- IRB approval and patient consent obtained. - Adherence to the Declaration of Helsinki.
Image Extraction	- 2D slices extracted using RadiAnt DICOM viewer, converted to DICOM format.
Image Resolution Standardization	- Images standardized to 256x256 pixels.
MRI Acquisition	- Siemens Verio 3T for T2-weighted MRI without contrast. - Standardized resolution: 0.7x0.6x5 mm^3.
CT Acquisition	- Siemens Somatom scanner used for CT. - Standardized resolution: 0.6x0.6x7 mm^3.

V. INFERENCE RESULTS

An sophisticated deep learning model can transform MRI data into CT-like pictures, as seen in Figure 3. On the left side of each picture pair are the original magnetic resonance imaging (MRI) scans, which display the soft tissues in excellent detail and with high contrast. The model's ability to transform MRI data into CT scans, which highlight denser structures like bones and are lighter, is seen in the photographs on the right side. The pictures demonstrate that the model has been trained and improved to the 793rd epoch to simulate the changeover from magnetic resonance imaging (MRI) to computed tomography (CT) imaging.

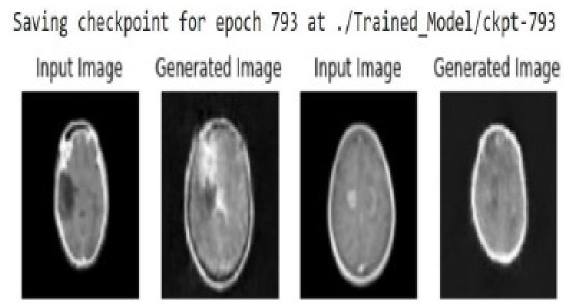

Figure 3. Comparative visualization of MRI to CT scan conversion during epoch 793

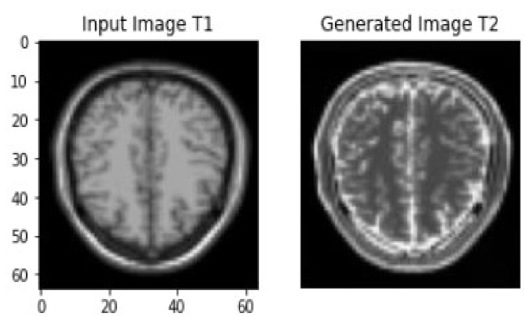

Figure 4. Transformation of T1-MRI to T2-MRI using CycleGAN Inference

Figure 4 shows how UNet changes T1-weighted MRI scans to T2-weighted ones. The T1-weighted MRI on the left side of each set of images depicts fat as bright and water as dark. To aid in the identification of pathology, the right picture is a modified T2-weighted MRI that emphasizes fluid and edoema. The fact that UNet can adjust the contrast of T1 images to make them seem like T2-weighted scans suggests that the model can mimic the way the brain looks when tested with T2-weighted parameters. Particularly in cases where T2-weighted images are not accessible, this AI-driven modification offers substantial therapeutic advantages. It saves MRI time for patients while improving diagnosis and treatment planning with no extra scans.

VI. CONCLUSION AND FUTURE SCOPE

Digital healthcare has the potential to undergo a revolutionary shift in medical diagnosis, treatment, and research with the integration of artificial intelligence (AI). On the other hand, as this field develops further, there are pressing ethical and practical issues that need fixing. Issues including algorithmic bias, privacy risks, equitable access to AI developments, and sufficient human oversight will greatly impact how this technology develops. To ensure health equity and safeguard patient rights in the age of digital twins, blockchain, and artificial intelligence, academics, tech firms, and policymakers must work together. As we include these digital tools, we need to make a greater effort to strike a balance between human expertise and automation. It is of the utmost importance to safeguard blockchain data, eliminate prejudice, and guarantee AI transparency. Blockchain technology enhances transparency, traceability, and the security of patient data via its decentralized and immutable nature. Digital twins have the potential to enhance patient modeling and predictive treatment in the healthcare industry. To establish standards and guidelines for blockchain technology and digital twins, cross-sector collaboration is crucial. No digital health strategy is complete without these cutting-edge tools. Healthcare AI, blockchain, and digital twins have the potential to surpass current limitations with careful deployment and perseverance. Medical treatment that is more accurate, personalized, and accessible to everyone would be possible with this. Complex sociotechnical factors must be continually interacted with in order for this transition to occur. Proactive human rights and welfare policies are necessary to make full use of these technologies. Dangers lurk in the actual world, as they are with all new innovations. Use of blockchain and digital twins, however, may provide enormous advantages within established ethical parameters and with a focus on the patient.

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