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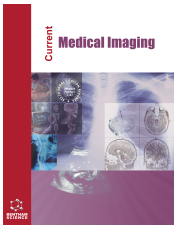

REVIEW ARTICLE

How to Collect and Interpret Medical Pictures Captured in Highly Challenging Environments that Range from Nanoscale to Hyperspectral Imaging

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Abstract:

Digital well-being records are multimodal and high-dimensional (HD). Better theradiagnostics stem from new computationally thorough and edgy technologies, *i.e.*, hyperspectral (HSI) imaging, super-resolution, and nanoimaging, but advance mess data portrayal and retrieval. A patient's state involves multiple signals, medical imaging (MI) modalities, clinical variables, dialogs between clinicians and patients, metadata, genome sequencing, and signals from wearables. Patients' high volume, personalized data amassed over time have advanced artificial intelligence (AI) models for higher-precision inferences, prognosis, and tracking. AI promises are undeniable, but with slow spreading and adoption, given partly unstable AI model performance after real-world use. The HD data is a rate-limiting factor for AI algorithms generalizing real-world scenarios. This paper studies many health data challenges to robust AI models' growth, aka the dimensionality curse (DC). This paper overviews DC in the MIs' context, tackles the negative out-of-sample influence and stresses important worries for algorithm designers. It is tricky to choose an AI platform and analyze hardships. Automating complex tasks requires more examination. Not all MI problems need automation *via* DL. AI developers spend most time refining algorithms, and quality data are crucial. Noisy and incomplete data limits AI, requiring time to handle control, integration, and analyses. AI demands data mixing skills absent in regular systems, requiring hardware/software speed and flexible storage. A partner or service can fulfill anomaly detection, predictive analysis, and ensemble modeling.

Keywords: Medical imaging, Visualization, Cyber-physical systems, PACS, Content-based image retrieval, Virtual reality (VR), Augmented reality (AR), Public health, Data imputation.

Article History	Received: April 07, 2022	Revised: August 29, 2022	Accepted: October 20, 2022

1. INTRODUCTION

Extant biomedical signal processing advances often stem from classification/subdivision methods handling pixel/voxel data, *e.g.*, imagery segmentation, or their uses in diagnostics, treatment planning, and follow-ups. This text tries to represent properly large image data volumes at different parts of a medical cyber-physical system (MCPS) [1, 2], besides scale/resolution challenges. Lately, data has grown due to health systems' evolvements, expanding pixel/voxel resolutions with faster reconstruction. Computed Tomography (CT) with Magnetic Resonance Imaging (MRI) allow scaling resolutions and reconstruction time in high-resolution (HR) body scans to grasp massive data. Large medical imaging (MI) stems primarily from huge picture archiving and communication systems (PACS) and single data type repositories. High-dimensional (HD) data display erraticism (Fig. **1**). *Viz*, X-rays are usually 2D but can be 3D or 4D, making them very large. MicroscopePathology Slides (MPSs) can have pixel/voxel ranges needing much memory.

Depending on their distance, scene objects possess different resolutions. When observing a parking lot from a distance, one instantly spots buildings, autos, and parking. At the entry, the driver could only see parking spaces immediately next to the vehicle. When an individual approaches other vehicles with resolutions equivalent to observer-perceived details, a desirable location becomes visible. Signals' extremes and their first derivatives help in qualitative descriptions. Scale and resolution impact much when calculating a neighborhood derivative. Stability criteria can detect events surviving large-scale changes depicting an MI as a mix of family basis signals, enabling various representation levels' analysis. Those with the

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most interest are chosen. Multiscale (or multiresolution) image decompositions (MIDs) get scale-specific traits. MIDs decompose MIs into essential representative parts at a certain scale for compression, description, segmentation, and registration [3 - 6]:

(a) Gaussian pyramids (GPs) render multiscale MIs *via* low-pass (LP) filters and decimation.

(b) LaPs exhibit bandpass (BP) MID components. Likewise, GP and LaP have 30% more pixels (overcomplete) than the original image.

(c) Wavelet decompositions (WDs) depict signals effectively, being large MIDs with scale/orientation analyses, LP, and HP filter banks. LP filters' regularity and vanishing-moment qualities affect shapes and representations.

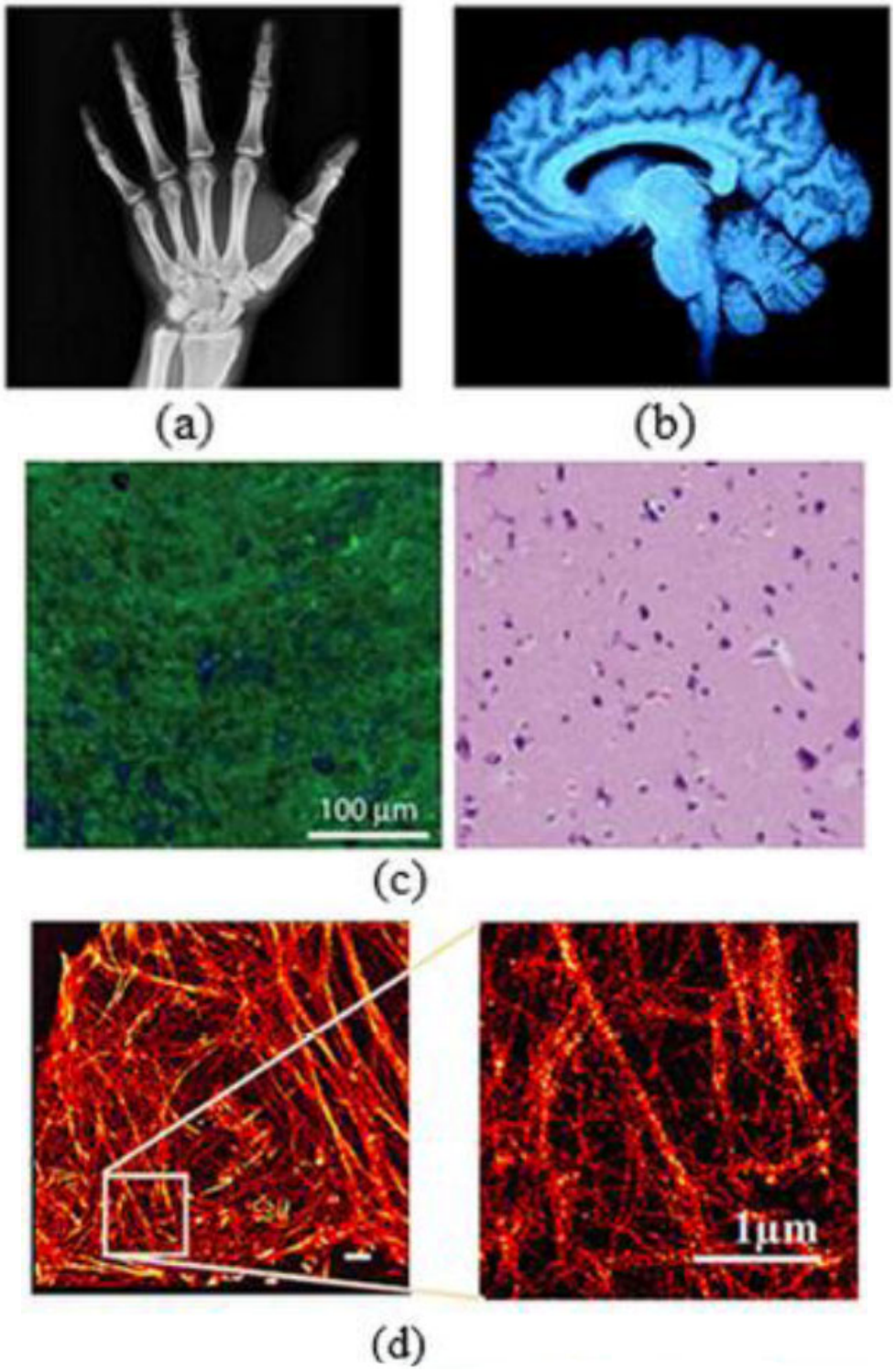

Fig. 1 contd.....

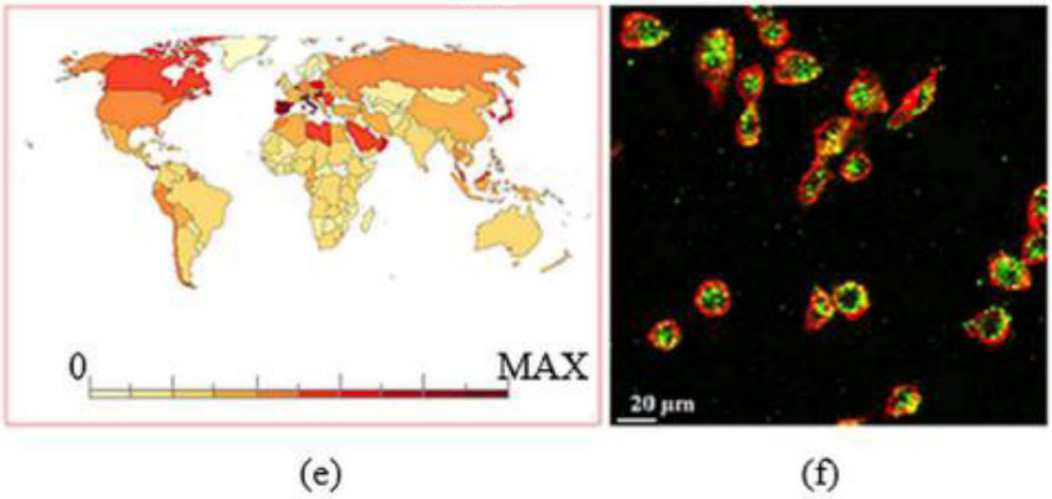

Fig. (1). Image modalities/resolutions: (**a**) X-ray, (**b**) MRI scan, (**c**) microscope slides, (**d**) SR, (**e**) RS drug use study, and (**f**) nanoparticles with drugs in cells.

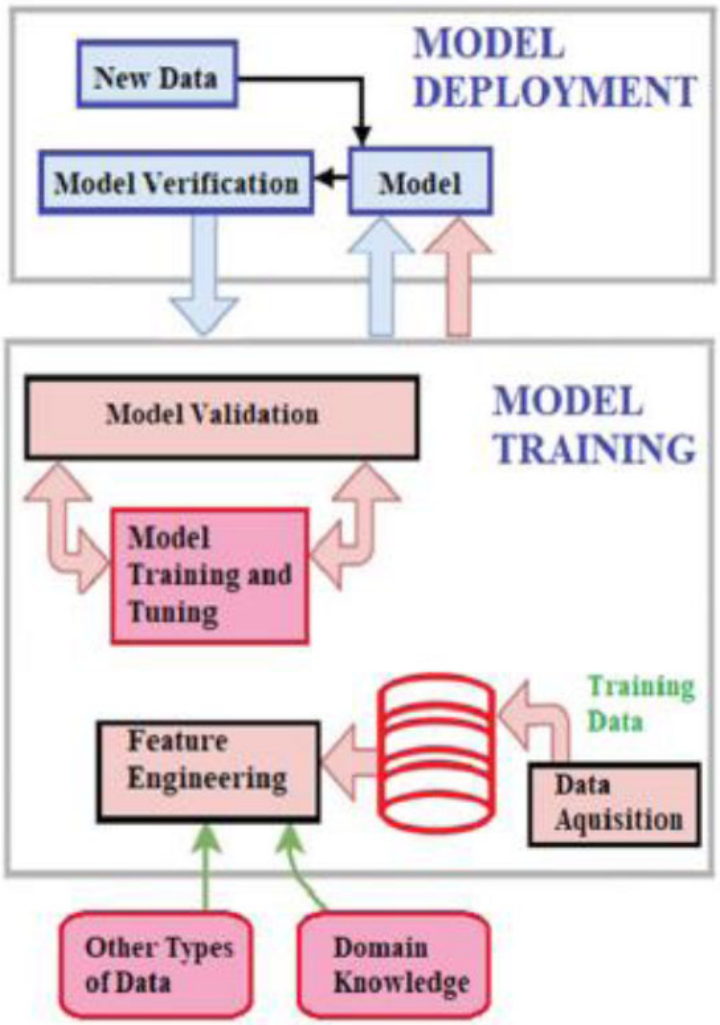

Fig. (2). Medical AI model block diagram.

Section 2 checks dimension and resolution issues. Section 3 presents Medical Information Fusion (MIF). Modalities, control, and storage appear in Section 4. Section 5 parleys AI image handling. Microscopy, nanoimaging (NI), and super-resolution (SR) are in Section 6. Section 7 treats Virtual Reality (VR) and Augmented Reality (AR). Hyperspectral (HSI) and multispectral imaging (MSI) in health appear in Section 8. Section 9 recaps and closes this text.

2. DIMENSIONALITY AND RESOLUTION ISSUES

The dimensionality curse (DC) labels the unpredictability of MI dimensions augmentation with snowballing computational efforts. DC explains MI volume growth from HD spaces as extra dimensions emerge in AI, data analysis, and data mining, among others. While dimensionality growth adds more MI knowledge, thus taming data quality, it can boost noise and redundancy.

Object features can be attributes defining entities; each denotes a feature vector (FV) entry. A group of n-dimensional entries typifies a data point (n-tuple) in AI algorithms. More dimensions imply more features describing data and a longer FV. *e.g.*, in cancer studies, age, the total of cancerous nodes, and shape descriptors can be a patient's prognosis features. But factors like past surgeries, patient history, tumor type, and other features help define the prognosis better. Yet, adding features tends to widen dimensionality, increasing exponentially the quantity of points, giving a good performance of any AI process as more points for any given FV are required for any AI model to be valid. Feature engineering (FE) gets an FV using handcrafted (HC) or DL features from a raw MI to represent it. A model specialist plans HC features, *i.e.*, an AI algorithm estimates, learns, and automatically gets them by design from the phenomenon knowledge, *e.g.*, Gaussian mixture model (GMM) hyperparameters and texture-related metrics. DL represents and learns multiple representation levels, beginning with the raw input. They merge simple, non-linear subdivisions where each transforms one level's representation into another more complex and slightly abstract level. DL shows potential for automatic predictive features' discovery. DL can cut graph dimensionality well while keeping much structural info [7]. So, FE can form a predictive model employing AI, such as DL, whose main gain is to infer high-level features incrementally without domain expertise and conservative feature extraction. DL outperforms HC models by a large margin in learning and extracting features for a certain task. Still, designers cannot control what features will emerge. Features can be only good for data classification without real-world (RW) insights, *i.e.*, they excel only for the trained task.

The health data DC is huge and rising fast. Electronic Health Records (EHRs) have biometrics from images, voice, wearables, genetics, and other sources, portraying a rich patient's HD health data (HDHD) [8 - 10], *viz*. sub-mm resolution brain MRI pixels afford voxel-rich imaging. Wearables have massive samples per second, besides millions of other human details (a vast clinical data footprint). HDHD gives algorithm developers vast data streams. The HD *vs*. small sample dilemma occurs if features exceed sample sizes. Raw data location limits doctors' understanding. AI may fix this problem since it can learn from clinical data streams (Fig. **2**). Software (SW) as a medical device leverages AI in its lifespan. Designers get big training samples from many modalities for model making. Cross-validation helps pick the final model and feature sets, assessing post-model precision [11, 12]. Virtual Worlds (VWs) help monitor and redeploy RW models.

Short training datasets with too many features may enhance training but with poor generalizability [13, 14]. Tracking all health metrics' potential combinations can be challenging. Tricky events need larger sample sizes. Dataset blind spots (DBSs) produce DC, hindering model development/ generalizability and causing negative effects. Too many DBSs cause disastrous failures when dealing with unknown data. Small HD training samples are sensitive to DBSs, causing errors; *e.g.*, massively labeled MIs are required to train AI models mapping participants' gut signals. AI helps many HDHD models trained with few samples [15]. Dimension reduction (DR) can curb the feature space with principal descriptive features, thus overcoming the DC in several ways [16, 17].

3. MEDICAL INFORMATION FUSION

Progress in sensors has improved their robustness and enlarged MI resolutions. More notably, low-cost fabrication has popularized multiple sensors in many imaging uses. This growth vastly enlarged the data depicting the same scene from various sensors. Yet, the subsequent sensor information processing can be heavy since augmenting the number of sensors increases raw sensor data to be stored and processed, meaning longer execution times or increased processing units and storage devices, leading to costly solutions. Also, humans may face difficulties visualizing various images, leading to significant performance drops [4, 18 - 22]. A potential solution is to replace the whole set of sensors with a single composite depiction, tying all pertinent sensor data as MIF. The idea is to mix complementary, redundant data from multiple images to render a composite image with a better scene description than any individual source image. Hence, the fused image should aid in inspecting or extra handling.

3.1. MIF Fundamentals

MIF tends to be nontrivial since (i) attained images may involve different sensors' dynamic ranges and resolutions; (ii) there exists matching evidence (*e.g.*, structures appearing only in some input imageries; and (iii) some common data may have reversed contrast, much confusing the process. Still, fusion should not rely on a priori sources' evidence to yield naturally appealing fused images with these requisites:

(a) All relevant input images' info must be preserved;

(b) No artifacts or inconsistencies should confuse an observer or subsequent processing task; and

(c) It needs reliability, robustness, and error tolerance (*e.g.*, noise and misregistrations).

MIF may use multitemporal sensors with several focal lengths, many views, or various exposure settings. MIF happens at different data representation levels as follows:

3.1.1. Pixel-level

It means the lowest representation data blend level since each fused pixel comes from a set of pixels in the source images customarily within small windows like 3×3 or 5×5. Pixel-level fusion is easy and time-efficient. The resulting image contains the sources' data but is very sensitive to misregistration [18].

3.1.2. Region-level

It identifies major image parts' qualities like size, shape, contrast, texture, or gray levels. A region map ties each pixel to a feature based on segmentation to merge extracted sections. This avoids snags, *e.g.*, blurring, high noise sensitivity, and misregistration [18]. Segmentation affects the final fusion performance quality since mistakes might cause missing or degraded items in the fused image.

3.1.3. Voxel-level

Low-resolution (LR) and poor 3D scans [20 - 25] prevent fancy processes from matching local features on RW depth pictures. Each local volumetric patch descriptor learns a partial 3D data match label. Unsupervised learning collects data but hinders RGB-D reconstruction. Descriptors generalize fusion to varied deeds and scales. Better depth results from merging 3D-point clouds with other modalities, fine-grained texture, and color evidence. Techniques include:

(i) Object-centric fusion does Region of Interest (ROI)-pooling on each modality from a shared set of 3D end-to-end optimizations despite being sluggish and bulky.

(ii) A priori mapping for each point-cloud sample permits continuous fusion across all stages. Feature blurring occurs when an FV matches many voxels in view.

(iii) Imitates the initial point cloud, but it is slow and needs multiple steps to create it.

(iv) Point cloud seeding detection with semantic features taken from an image boosts accuracy but limits recall.

3.1.4. Volumetric-region

Grouping similar voxels is difficult [24 - 26]. Remote sensing (RS) has powerful 3D merging. Mixing multiresolution sets of geometrically overlapping surface measurements is hard but lowers representation costs. A discrete surface depiction allows fast complex object reconstruction, but rebuilding a single-resolution big thing is unviable since restoration is object size independent.

3.1.5. Decision-level

Various sensors' data merge at the greatest abstraction degree. A decision map exists for each picture by sorting all input pixels. Fused maps results from distinct decision map merging discrepancies [24 - 26]. The proper level rests on source attributes' use, execution time, and nearby tools with fusion stages strongly linked where rules shaping composite images' pixels may also help fuse regional features. Decision-level fusion often employs a regional-level map to merge visible and infrared (IR) imagery. Some views about key MI analysis stages follow.

3.2. Data Acquisition Protocol

Most data-rich modalities in EHRs are acquired in-clinic per procedure. While collecting RW sensor health data and creating robust models is challenging because of (i) background noise, (ii) unknown variables, and (ii) intrinsic DC with growing DBSs, especially when the sample size is small. Designers could explore active tasks to replace passive data collection since data describing characteristics may produce DC issues with DBS consequences. Top performance tasks reduce the relative impact of unmeasured changes to estimate clinical contrasts of interest. Viz patients' speech may be slower and less precise when tested under a top-performance job [27 - 30]. It would never emerge in passive data collecting since most maximum performance challenges are outside normal speaking patterns.

3.3. Training Data Collection

The training set size and variety should reflect the conditions after model deployment [27 - 30]. More samples train intricate HD models properly, even when sampling is varied (*e.g.*, data from many sites). Designers can leverage current policies to estimate the sample size for training classification. As regional biases in clinical AI models, a mismatch between training and post-deployment data problematizes a covariate shift [28]. Biased sampling causes marked DBSs between training and post-deployment data distributions. Creating representative datasets for training involves previous knowledge of which stratification characteristics correlate with predictors. Carefully mapping these parameters and ranges can robustify AI models [29] but not assure performance likeness between layers. To quantify model performance variability across key groups, scientists need representative data.

3.4. Model Validation

Before being used for analytics, professional intelligence, or AI model training, data is validated for integrity, correctness, and structure. Model validation verifies that the model achieves its intended goal and confirms its predictive capacity. Smaller data sets require rigorous model assessment processes. Better models must preserve individual samples and use accurate measurements to reuse a test dataset. Designers should not strive to boost performance by finding troublesome test set instances but by accepting and addressing data irregularities and DBSs. Without DBSs or DI processes, more data must be collected.

4. MODALITIES, MANAGEMENT, AND STORAGE

4.1. Multispectral and Hyperspectral Imaging

HSI and MSI can develop healthcare *via* spectrometers settled for RS to get images over ample electromagnetic spectrum wavelengths. Although RS can aid in illnesses' and vectors' spatial mappings, existing HSI/MSI data extraction means are not standardized for disease detection. Acquisition schemes, spectral ranges, spatial/temporal resolutions, measuring mode, dispersive methods, detectors, and other techniques play a role in medical HSI (MHSI) technology with

preprocessing, feature extraction/selection, and classification processes for MHSI image analysis. MHSI mainly includes the ultraviolet (UV), visible (VIS), near-infrared (NIR), and mid-infrared (MIR) ranges.

A slide can be an RGB image with only three bands. Because of multiple spectral bands or channels beyond visible light, digital HSI/MSI pathology helps diagnose/treat illnesses, handle inter-observer variability, and save examination time [31]. The HSI/MSI spectroscopy directly measures light's incoming radiance spectrum (reflection or transmission) and the sample's scattering and absorption. It may, yet, be used to quantify fluorescence. Each HSI/MSI pixel represents the light captured by the camera from a series of measures showing the substance's spectral signatures and permits identifying parts [32, 33]. CAD tools, as well as HSI/MSI, can tackle color, autofluorescence, as well as immunohistochemistry for stained and unstained histology samples. Refraction and reflection in non-homogeneous biological tissues are linked to light speed and direction differences, and changes in reflective/refractive indices detect illnesses. When molecules exhibit radiation absorption peaks at a certain wavelength, they show transitions between two energy levels and serve as molecules' response fingerprints for diagnostic info. Finally, certain tissues glow when boosted by external light sources. *e.g*., proteins and nucleic acids produce fluorescence when stimulated by UV light. New HSI/MSI cameras, analytic schemes, and computer power can aid automatic *in vivo/ex vivo* disease detection and image-guided surgery using data about spectral and morphological samples after proper knowledge mining. There are several analytical options for HSI/MSI processing. AI can treat spectral data directly or after feature extraction. DR alters records mathematically to retain just the most vital information. Band selection ways identify major spectral bands. Recently, DL has permitted autonomous HSI/MSI feature extraction and categorization [33, 34]. The key DL benefit for supervised classification is clarifying which dataset traits better identify different constituents [35 - 37]. HSI data cubes with many IR spectra bands can get reliably through a narrow bandwidth laser continuum [38], permitting multivariate analysis, besides spatial distribution nanoscale maps of materials.

4.2. Super-resolution

Super-Resolution (SR) creates an HR image from LR ones with high-pixel density and richer scene details. Applications need HR for pattern recognition, image analysis, diagnostic imaging, surveillance, forensics, and zooming in on a specific image. HR pictures are scarce, given their cost and practical sensor restrictions. Affordable MI processing can solve SR challenges less costly and use existing LR devices.

4.3. Molecular Imaging and Nanoimaging

Because light travels through water and air, optical microscopes (OMs) can observe *in vivo*. So, they deal with biological things and other elements in natural settings. Color photos from OMs are more detailed than monochrome images. OMs can offer intrinsic sample properties up to 0.5 μm in the visible and mid-IR light bands [39]. Since visible light cannot photograph nanomaterials, optical microscopes (OMs) suffer from light diffraction. Surface plasmons for superlensing allow faultless NI capture with a nanoprobe. Multicolor, 3D stochastic reconstruction microscopy can now see cellular structures with molecular-scale detail. When paired with many fluorescent probing and biochemical-specific labeling procedures, multicolor fluorescence microscopy visualizes molecular living organisms' interactions and processes. Yet, as fluorescence microscopy has a diffraction-limited resolution, many detailed, tiny biological structures are not tested. Molecular imaging (MolIm) handles living patients' molecules of interest *versus* histology, which takes preserved tissue samples' molecular data [26]. The patient's body may create molecules suddenly or receive them from a specialist. In MRI, CT, and PET, a contrast agent is injected into a patient's bloodstream to follow its travel throughout the body. MolIm evolved from radiography to better understand and monitor organisms and metabolic processes. Currently, MolIm research includes (i) finding previously unknown molecules, (ii) finding additional contrast agents, and (iii) seeking functional contrast agents to educate about healthy *vs*. sick cells and tissues. HSI IR with NI can detect and chemically analyze molecules without risky extraction or taggings. Some HSI IR potentials in NI include drug use and deep MI analysis. This yields nanoscale-resolved chemical and compositional maps to recognize local chemical interactions.

4.4. Virtual and Augmented Realities

VR is immersive, allowing users to fully engage in a realistic or lifelike virtual world (VW), distinct from reality. Medical AR is very effective for combining RW with VR so specialists can view things like X-rays, arm veins, shattered bones, head tumors, EHRs, *etc*., before employing AR. Something floats in front of an expert in AR, with data overlaid in distinct realms. Recent developments extended VR/AR to healthcare. While patients prefer VR, clinicians employ VR/AR in various ways. Adoption to clinical usage has been hampered by issues with QoE [26, 40, 41]. Many healthcare settings now have consumer-level VR/AR HW accessible. Experts will determine the safety and patient benefits. Costs and integration are other factors. Experts predict more medical VR/AR uses like.

4.4.1. Clinic-based AR/VR

AR/VR impacts primary care, clinics, surgeries, emergency room, and dental offices as it matures [42]. *e.g*., surgeons can plan complex surgeries with AR/VR with SW to enhance RW locations. There are several chances to educate people and improve actions/care. Handheld laser devices can see through skin and veins to find veins to pull blood or insert an IV. Health suppliers can lower superfluous needle pokes risks and save time.

4.4.2. Surgery

AR/VR aid in high-risk treatments like AR surgery [43, 44]. Headgear can simultaneously project X-rays or CT scans onto the body, with MIs lining up perfectly. Still, radiation exposure entails X-ray care with fast freehand gain, though it needs comprehensive body data and practice. Its early spinal surgery use is due to the spine's rigidity. Moving the belly or

chest confuses the VW and RW alignment. AR/VR is slowly entering high-risk actions.

4.4.3. Medical Education

AR may help in training [45, 46] and solving mistakes in surgeries. Teaching and learning do not need precision. AR allows mobile users to study items and anatomy by rotating a 3D model and scanning a QR code in the anatomy lab (or on a corpse) to access videos or talks.

4.4.4. 3D Models

MIs are no longer inferred by thoughts. Segmenting anatomical regions involves human mediation. Other SW platforms include AR/VR visualization engines, DICOM input, automated segmentation, and 3D-mesh creation. VR/AR offer novel 3D MI representations [47].

4.4.5. Molecular Imaging (MolIm)

MolIm can potentially play a critical role in healthcare [26]. With increasingly high-resolution systems, multimodal imaging platforms, and large datasets generated by modern MolIm methods, it has become imperative to develop new approaches to store, process, and visualize information. VR/AR adaptation to visualize MolIm is an intuitive emerging trend that can accommodate the growing complexity and volume of multimodal molecular data. Clinical VR/AR applications highlight existing challenges for these technologies' wider adoption before concluding with anticipated future directions.

5. HANDLING HD IMAGERIES WITH AI

HD confounds settings because if one applies DL to raw images, the result may be a very long FV, making it difficult for humans to understand images' traits. Likewise, when it comes to content-based image retrieval (CBIR), it is better to curb having an FV that does not make indexing and handling databases too hard. Short sample numbers favor DBSs, *i.e.*, the training data contains blind spots or rare patterns. Hence, this constrained data domain (small info scenario) does not have every possible variation in the training set, leading to poor performance. Data imputation (DI) helps bypass data scarcity by replacing missing data to get a more complete data set. Single DI fills in one value for missing evidence without a clear model. CBIR indexes MIs to extract attributes and conduct breakdowns. Growing social and varied media acquisition systems can shatter regular systems. Optimizing dimensions to speed up exploration is crucial. An expert may reduce searches *via* metadata and a simple FV. CBIR data dimensions and complexity grow. DR expedites MI processing and overcomes DC.

Hard (adversarial) phenomenon-descriptive datasets have achieved robustness for specific inference types *via* DI. These datasets can train many models, often consenting to learn the emphasized manifestation and improving the tough dataset, showing blind spots in the initial training data. Albeit improving a model in training, it might still be exposed to other tricky datasets for the same phenomenon but extracted from a different distribution, *e.g.*, having a dissimilar syntactic complexity level. Extending methods to drive inferences about a model's aptitude to learn and generalize a given phenomenon rather than learning a dataset may introduce hardships. AI-oriented policies help build enhanced datasets for more robust and broadly ameliorated models. Validation scrutiny practices can assess the model's performance and detect DBSs. While hard, several AI tactics can support robust models that emulate missing data, ease usage, and handles difficult HD representations well.

5.1. Feature Engineering

Features are a major model design aspect. The ideal feature space for typifying a scenario is unknown. They help merge data improving a model's process of exploratory feature choice. Deleting extraneous model characteristics enhances its robustness but does not remove DBSs if HD and small data regimes occur. Selecting a small feature collection that changes with illness but remains constant daily aids in reducing DC [48, 49]. A small sample size favors a priori attention to fewer features. Clinical labeling is costly, yet sensor data are usually bulky. Transfer learning keeps reusable clinical traits in lower-dimensional (LD) feature space [48, 49] as sensors collect daily high-density data. Repeatable AI studies utilize statistics to examine human impact on measurements while minimizing variance. Before creating a model, feature variability with frequently-used characteristics help with HW and settings.

5.2. Model Training and Tuning

After collecting training sets and choosing features, model training and tweaking should follow HDHD machine learning (ML), metaheuristics, and other DC-sensitive AI practices [50 - 52]. Data-driven regularization and ensemble averaging better HD robustness. Training and testing datasets are split. The first dataset learns and validates the model with candidates compared to ignoring sparse data [50 - 52]. Small sample numbers can cause overfitting, optimistic forecasts, chiefly for HD models. Overfitting fits data too well into a model. Ideally, a model must do training superbly and generalize well for predictions with other training sets. Larger sample sizes impede test data reuse.

5.3. Deep Learning

AI can also enrich HD data usage with DBSs. Deep Learning (DL) can handle ranked feature representations [53] to remediate dataset problems. DL algorithms may focus on LR images due to HD features' caching. Novel DL approaches for huge MIs must

(a) Process detail pertinent MI components;

(b) Scale to an unlimited number of valid MI parts;

(c) Scale to an infinite number of input data types.

(d) Experiment with acceleration hardware (HW); and

(e) Show object parts' dependency.

Growing data must use less processing time, energy, and HW assets. A large bias may occur if data are missing. Applying DI to MIs is still hard due to the images' nature and complexity. Generative Adversarial Networks (GANs) variants can address this problem. Datasets may be compressed to feed

a DL model, saving memory while locating relevant parts from a possibly fuzzy LR image. Estimated improved-quality areas can populate parts of DBS locations to aid in patch extraction from the total or a portion of the HR image via, *e.g.*, SR, focusing on certain scene elements. The final estimate combines patches and LR embedding representations. A DBS only matters if the model meets data from that faulty part of the feature space. While one may cut DBS volumes during training, one will not know if a consequential, coherent DBS exists until deploying the model. SR has boosted systems and defeated the optical SR diffraction limit with strengthened sensor resolutions.

5.4. Model Generalization

Generalization rates how a model predicts unobserved data with optimum generalized error (GE) performance. A bigger regularized model thru training can shrink GEs, cut overfitting, optimize speed, and boost performance. Feature selection betters classification accuracy by removing non-informative components and enhancing class contrast. HD MIs are hard to study, unmanageable to grasp, and costly to store. Their points often lie near lower-dimensionality (LD) spaces, hinting at small DC and converting HD MI to LD without wasting data. DR gains include:

(a) As dimensions shrink, storage space diminishes;

(b) Less computational burden with fewer dimensions;

(c) Poorly performance with HD, forcing DR;

(d) Cut features help multicollinearity (if more exercise burns more calories, a stored variable links factors);

(e) Better HD handling by reducing to 2D or 3D.

DR includes missing value ratio, linear discriminant analysis (LDA), factor analysis (FA), principal component analysis (PCA) [54 - 56], independent component analysis (ICA), high-correlation filter, low-variance filter, random forest (RF), projections' centered ploys, backward feature veto, forward feature choice, t-distributed stochastic neighbor embedding (t-SNE), and uniform manifold approximation and projection (UMAP). Other schemes can have higher variance in the first feature space. Trendy manifold learning entails locally linear embedding, multidimensional scaling, Isomap, and Laplacian eigenmaps. Not all data types do well. Tumor and proteome data help choose MI DR settings. Reduced-space classification followed by performance estimation is better.

6. DISCUSSION

MI benefits from diagnosis to surgery and follow-ups, dealing with ever-increasing data volumes and resolutions due to MI modalities. This paper includes managing, treating, and portraying scaled MI for customized bioimaging, VR/AR, MSI/HSI, NI, and SR. MI processing and visualization must meet MCPS projections. Scalable HW/ SW parallelizations help high-performance multidimensional HR recordings and processing on dissimilar machines/MCPSs. Such systems provide quick access to numerous tools *via* a health-programming environment with varied SW requirements for development and several representation structures. Complex datasets must fulfill robustness tests for specific inference types relying on DI to explore models and datasets to learn/refine the phenomenon, showing blind spots in the training data. A model may still be exposed to other tricky datasets aiming at the same phenomenon but extracted from a different distribution, *e.g.*, having various syntactic intricacies. Extending a model's skill to learn and generalize with AI may improve robustness and model comprehension. Besides spatial distribution and nanoscale MI maps, HSI data with many IR spectra bands permit multivariate analysis. HSI IR with NI can become mainstream as enhanced computer power and algorithms detect and analyze cells/molecules. HSI and SR combined facilitate MI tasks. Indexing MI *via* CBIR happens often. Social and varied media acquisition methods have strained standard multimedia processing systems. Reducing the data's size can speed up the search phase and make it computer-readable. DR approaches help defeat DC.

CONCLUSION

Multimodal HSI, super-resolution, and HD NI increase theradiagnostics but defy dataset representation and retrieval. A patient's condition can incorporate wearable signals, MI modalities, clinical considerations, information, genetic sequencing, and clinician-patient dialogs. AI inferences, prognosis, and tracking have improved with high-volume data, showing clear promises, but RW applications are unpredictable, slowing adoption. HD data restricts AI's real-world growth. This study explores how MIs' properties prevent AI models from overcoming the dimensionality curse, out-of-sample biases, and designers' concerns. Choosing and assessing AI platforms is complex. Study complex automation. MI concerns do not always require DL. Hence, while AI professionals must use high-quality data, unclean data delays AI governance, integration, and analytics. AI needs rapid, versatile HW/SW and data-mixing skills as part of a service for anomaly detection, predictive analysis, and ensemble modeling.

LIST OF ABBREVIATIONS

AI	=	Artificial Intelligence
DC	=	Dimensionality Curse
HD	=	High-Dimensional
HSI	=	Hyperspectral
MI	=	Medical Imaging

CONSENT FOR PUBLICATION

Not applicable.

FUNDING

None.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

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