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Integration of AI and Big Data for Smart Healthcare Diagnostics

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Abstract: The integration of artificial intelligence (AI) with big data is widely perceived as a promising direction for smart healthcare diagnostics. Various definitions and conjectures sustain the power of such an amalgamation. Data-driven medicine constitutes the theoretical foundation and encompasses both mainstream and alternative AI paradigms. To capture the potential, a data ecosystem addressing the data supply, an arsenal of AI algorithms appropriate for diagnostic testing, and a big data infrastructure capable of handling large volumes are outlined. The data ecosystem focuses on knowledge dissemination, reproducibility, and the avoidance of data leakage effects. Moreover, a supporting diagnostic AI lifecycle emphasizes AI validation and evaluation in terms of accuracy, bias, fairness, and generalizability in a health-related context.

The recent interweaving of AI and big data with clinical practice and healthcare activity has drawn considerable attention over the past few years, bottoming out at various facets. Despite an initial quest for solutions targeting real-world problems, several AI leaders have steered the discussion toward testing AI algorithms under their own terms, fostering some bewilderment. Data-driven medicine—medicine addressed towards its own data by applying data-centric solutions—has remained a shadowy concept because diagnostic testing or diagnostic examination is understood differently across the clinical landscape. Clinical practitioners specializing in a certain disease group commonly talk about diagnostic testing or core diagnostic tests for such diseases, whereas diagnostic pathology and forensic medicine are sometimes perceived as distinct specialties dealing with much less population-associated diseases.

Keywords: Integration of AI and Big Data for Smart Healthcare Diagnostics; Big Data; Artificial Intelligence; Decision Support Systems; Diagnostics; Healthcare Cloud; Machine Learning; Smart Healthcare.

1. INTRODUCTION

In recent years, AI and Big Data have proven their instrumental and essential role in supporting and augmenting various complex and labour-intensive processes within the healthcare domain. Diagnostics stands out as one of the most promising application fields where AI and Big Data can be integrated to greatly improve accuracy, reliability, and speed. Despite some limited successes, a comprehensive synthesis of recommendations, concepts, and guidelines for the effective deployment of such technologies remains elusive. Even so, the establishment of a conceptual data ecosystem for Diagnostic AI and the specification of operational requirements for its construction, together with the review of the main classes of AI techniques presently available for such tasks, form an essential foundation for future progress. As all medical specialists recognise, diagnosis constitutes the cornerstone of healthcare and medicine. If the diagnosis of a health condition is wrong or delayed, the suggested treatment is unlikely to alleviate the problem and might even result in additional harm.

The prognosis of disease onset and management decisions also depend considerably on case classification. Conversely, new technologies, including the Internet, image and video acquisition and analysis, telemetrics, data mining, and Artificial Intelligence (AI), have revolutionised the development of diagnostic tools and advanced the paradigm of data-driven medicine. Data-driven or empirical efforts rely on using known examples of a phenomenon, disease, or condition to teach a computer-aided platform to predict the state of new cases with the support of AI techniques. Digital data generated by these novel technologies constitute vital 'big data' resources that, if effectively analysed, modelled, and understood, can ultimately support diagnostic and prognostic functions through direct prediction or by informing decision support and clinical expert systems.

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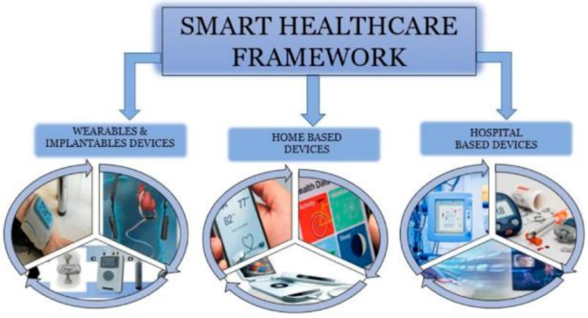
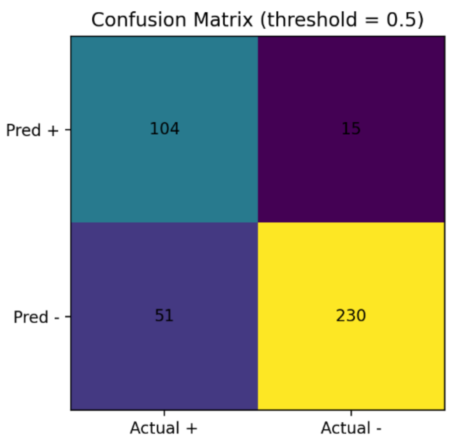


Fig 1: Smart Healthcare Systems in the Era of Big Data

1.1. Rationale for AI and Big Data in Diagnostics Despite major advances in disease diagnostics, AI-enabled diagnostic systems remain scarce. This absence stems from two fundamental challenges.

The primary impetus is the extraordinary volume of medical data now being generated. Dense sensor networks, real-time stream acquisition, increased image resolution, sequencing of individual genomes, and the rapid proliferation of electronic health records provide a wealth of high-fidelity data that is undergoing continual growth. Although AI techniques such as deep neural networks excel in extracting predictive information from huge datasets, these methods cannot perform well when only modestly sized training datasets are available. Big Data thus holds the promise of enabling superior diagnostic capabilities founded on software systems powered by AI methodologies.

The second factor limiting the application of AI to diagnostic problems is the lack of a concrete methodology for performing a diagnostic task without human involvement. The goal of a diagnostic test is to identify the disease underlying a set of clinical symptoms, with the eventual aim of developing effective treatment strategies. Supervised learning algorithms trained on appropriately labeled data can successfully classify such disease states, but the requisite, adequately labeled data are rarely available. Consequently, unsupervised and semi-supervised methods capable of discovering such labels are gaining currency. A growing literature has emerged detailing their application to clinical diagnostics.



1.2. Definitions and scope A formal, pragmatic integration of AI and Big Data into healthcare diagnostics does not simply involve the assembly of a large dataset with corresponding ML solutions, but rather the creation of a scalable, data-driven diagnostic ecosystem that employs the full breadth of techniques and methods from the Big Data and AI terrains. Such an ecosystem must ensure the availability of interoperable, high-quality healthcare datasets that are continuously updated, governed, and privacy-protected; a variety of ML, DL, and other AI-based approaches suitable for

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a broad range of diagnostic tasks; and a robust, scalable Big Data infrastructure that supports both operational and analytical Big Data for real-time diagnosis and prediction.

Such AI and Big Data-based solutions are usually explicable, interpretable, and clinically credible, thus able to support the end-users—patients and clinicians—in making evidence-based healthcare decisions. These aspects remain especially relevant in smart diagnostics that respect the principles of equality, fairness, and privacy, allowing patients to have a share in their Healthcare Decision-making process and supporting the Clinician–Patient Decision-shared Process. Each of these aspects can be viewed as a sub-problem of smart healthcare diagnostics.

2. THEORETICAL FOUNDATIONS

Two main paradigms in data-driven medicine are predictive analytics and data mining. Predictive analytics for diagnosis typically relies on supervised learning, where known diagnostic outcomes predict model behavior for new cases. While widely employed, supervised learning depends on the availability of labeled data and may fail for minority classes; supervision may be achieved indirectly via transfer learning or with a weaker labeling scheme. Data mining for diagnosis seeks to discover hidden labels or relationships in unlabeled data by seeking clusters, associations, or patterns with varying levels of supervision. A popular data-mining application is anomaly detection, conceived for safety-critical systems, where abnormal patterns (e.g., disease states) are exceedingly rare.

Supervised, unsupervised, and semi-supervised learning are the predominant Artificial Intelligence methodologies in diagnostic contexts. Standard supervised learning is a well-established area of Big Data Research known for its maturity, utility, and ease of communication with healthcare practitioners. While achieving high accuracy, it may prove infeasible for certain application areas. Unsupervised methodologies assist in probing uncharted territory and filling gaps in labeled case distributions. semi-supervised and weakly-supervised learning attempt to mitigate these shortcomings with reduced labeling effort.

Equation 1: Step-by-step derivations of the metrics

Among **predicted non-diseased** $(TN+FN)$, how many truly do *not* have disease?

$$\text{NPV} = \frac{TN}{TN + FN}$$

The paper lists *F1-score*.

_Integration of AI and Big Data…

Start from the harmonic mean definition:

$$F1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

Substitute:

$$F1 = \frac{2}{\frac{1}{TP/(TP+FP)} + \frac{1}{TP/(TP+FN)}} = \frac{2}{\frac{TP+FP}{TP} + \frac{TP+FN}{TP}} = \frac{2}{\frac{2TP+FP+FN}{TP}} = \frac{2TP}{2TP+FP+FN}$$

2.1. Data-driven medicine paradigms The necessary integration of Artificial Intelligence (AI) and Big Data for smart healthcare diagnostics raises important conceptual issues, in terms of how these data can be collected, made accessible, processed, and eventually deployed within diagnostic solutions capable of supporting both decision-making by medical

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specialists and informed patient involvement for treatment choices. Patients are increasingly demanding "smart" healthcare solutions that provide timely and accurate information on their health status, personalized treatments and medications based on Big Data analysis and mathematical models rather than intuition. Big Data can serve to improve the diagnostic process through four principal factors: decision support for specialists to reduce the risk of error and delay; readiness to start treatment immediately, upon receiving alarming results; knowledge acquired through experience-program assessment and developed-knowledge-DSS capable of supporting decision making, based on the incremental medical knowledge acquired, and using the experience of multiple patients to cure future cases more accurately; and allowing patients to choose their course of treatment, through assisted diagnosis.

The areas of Artificial Intelligence, Machine Learning, Deep Learning, and Big Data are playing an increasingly important role in smart healthcare diagnostics. AI and ML are components of a new and vibrant paradigm in healthcare – data-driven Medicine – where the massive availability of digitized data is coupled with sophisticated AI algorithms, focused primarily on supervised Disease Classification. The algorithm receives a multitude of Data Input points from the patient and provides the output of disease Classification (e.g., healthy/unhealthy). In its simplest form, the performance of the algorithm can be evaluated through metrics such as accuracy, precision, recall, area under the receiver operating characteristic curve (AUC), and classified samples. The research community is also exploring methods for Unsupervised Disease Classification, and Semi-supervised Disease Classification is receiving increasing importance as it can potentially overcome the principal limitation of AI-based solutions in healthcare – the scarcity of labeled allegations.

2.2. AI methodologies in diagnostic contexts Diagnostic decision-making for disease classification remains an important area for the application of AI technologies. Most AI diagnostic solutions are built under a supervised learning paradigm using an open dataset or closed datasets in collaboration with clinicians. Unsupervised and semi-supervised learning paradigms are emerging for diagnostic tasks and are suitable for data-scarce domains. For instance, AI methods attracted enormous attention for the early diagnosis of COVID-19 pneumonia from chest X-ray and CT images based on supervised learning. Rapid advances in high-throughput sequencing technologies and the development of open databases enable researchers to predict the possibility of different mutation sites associated with drug resistance in many pathogens. These enable novel insights for developing new drugs and vaccines.

Despite better performance than classical methods, AI methods for disease classification are typically treated as black boxes and do not deliver interpretable results. To address this issue, the development of explainable AI is now a hot topic. Many visualization tools have emerged to interpret the predictions of convolutional neural networks and explore tumor infiltration and heterogeneity in histopathology images, while capturing the interaction of heterogeneous cells in a tumor. Similar concepts are being developed in other areas of machine learning and other types of data. Currently, researchers are actively developing interpretable AI models while evaluating the current problems and challenges.

3. DATA ECOSYSTEM FOR DIAGNOSTIC AI

The successful development and deployment of AI applications require large amounts of high-quality datasets. Accordingly, the second phase of the AI diagnostic process aims to identify, collect, and organize suitable data sources. This is a collaborative endeavor that involves multiple stakeholders to ensure that the necessary and sufficient data are available and, ideally, integrated within a common infrastructure—the diagnostic data ecosystem. This includes three fundamental properties: a sufficient amount of data collected from diverse sources; sufficient quality, trust, and provenance of the data; and, last but not least, compliance of the diagnostic data ecosystem with privacy regulations and ethical standards.

More than a decade ago, the data-driven paradigm called "big data" emerged in health-care diagnostics, which integrates all the different sources of data available in external and internal health systems into a single ecosystem with high interoperability. With the continuous increase in clinical, genomic, experimental, and post-mortem databases, data-driven medicine is moving toward an "evidence-based data-integration" approach for patient diagnosis, treatment prescription, and prognosis estimation. Recent technical breakthroughs in big data storage, parallel distributed processing, and high-performance cloud-based data storage and analysis tools make these ideas feasible.

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3.1. Data sources and interoperability Accurate data are essential for reliable machine learning-based diagnostic systems. Artificial Intelligence (AI) models learn patterns from historical data that are generalizable for the classification of unseen data. Diagnostic AI systems take the data-driven medicine paradigm approach in which a certain disease is classified as positive or negative using disease-specific features. Generally, the larger the dataset, the better the accuracy. Diagnostic models achieve high accuracy using datasets of thousands to millions on diseases like pneumonia, diabetes, heart disease, breast cancer, etc. Despite the success of these AI applications, many relying on supervised learning models have not been implemented in the real healthcare environment.

The underlying reason is insufficient data, especially in the medical domain, where expert-labeled data are harder to come by. Data accessibility is a fundamental issue because, in most cases, the data is owned by the originating sources, i.e., hospitals, and is not easily shared with external parties. Medical datasets made available such as ImageNet or the Kaggle repositories, do not contribute to knowledge discovery in standard supervised learning. Hospitals protect the patient data, owing to privacy laws such as Health Insurance Portability and Accountability Act (HIPAA). In reality, few datasets across multiple institutions are connected to train a diagnosis model. Therefore, collaborative AI models that implement federated learning are the need of the hour.

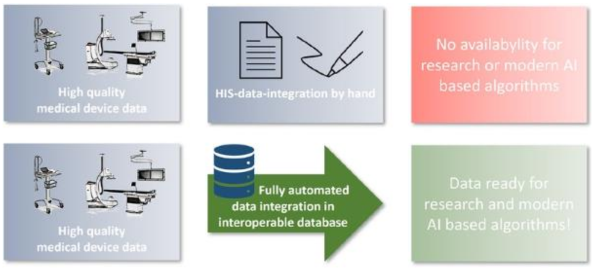

Fig 2: Smart hospital achieving interoperability

3.2. Data quality, governance, and privacy The information quality for supported applications in diagnostics must be comparable, even superior, to that encountered in the diagnostic process itself, for which clinicians have been trained to cope with the intrinsic limitations of the available information. AI applications should comply with the synthetic continuity principle to ensure informative output flows. Consequently, they should be qualified in terms of precision, sensitivity, specificity inclusion, and exclusion risk, along with their potential biases and appropriateness under different correspondence scenarios.

In an increasingly AI-based environment, data security is a growing concern. Enabling data sharing through proper governance is also paramount. Well-structured, clean, and labeled data constitute important assets for supervised ML methods. Data required for learning, testing, and deployment must be clearly delineated to enable ML-based applications to deliver their expected benefits, either in supporting clinicians in the decision-making process or in favoring a better informed direct engagement of patients in the decision-making process.

4. AI TECHNIQUES FOR DIAGNOSTICS

Supervised learning is by far the most widely used AI technique for disease classification and has been applied to almost all types and categories of diseases, medical conditions, and diagnostic tasks. The learning model incorporates feature representations of the data, called features, which identify and separate distinct classes of data corresponding to various diagnostic categories in the training data set. For novel diagnostic cases, the class label (diagnosis) is mapped to patient data using the learned classifier. The accuracy of these diagnostic classifiers is highly dependent on the inclusion of relevant, representative, and faultless features. Consequently, feature generation is a critical domain-dependent data engineering step and can be performed manually by a domain expert or with the help of other knowledge-driven AI techniques.

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Unsupervised and semi-supervised learning methodologies have been used in less than 20% of all AI studies in the healthcare domain because, until recently, most such studies were targeted at the classification problems. These techniques are, however, ideally suited for exploratory data analysis tasks in healthcare diagnostics when class labels are not available or too few to learn discriminative classifiers. A big share of the available healthcare data is unlabelled, noisy, and not trustworthy; these properties of the data are well accommodated by the definition of unsupervised learning algorithms. Automatic anomaly detection on diagnostic data can further assist clinician decision-making. The semi-supervised methodology harnesses the strengths of both labelled and unlabelled data for improved classifier accuracy in challenging small-data scenarios.

Equation 2: ROC curve quantities and AUC

A classifier often outputs a **score** $s(x)$. Pick a threshold t:

- Predict positive if $s(x) \geq t$

For each t, compute:

$$TPR(t) = \frac{TP(t)}{TP(t) + FN(t)} \text{(Sensitivity)}$$
$$FPR(t) = \frac{FP(t)}{FP(t) + TN(t)} = 1 - \text{Specificity}(t)$$

Plot $TPR(t)$vs $FPR(t)$across thresholds → **ROC curve**.

AUC is the area under that ROC curve:

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

4.1. Supervised learning for disease classification Supervised learning is widely used for classification tasks within smart diagnostic systems. Given a set of labeled disease data, a diagnostic model is trained to map the attributes of new input cases to disease labels. In attempts to automate or augment human-like diagnosis, attempts in the literature range from the recognition of diabetes, heart disease, and Alzheimer’s with clinical and physiological data to the assessment of COVID-19 severity with clinical reports and medical images. Besides supervised classification techniques commonly used in machine learning, deep learning models such as convolutional neural networks (CNN) are increasingly popular for imaging diagnostics.

State-of-the-art performance may only be achieved with large labeled data, as demonstrated in the ImageNet challenge. Yet, such comprehensive datasets are scarce in medical diagnosis, not least because data sharing is often limited by the protection of sensitive patient information. Consequently, supervised models can introduce bias or be poorly generalizable. Therefore, the high stakes of clinical decision making have encouraged clinical practitioners to avoid black-box deep learning models based on CNNs that exhibit such weaknesses.

To overcome these limitations, researchers have investigated hybrid diagnostic systems. In these systems, AI guides patient examination, thereby enriching the model-training data pool and addressing the shortage of labeled data. Clinicians confirm the effectiveness of such procedures as a result of shared decision making and result verification.

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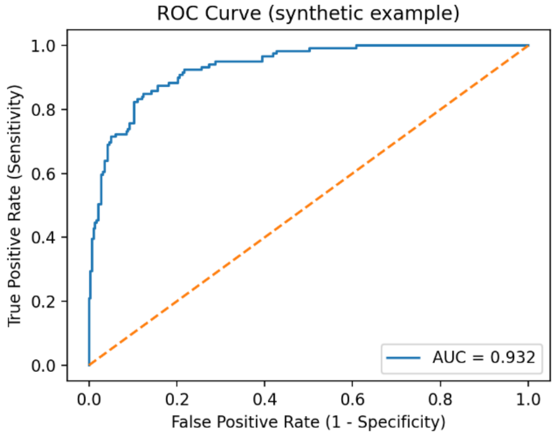

4.2. Unsupervised and semi-supervised approaches Several diseases exhibit only a few labeled instances, preventing the application of supervised learning methods. Unsupervised learning, specifically clustering, as well as semi-supervised and transfer learning, allow leveraging large amounts of available unlabeled data. Unsupervised learning finds similar groups of tests, radiology images, or patients without predefined labels. Clustering histopathology images enables high-accuracy tissue type prediction by aggregating features from similar patches. Aiming to loosen that constraint in other domains, semi-supervised methods leverage unlabeled samples for classification, although a small set of labeled data is still needed.

Pneumonia is an example of a disease with a very small training sample, available only in a few hospitals. Labeling the training set is laborious, as it requires radiologists to verify the presence or absence of pneumonia in chest X-ray images. An application of semi-supervised learning merges self-training with dropout from neural networks. Transfer learning provides an alternative when a direct data source is missing. For instance, models trained for chest disease classification have been successfully transferred to a community health care system in India. Solutions to further boost the performance of models in low-data environments include the thickening of training data via image augmentation and the synthesis of additional samples using a generative adversarial network. In histopathology image analysis, semi-supervised learning improves the segmentation and detection of cancer regions.

5. BIG DATA INFRASTRUCTURE AND PROCESSING

Real-time analytics and a resilient backend supporting multi-modal, redundant, and secure access are essential when managing Big Data for medical diagnostics. Protocols to guarantee controlled and authorised access improve usability both for enterprises and common users. Distributed and parallel processing combined with dedicated GPU clusters can offer an effective solution for processing large datasets and achieving quick and precise results.

Big Data storage systems must consider whether the primary need is for low-cost, high-availability, or hundred-per-cent durable storage. Further considerations on data storage include the type of data hierarchy, the access frequency of the data to be stored, its lifespan, and the need for notifications about data access. The straightforward integration of machining engines into storage systems accelerates the analysis of massive amounts of data. Traditional data processing is a mature and generally accepted concept. Nevertheless, it is now necessary to migrate real-time data from mobile phones/devices using mobile applications or web interfaces. Special care must be taken to ensure high usability for the end users who work on the Data Mind and engage with Big Data via Web- or Mobile-based applications.

5.1. Data storage solutions and retrieval Tailored solutions are required to store heterogeneous, complex, and multi-modal data in diagnostic AI collections. Document-oriented NoSQL databases, such as MongoDB or Amazon DynamoDB, allow the native storage of images and text. Data retrieval is accomplished with structured query language

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or programming interfaces. Common search engines such as Elasticsearch and Solr offer near real-time distributed full-text search and retrieval across various input types.

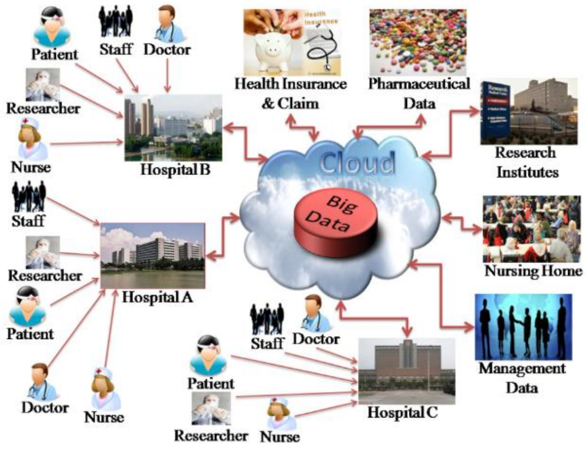

Fig 3: Healthcare Big Data Analysis

Unstructured, time-stamped, streaming, and semi-structured data from social media, sensor networks, and the Internet of Things is efficiently retained in key-value stores (e.g., Redis, Amazon DynamoDB) and time-series databases (e.g., InfluxDB, TimescaleDB). These solutions are designed for high-throughput and low-latency workloads, providing fast access to high-speed data and Continuous Queries for complex pattern matching. SQL-based technology can also be used to store large volumes of data in personalized diagnostic AI applications, with cloud providers such as Amazon Web Services and Google Cloud Platform offering integrated support for storage and computation.

5.2. Real-time analytics and streaming data Health-generated data are dynamic and continuously evolving with time. Such data require continuous assimilation and real-time analytic and predictive solutions; otherwise, they can become valueless. Artificial intelligence (AI) methods for data analytics can only be effective if the data generated are accessible within the comfort of time. AI has restarted the importance of real-time analytics within a supervisory or predictive model through a modelling strategy that connects the use of under-utilised data with a strongly related more concentrated data.

Tele-monitoring and sensor-driven health applications enable health providers to provide timely services through real-time analytics but these applications generate data that should be monitored continuously in order to establish their role in early detection of critical events (e.g. heart failure). These data are invalid if they are analysed after an event occurred. Near real-time information becomes essential when data are generated and consumed with a time cycle of seconds or minutes. Care systems are constantly working towards the provision of always-available services and to avoid or mitigate the impact of critical events for the patients and the service providers. These near real-time capabilities imply that even a delay of a few seconds in the delivery of these results may be unacceptable: the introduction of soft-skills models that automatically simulate possible situations may be essential to overcome short analysis time (less than 15 seconds). One of the reasons that makes near real-time analytics interesting is the summer–winter temperature oscillation, which is regularly present in some temperate regions. In these situations, pop-up calorimetric islands are expected in areas close to the coast in the summer; they appear as abrupt variations of temperature of a narrow band and a few hours of duration, easier to describe with near real-time analyses rather than being ignored and discovered with normal or delayed analyses.

6. VALIDATION, EVALUATION, AND EVIDENCE

Many AI systems have been developed to assist in disease classification and diagnosis; however, many of these do not originate from a biomedical or medical standpoint. The use of AI is also new and presents risks related to its governance and reliability. Therefore, a key challenge remains how to validate and evaluate diagnostic AI models. Furthermore, evaluation and validation must develop beyond common accuracy metrics to consider fairness and bias, including cohort transferability and generalizability, as well as how end-users, such as clinicians or patients, will use diagnostic AI systems

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in their decision support workflows. Consequently, evidence of clinical utility remains a crucial requirement before being used in practice.

Despite hidden pathways remaining a barrier for patients, the AI paradigm shift enables drug discovery and toxicity prediction, in silico human-based trials, and diagnosis support by:

1. Performance metrics such as accuracy, sensitivity, specificity, AUC, and F1-score;

2. Classification-based model evaluation using k-fold cross-validation;

Given that prediction or representation accuracy of the AI-driven diagnostic models is an accuracy measure, other metrics need to be optimized to decrease bias and increase fairness. These include cohort transferability, latent exploration capability, and generalization stability by quantifying how performance varies across subpopulations likely behaving differently in the presence of that disease. Furthermore, the risk–benefit balance or resource allocation potential of all proposed models determines if their deployment is meaningful or spurious.

Equation 3: k-fold cross-validation

Procedure:

1. Split dataset Dinto $k$disjoint folds $D_1, \dots, D_k$.
2. For each fold i:
    - Train on $D \setminus D_i$
    - Test on D_i
    - Compute metric M_i(e.g., accuracy, AUC, etc.)
3. Report mean (and usually variability):

$$\bar{M} = \frac{1}{k}\sum_{i=1}^{k} M_i$$

A common spread measure is the standard deviation:

$$s = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}(M_i - \bar{M})^2}$$

6.1. Performance metrics for diagnostic accuracy Given that diagnostic systems should ideally classify the data in accordance with the clinical reference standard, performance metrics mainly focus on the binary or multiclass classification of test labels for a test set where the label values are known. The traditional evaluation metrics used in AI-based disease detection and classification for supervised learning algorithms specifically focus on accuracy (the ratio of correctly classified cases out of total test data) or simply the confusion matrix with more specific information about false positives and false negatives, which are crucial for certain diseases.

Yet, whether simply using accuracy as the main metric or relying on the confusion matrix for using more advanced metrics, these evaluations are performed on a dataset that is ideally independent and comes from a different distribution than the training dataset. However, AI-based disease detection and classification systems address all types of disease prediction. Furthermore, these systems are developed for measuring illness present or not in the patient with the respective

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score, hence cannot rely on the accuracy of their predictions alone. If bias persists in the model that affects a minority class, the accuracy may still be high as a result of accurate predictions on the major class.

6.2. Bias, fairness, and generalizability To achieve robust, reliable, and trustworthy diagnostic AI, it must be evaluated on unseen data before deployment in clinical practice. Only after thorough validation, where AI performance is compared with trustworthy benchmarks, can dependable integration into the full diagnostic pathway occur. Both statistical and clinical considerations govern the decision to deploy diagnostic AI. Statistical significance relates solely to how well AI will perform on further unseen data. Clinically differentially significant relates to whether the performance is expected to lead to better patient outcomes when applied in clinical practice. The evaluation of diagnostic AI and expression of performance should be tailored to the clinical task. Clinicians and patients expect performance and clinical utility to be expressed in clinical terms: that is, sensitivity, specificity, positive predictive value, negative predictive value, and diagnostic odds ratio.

Bias and fairness are high-profile topics in AI. There is a danger that AI-human decision making could reinforce and exacerbate historical bias and inequity when allowing AI to assist in predicting, recommending, or making decisions about the consequences of a diagnosis. Diagnostic AI using supervised learning can also suffer bias, that is, reduced performance on certain patient subgroups due to lack of representation of those subgroups in the training data. Without sufficient examples in the training data, supervised learning models can fail to learn the patterns pertaining to those groups. Bias can thus result from a shift in the underlying population distribution, leading to changes in the proportion of patient subgroups, or by a skew in the training data beyond that inherent in natural population disparity. Quantifying bias and assessing fairness are important for AI-based decision support systems and tools, in order to determine whether deployment should occur and, if so, whether the models should be integrated into clinical consensus decision making or be linked to deeper or more contingent levels of support in the workflow.

7. CLINICAL INTEGRATION AND WORKFLOW

The deployment of AI methods and models in diagnostic decision making is often achieved with a clinical–decision-support system (CDSS) interface. A CDSS is designed to deliver, as needed, patient-specific clinical advice to aid health professionals making diagnostic decisions in consultation with the patient. A well-designed CDSS, thus, is a valuable support tool for healthcare professionals working in conjunction with a patient. A CDSS consists of the following four components: an input module where the clinician provides data, a knowledge base of symptoms and disease associations that can be inferred by the CDSS, an inference engine that evaluates the input data, and an output module that returns a list of likely diagnoses to the clinician.

As patients increasingly use smart devices to monitor their health and download health records, an AI assistant can engage patients directly. Patients are turning to digital sources not just to educate themselves about their conditions but also to have digitally informed conversations with their clinicians. Collectively, these trends point to a move toward shared decision making for patients and clinicians.

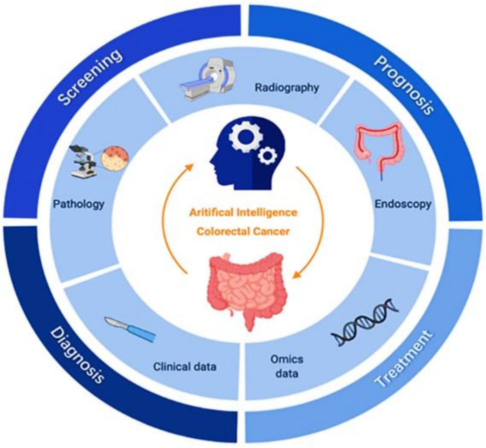

Fig 4: Artificial intelligence in healthcare and medicine clinical

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7.1. Decision support interfaces for clinicians A clinical ecosystem comprises of a cohort of patients, examination, diagnosis, treatment, parturition, rehabilitation and recurring health checkups. AI based decision support systems are used to aid in diagnosis. Key contributors to accurate diagnosis are Data-driven medicine paradigms, AI methodologies targeted at diagnostic tasks, Data Ecosystems for Diagnostic AI covering Data Sources & Interoperability, Data Quality, Data Governance & Privacy, AI Techniques for Diagnostics focusing on Disease Classification with Supervised Learning, Unsupervised and Semi-supervised Techniques and Model-in-the-loop Training & Testing, Big Data Infrastructure & Processing including Data Storage & Retrieval, Real-time Business Analytics & Streaming Data Processing, Validation Evaluation & Evidence covering Metrics of Performance in Diagnostic Accuracy, Bias, Fairness & Generalizability and Clinical Integration & Workflow summarizing Decision Support for Clinicians & Patient Engagement & Shared Decision Making.

The goal of a diagnostic decision-support system is to help clinicians make diagnostic decisions by suggesting possible diagnoses and their relative probabilities based on patient characteristics and symptoms. Such systems can have a small role in medical practice, identifying a limited number of diseases requiring confirmatory tests and the potential for error and unwanted cost driving down usage. More common has been AI deployed in risk-scoring tools, decision trees, expert systems and chatbots to predict the probability of a specific outcome or classify patients into groups at differing risk. AI can generate alerts about unusual test results or predict decompensation before it occurs, with varying accuracy, and increasingly incorporates social determinants of health, medication adherence and connectivity. AI represents a valuable addition to probability bias, showing promise in the development of clinical decision-support systems, but successfully taxonomising and deploying it requires adherence to established best practice.

7.2. Patient engagement and shared decision making Applied AI, combined with the concepts of Smart Healthcare, exerts great influence on healthcare diagnostics. Applied AI can assist healthcare professionals, adopting a fail-safe approach, by overcoming limitations in accuracy, robustness, interpretability, fairness, or generalizability. This is achieved through information integration for fault-tolerant failures and detection for lower diagnostic performance. Although AI methods have great potential, research is still limited compared with disease classification and disease progression prediction. Treatment decisions or patient self-management using AI have advanced only in the areas of mental health problems and therapeutic applications.

Smart Healthcare Diagnostics are finally becoming possible, owing to a plethora of new technologies and the gradual establishment of Big Data AI technologies. Nevertheless, the development of Smart Healthcare Diagnostics remains a challenging open issue. The four-stage Data-Driven Medicine Paradigm provides a unifying structural description of diagnosis, and applies established theory and techniques to more accurately classify diseases and improve using human-ground-curated information. The exploration of AI clinical decision support or realistic patient engagement with shared decision-making remains in its infancy for most diseases or conditions. Despite current trends, many ideas reflect the simplicity of the approach rather than its power, especially at the disease level. The full evidence requested by evidence-based medicine poses a hard challenge, and requires the integration of fault-tolerance research with big-data methods for synthetic datasets.

8. CONCLUSION

Research on the application of AI and Big Data in healthcare, especially in diagnostics, is increasingly active due to rapid technological advancement. Evidence-based arguments for adopting AI and Big Data for smart healthcare diagnostics are evaluated, with a focus on four key problems faced by Data-centric healthcare in general and Data-centric AI in particular: how to obtain sufficient quantities of good quality training data, how to validate the solution, how to integrate the AI solution into the clinical workflow, and how to find relevant AI solutions for Big Data.

A survey on contemporary diagnostic Data-centric AI solutions shows that most safety-critical problem areas still rely on classical AI or are at the reinforcement-learning stage. AI solutions are available in numerous disease areas, but only in a few problem areas are they addressing complex diagnostic problems with the potential to achieve super-human performance. Methods for the evaluation of diagnostic Data-centric AI are discussed, pointing to an urgent need for the

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integration of clinical bias-detection capability, clinical and patient confidence management, and clinical safety analysis into the tools for AI AI-Data Drivencentric Data-centric AI Data-driven AI Data-centric AI Data-centric AI Data-centric AI Data-driven AI Data-driven AI Data-centric AI Data-centric AI AI monitoring and evaluation. The continued push in Data-driven Data-centric Data-centric Data Drivencentrice Data Drivencentrices Data Drivencentric Data Drivencentric Data-centric Data-centric AI AI.

8.1. Emerging Trends The development of AI-oriented smart healthcare diagnostic techniques offers significant promise—and at a rapid pace. Yet, the continuing integration of such techniques in real clinical settings remains a complex and perilous pursuit. When clinical adoption does occur, it often involves a narrow range of pathologies. This limited scope relates, in part, to the requirement for voluminous high-quality data underpinning deep-learning models: typically vast datasets are often available only for traditionally high-profile disease areas. Within AI-oriented smart healthcare diagnostics and decision-support systems, big-data-driven medicine constitutes the new paradigm.

Shifting towards more exploratory data-analysis processes opens diagnostics to other domains with smaller training datasts for disease classification. Ultimately, data-driven diagnostic methods may allow patients to take the initiative through health evaluation and self-disease-management decisions. Developing high-quality AI-based diagnostic systems requires joint consideration of three intertwined issues: the underlying big-data-driven ecosystem enabling predictive modeling; the AI learning and inference techniques used; and the design of the prototype application delivering the resulting evidence in a form suitable for clinicians and patients. Supporting other paradigms and more exploratory data analysis may facilitate developing decision-support systems for other diseases.

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