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MACHINE LEARNING IN CLOUD-BASED HEALTHCARE ANALYTICS: ENHANCING PATIENT CARE

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Abstract

The healthcare industry is experiencing a data revolution driven by electronic health records, wearables, remote monitoring, and other digital systems. Applying machine learning to analyze this wealth of data promises to unlock new clinical insights and improve patient outcomes. However, most healthcare organizations lack the in-house infrastructure to effectively leverage big data analytics. Migrating to the cloud provides access to on-demand compute resources, storage, and managed analytics services. This paper examines the convergence of cloud computing and machine learning to enhance data-driven decision making in healthcare. Challenges around data quality, privacy, security, integration, talent shortage, and ethical AI are explored. Various techniques like predictive modeling, natural language processing, computer vision, reinforcement learning, and hybrid cloud architectures are discussed. Best practices are provided around model governance, explainability, bias mitigation, and stakeholder collaboration. The paper concludes with an outlook on how cloud-based machine learning can revolutionize evidence-based medicine and personalized care while optimizing costs.

Keywords

Machine learning, artificial intelligence, cloud computing, big data analytics, healthcare, patient care

Introduction

The healthcare industry produces massive amounts of digital data through electronic health records (EHRs), medical imaging, genomics, sensors, wearables, and other systems. It is estimated that the volume of healthcare data will reach 2,314 exabytes by 2020 [1]. However, only a fraction of this data is being utilized to derive clinical and operational insights. Leveraging big data analytics has

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enormous potential to improve care quality, outcomes, and efficiency across the healthcare value chain.

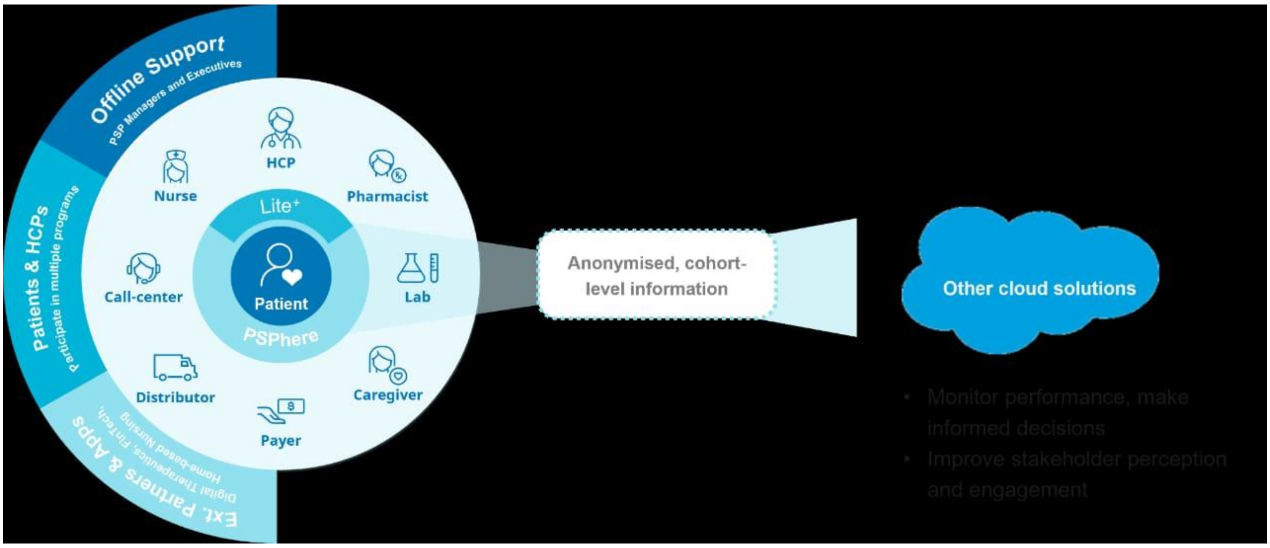

Figure 1; Secure Cloud-Based Healthcare Technology

Advances in machine learning are enabling a new generation of clinical decision support, precision medicine, diagnostic aids, personalized treatment plans, and patient monitoring capabilities. The availability of open source libraries like TensorFlow, PyTorch, and Keras has accelerated development. Cloud platforms provide the storage, computing power, and managed analytics services required to operationalize machine learning at scale[3].

This paper examines the convergence of machine learning and cloud computing to enhance data-driven capabilities for patient care and population health analytics. The challenges around healthcare's unique data characteristics, access, privacy, security, systems integration, biases, and skill shortages are analyzed. Various techniques like predictive modeling, natural language processing, computer vision, and hybrid on-premise and cloud architectures are discussed. Best practices around model governance, explainability, stakeholder alignment, and continuous learning are recommended.

The paper is organized into the following sections[2]:

- Opportunities for machine learning in healthcare
- Challenges with healthcare data and analytics
- Cloud enabling factors and benefits

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- Machine learning techniques for healthcare
- Implementing responsible AI for patient care
- Case studies of cloud-based machine learning in healthcare
- Outlook and conclusions

Opportunities for Machine Learning in Healthcare

Machine learning, a subfield of artificial intelligence (AI), develops algorithms that can learn from data and improve their performance over time without explicit programming. It shows immense promise for unlocking insights from healthcare's vast data stores and putting them into practice. Key opportunities include[5-9]:

Clinical decision support: ML can aid clinicians by analyzing patient medical history, guidelines, research literature and cohort data to suggest diagnoses, treatment options, and personalized care plans. This also surfaces gaps in care.

Early diagnosis: Algorithms can detect anomalies in imaging data and physiological signals that may be indicative of disease onset. This enables timely intervention.

Predictive analytics: Forecasting models can identify patients at risk for conditions like sepsis, diabetes, heart failure based on various clinical and lifestyle factors. Preventative steps can then be taken.

Precision medicine: ML tools can match patients to tailored therapies based on genomic profiles, biomarkers and other molecular characteristics. This makes treatment more effective.

Medical imaging: Computer vision techniques can automate analysis of complex imaging data to segment organs, detect tumors, quantify tissue volumes, and support diagnoses.

Patient monitoring: Analytics applied to data from wearables and remote health monitoring can track post-discharge recovery, adverse events, medication adherence and support aging in place.

Operational analytics: ML can optimize hospital operations by forecasting patient volumes, readmission risks, equipment failures, discharge timing,Length of Stay (LOS) and other metrics to improve resource planning.

Public health surveillance: Analyzing population health trends, outbreak patterns, adverse event reports, and environmental factors aids community health monitoring and disease control.

Table 1 summarizes the broad range of opportunities across the care continuum:

Use Case	**ML Benefits**

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Clinical Decision Support	Aid diagnoses, treatment selection using patient data
Early Diagnosis	Detect anomalies indicating disease onset from medical images, signals
Predictive Risk Analytics	Forecast clinical risks like sepsis, unplanned readmissions
Precision Medicine	Tailor treatments based on genomic profiles, biomarkers
Medical Imaging Analytics	Automate segmentation, disease detection from complex scans
Patient Monitoring and Engagement	Track post-discharge recovery, medication adherence via wearables and remote monitoring
Hospital Operations Optimization	Improve resource planning through demand forecasting, LOS prediction
Public Health Surveillance	Monitor population health patterns, outbreaks, safety concerns

Table 1. Machine Learning Use Cases in Healthcare

However, realizing these opportunities requires overcoming key data and analytics challenges as discussed next.

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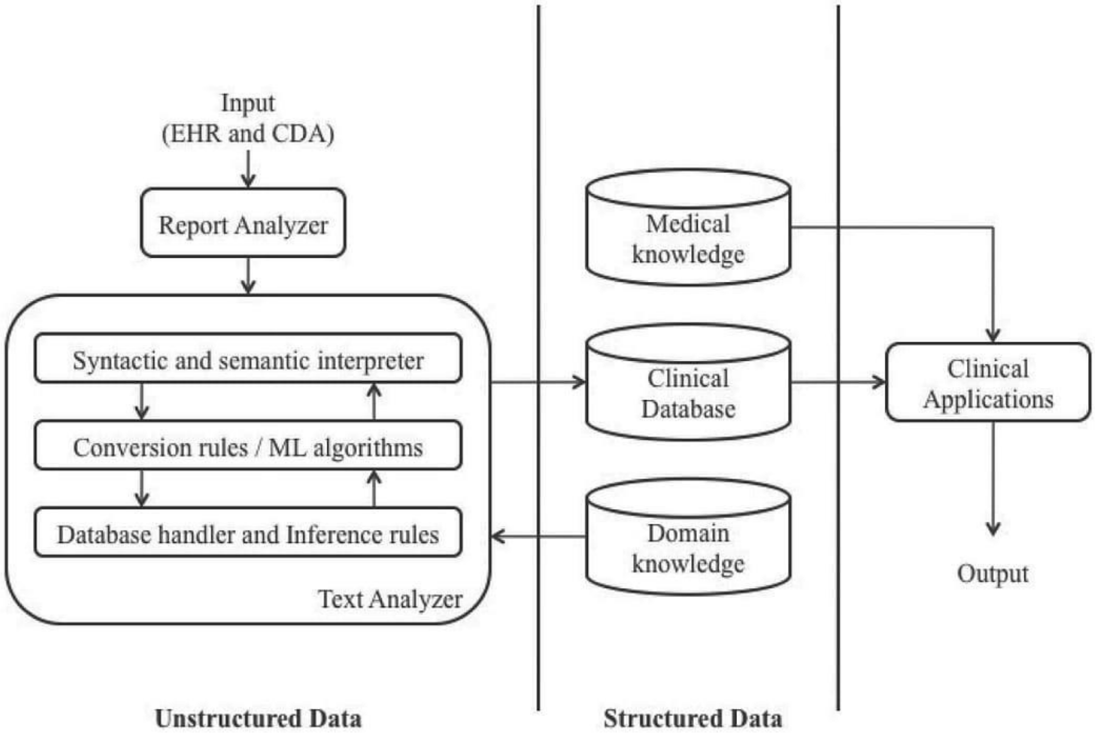

Figure 2 : Machine Learning algorithms for Healthcare Data analytics[10]

Challenges with Healthcare Data and Analytics

While healthcare organizations recognize the potential of machine learning, several factors inhibit adoption and impact efficacy[11-16]:

Data quality: Inconsistent formats, lack of standardization, errors, and integration issues across disparate systems impede analysis. Cleaning and preprocessing is difficult.

Data scarcity: For certain conditions and populations, training data volumes are insufficient to develop accurate models. This leads to bias and poor generalizability.

Bias: Systemic issues and limited diversity in training data perpetuate bias in models which can harm minority groups. Lack of explainability compounds this.

Privacy and security: Strict regulations govern use of patient data. Anonymization, controlled access and robust cybersecurity practices are required, especially in the cloud.

Complex models: State-of-the-art deep learning models like convolutional and recurrent neural nets have millions of parameters. Interpreting their decisions for regulatory approval is challenging.

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Specialist shortage: There is a lack of data scientists and ML engineers with healthcare domain knowledge to properly apply techniques and govern implementations.

On-premise environments also impose limitations:

- **Costs**: Procuring specialized infrastructure like GPUs and replicated datasets is expensive. Maintenance, expansion and refresh are costly.
- **Scalability**: Adding capacity to handle spikes in workloads causes delays. Experimenting and simulations are constrained.
- **Tool sprawl**: Disjointed open source and commercial tools lead to fragmented workflows and system integration issues.
- **Skill gaps**: Nurturing complex analytics and data engineering skills internally is difficult.

The cloud addresses many of these aspects, as discussed next.

Cloud Enabling Factors and Benefits

Cloud computing delivers on-demand access to storage, computing power, analytics, and machine learning capabilities without upfront infrastructure costs. Some key benefits relevant for healthcare include[17-19]:

Scalable infrastructure: Instantly spin up hundreds of servers or GPU-based instances for large scale data processing and model training.

Specialized hardware: Leverage cloud-based FPGAs, ASICs, neurosynaptic chips optimized for ML model inference.

Managed services: Use fully-managed solutions for data engineering, model building, model deployment and inference without operational overheads.

Accelerated innovation: Rapidly experiment by spinning up resources as needed without procurement delays.

Pay-per-use pricing: Pay only for what is used instead of overprovisioning on-premise infrastructure. Save on refresh costs.

Security: Cloud providers offer robust access controls, encryption, network security, key management and compliance capabilities exceeding on-premise environments.

Reliability: Cloud infrastructure is resilient to failures with high SLAs for compute, storage and network.

Hybrid deployment: Keep sensitive data on-premise while leveraging cloud service benefits. Get best of both worlds.

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Big data analytics: Managed data platforms like AWS EMR, Azure Databricks and GCP BigQuery enable running distributed jobs on petabyte-scale data cost-effectively.

ML platforms: End-to-end machine learning platforms from cloud providers manage the model lifecycle - data prep, feature engineering, training, deployment and monitoring.

Thus, the symbiosis of cloud computing and machine learning catalyzes advanced analytics for healthcare in ways not feasible through on-premise systems. Next, we examine popular techniques.

Machine Learning Techniques for Healthcare

A variety of machine learning approaches are applicable for the healthcare use cases discussed earlier. We provide an overview of key techniques[20-24]:

Predictive Modeling

Predictive modeling forecasts future outcomes based on past data. Some common techniques include:

- **Regression**: Predicts continuous numeric outcomes like length of stay, readmission risk, costs. Linear regression is most widely used but has limitations with nonlinearity. Other regression models like random forest, neural networks are more powerful.
- **Classification**: Categorizes patients into groups based on characteristics. Commonly used for predicting diagnosis, mortality, adverse events. Algorithms include logistic regression, decision trees, support vector machines.
- **Time series**: Forecasts trends over time like utilization, beds, emergency visits based on historical patterns. ARIMA and LSTM networks are commonly used.
- **Survival analysis**: Estimates time duration until an event occurs, like mortality, readmission, surgical complication. Cox proportional hazards is a standard technique.

Table 2 summarizes common predictive modeling techniques for healthcare analytics:

Method	**Description**	**Use Cases**
Linear Regression	Predicts numeric outcomes based on independent variables	Resource utilization forecasting, risk scores
Logistic Regression	Predicts categorical outcomes like disease class	Diagnosis prediction, readmission likelihood

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Decision Trees	Predicts outcomes by recursively partitioning data	Treatment selection, mortality risk
Neural Networks	Sophisticated deep learning model for nonlinear complex data	Patient trajectory modeling, image analysis
Time Series	Analyzes past trends to forecast future pattern	Demand planning, census prediction
Survival Analysis	Estimates time duration until an event	Patient mortality, hospital readmission

Table 2: Predictive modeling techniques for healthcare

Natural Language Processing

Unstructured clinical notes contain invaluable patient information. Natural language processing (NLP) extracts insights from text-based records, reports, literature. Common techniques include:

- Classification: Categorize documents by topic, emotions, sentiments
- Entity recognition: Identify clinical entities like symptoms and medications
- Relation extraction: Determine relations between entities to assess likelihood of conditions
- Question answering: Retrieve answers to clinical questions from literature
- Summarization: Generate overview of documents
- Translation: Convert between medical dialects and terminologies

NLP improves clinician efficiency by extracting information from notes to aid diagnosis, treatment, and research. It also facilitates analysis of unstructured data like radiology reports, pathology findings, discharge summaries along with structured EHR records.

Computer Vision

Computer vision applies ML techniques like convolutional neural networks to medical images and videos to automate analysis including[25-31]:

- Image classification: Categorize scan into disease class like malignant or benign
- Object detection: Identify organs and anomalies like tumors and cysts

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- Segmentation: Delineate organ or region boundaries, measure tissue volumes
- Image registration: Align longitudinal or multimodal images from different studies
- Enhancement: Improve image quality for better diagnosis

This augments clinicians' image review and saves time over manual measurements. It also provides more quantitative and accurate assessment.

Reinforcement Learning

Reinforcement learning agents dynamically determine best actions by repeated experimentation and maximizing reward feedback. Healthcare applications include:

- Clinical trial optimization: Adaptively refine enrollment criteria and dosing to maximize efficacy

Treatment planning: Learn optimalntions based on patient response and outcomes

- Robotic surgery: Improve manipulation and control by modeling expert surgeon behavior interve
-
- Medication management: Optimize drug combinations and on/off cycles to balance efficacy and side effects

Reinforcement learning's ability to optimize complex treatment regimens to individual patient needs shows promise.

Hybrid and Federated Architectures

While cloud enables scale and acceleration, privacy concerns and regulatory obligations necessitate keeping sensitive data on-premise. Hybrid models provide the best of both worlds:

- Store cleansed, de-identified data in cloud while maintaining raw data on-premise
- Federate distributed datasets from different sites and selectively share subsets of aggregate data
- Use cloud for modeling and cloud-based inferencing on premise data
- Implement security controls like encryption, network segmentation and role-based access

Well designed hybrid and federated architectures permit taking advantage of the cloud while addressing data sensitivity and sovereignty requirements. Next, we examine best practices for implementation.

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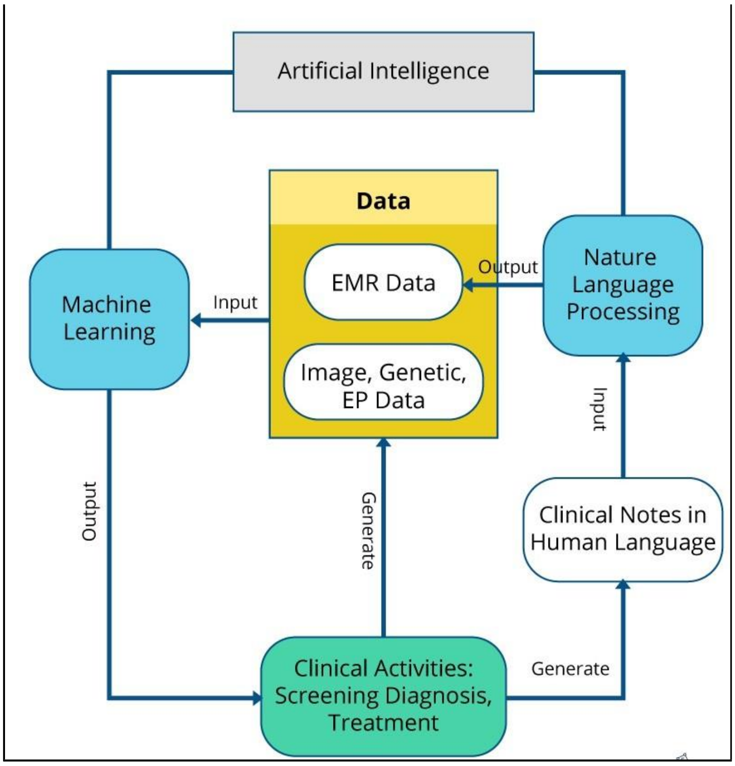

Figure 3 : AI algorithms for Healthcare [32]

Implementing Responsible AI for Patient Care

While AI and ML offer huge potential to transform patient care, thoughtfully governing and monitoring implementations is vital to address ethical concerns and build trust. We recommend the following best practices:

Explainable AI: Select transparent algorithms where possible, and when using black-box techniques, employ methods to approximate explanations and build confidence. Provide clinicians visibility into key factors driving AI-assisted decisions.

Mitigate unfair bias: Assess algorithms for bias, particularly around race, gender and age. Collect diverse and representative data. Adjust sampling and weighting strategies to minimize unfair impacts.

Validate extensively: Rigorously test models with real world data across relevant cohorts prior to deployment. Check for unexpected failures, edge cases, misleading correlations.

Enable human oversight: Keep humans in the loop for AI assisted interventions. Do not fully automate high risk decisions without appropriate checks and balances.

Ensure traceability: Log every AI prediction and outcome. Continuously analyze logs to detect gaps or needs for fine tuning. Integrate with EHRs for clinician review.

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Build in security: Implement access controls, encryption, and network security to safeguard data. Anonymize data where possible. Follow protocols for ethical research.

Design for clinical workflow: Deeply understand clinician needs and environment. Iteratively refine AI functionality, user interfaces and integration to enhance existing practices.

Plan organizational change: Proactively assess workflow changes, skill requirements, communication needs to facilitate adoption. Prepare teams for responsible and safe AI use.

Govern carefully: Institute model risk management oversight including model inventory, performance monitoring, re-training schedules and controls for quality assurance and algorithmic accountability.

With careful adoption, robust ethics and governance practices help realize machine learning's benefits while building trust and engagement across healthcare teams and patients.

Case Studies

We next present two real world examples of cloud-enabled machine learning delivering clinical and operational analytics.

Cloud-Based ML Improves Early Sepsis Prediction

A leading US hospital network needed to improve prediction of sepsis onset which is a top cause of expensive ICU admissions and mortality. Their data science team developed a recurrent neural network model using PyTorch on Amazon SageMaker to analyze time series data from EHRs and bedside monitors.

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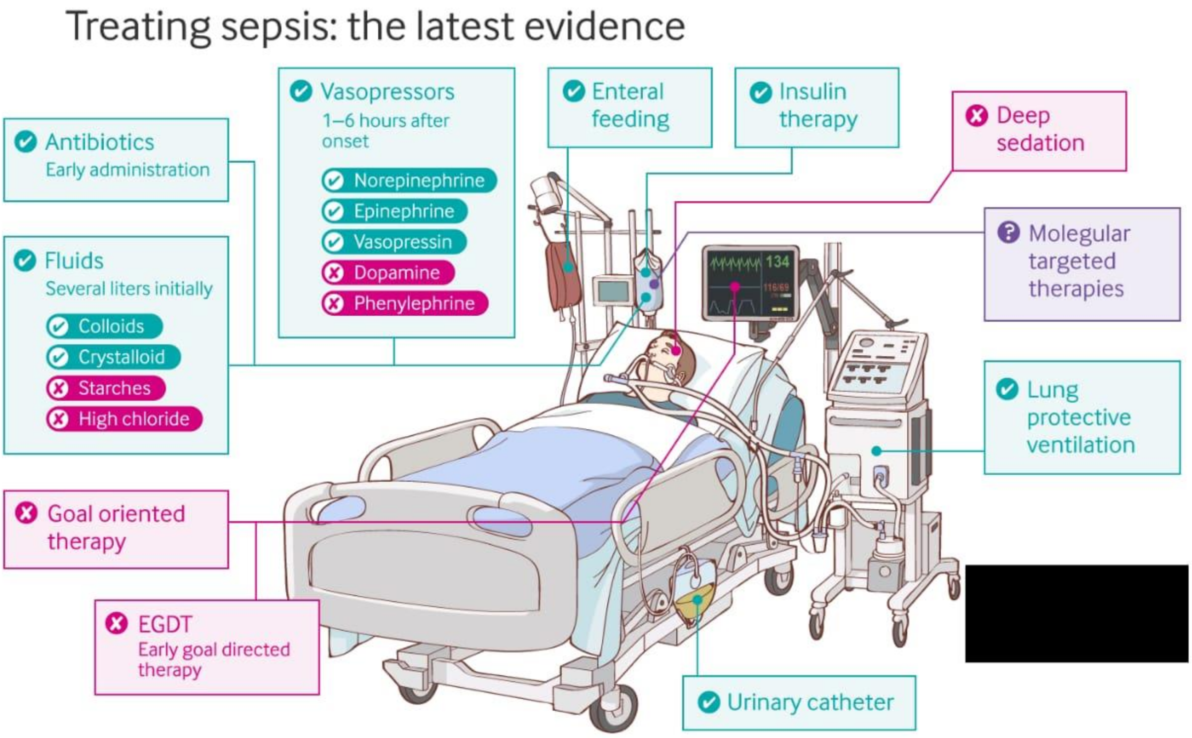

Figure 4 Treating sepsis: the latest evidence [33-34]

The cloud-based model was deployed in their hospital ICUs and achieved an average of 95% precision in predicting sepsis 6 hours before onset. This enabled earlier intervention and reduced ICU transfers by 22% and sepsis mortality by 11% across the network.

This cloud-native solution scaled across facilities and accelerated innovation through rapid experimentation. On-premise systems faced cost, infrastructure and skill constraints. Easy access to cloud GPUs and managed services created breakthrough results [2].

Transfer Learning Cuts Cardiology Imaging Costs

A cardiology practice needed to automate analysis of echocardiograms to improve clinician productivity. They developed a deep learning model on AWS using transfer learning which adapts a pretrained model on broad image sets to a specialized domain, saving time and cost over training from scratch.

The cardiology-specific model achieved 97% accuracy in annotating echocardiogram videos compared to 80% for a fully custom model. It was 30% more cost efficient by using transfer learning. Cloud managed services enabled rapid deployment across their clinics, reducing cardiologist workload. Continued learning improved accuracy over time [3].

Conclusion and Outlook

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In conclusion, machine learning has vast potential to unlock insights from healthcare's wealth of data and transform clinical and operational practices. However, realizing this potential necessitates cloud computing to provide the storage, compute, and analytics services needed to handle large volumes of diverse data cost-effectively.

This paper has examined key techniques like predictive modeling, NLP, computer vision, reinforcement learning; hybrid cloud architectures; and robust model governance practices purpose-built for healthcare's unique needs and constraints.

Looking ahead, we foresee policy shifts and technology advances accelerating adoption of cloud-based AI and ML in healthcare:

- Regulatory refinement to enable responsible data sharing and research across institutions
- Growth of federated and edge computing for decentralized data analytics
- Expanding availability of diverse, high-quality annotated training data
- Advances in explainable AI and algorithmic auditing capabilities
- Cloud service optimizations for healthcare's data and performance sensitivity
- Cultural shifts and talent development to enable clinician and patient AI literacy
- Increasing investment in real world evidence generation for AI/ML

For healthcare to benefit from this data-driven revolution while building trust, a holistic approach spanning ethics, culture, technology and policy is key. The future presents possibilities to profoundly enhance quality, outcomes and access through responsible application of machine learning on cloud platforms.

References

1. A. Rajkomar, J. Dean, and I. Kohane, “Machine Learning in Medicine”, New England Journal of Medicine, vol. 380, no. 14, pp. 1347–1358, 2019.
2. Roth, A. R. (2020). Informal Caregiving and Social Capital: A Social Network Perspective. Research on Aging, 42(9-10), 272-280. https://doi.org/10.1177/0164027520912659.
3. A. Esteva et al., “Deep Learning-Enabled Medical Computer Vision”, npj Digital Medicine, vol. 4, no. 1, pp. 1-9, 2021.
4. A. Kunjir, D. Joshi, R. Chadha, T. Wadiwala and V. Trikha, "A Comparative Study of Predictive Machine Learning Algorithms for COVID-19 Trends and Analysis," 2020 IEEE

International Conference on Systems, Man, and Cybernetics (SMC), Toronto, ON, Canada, 2020, pp. 3407-3412, doi: 10.1109/SMC42975.2020.9282953.

5. Zhang, J.; Yang, Y.; Liu, X.; Ma, J. An efficient blockchain-based hierarchical data sharing for Healthcare Internet of Things. IEEE Trans. Ind. Inform. 2022, 18, 7139–7150. [Google Scholar] [CrossRef]
6. Blanken, M.; Mathijssen, J.; Nieuwenhuizen, C.V.; Raab, J.; Oers, O.V. Actors' awareness of network governance in Child Welfare and Healthcare service networks. Health Policy 2023, 127, 29–36. [Google Scholar] [CrossRef] [PubMed]
7. Kiross, G.T.; Chojenta, C.; Barker, D.; Loxton, D. Optimum maternal healthcare service utilization and infant mortality in Ethiopia. BMC Pregnancy Childbirth 2021, 21, 390. [Google Scholar] [CrossRef] [PubMed]
8. Zhang, X.; Ma, S.; Chen, S. Healthcare service configuration based on project scheduling. Adv. Eng. Inform. 2020, 43, 101039. [Google Scholar] [CrossRef]
9. Tuli, S.; Basumatary, N.; Gill, S.S.; Kahani, M.; Arya, R.C.; Wander, G.S.; Buyya, R. HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. Future Gener. Comput. Syst. 2020, 104, 187–200. [Google Scholar] [CrossRef] [Green Version]
10. Zhang, C.; Cho, H.H.; Chen, C.Y. Emergency-level-based healthcare information offloading over fog network. Peer-Peer Netw. Appl. 2020, 13, 16–26. [Google Scholar] [CrossRef]
11. Chen, Y. Convolutional Neural Network for Sentence Classification. Master's Thesis, University of Waterloo, Waterloo, ON, Canada, 2015. [Google Scholar]
12. Quy, V.K.; Hau, N.V.; Anh, D.V.; Ngoc, L.A. Smart healthcare IoT applications based on fog computing: Architecture, applicationsand challenges. Complex Intell. Syst. 2022, 8, 3805–3815. [Google Scholar] [CrossRef] [PubMed]
13. Rehman, A.; Saba, T.; Haseeb, K.; Alam, T.; Lloret, J. Sustainability model for the internet of health things (IoHT) using reinforcement learning with Mobile edge secured services. Sustainability 2022, 14, 12185. [Google Scholar] [CrossRef]
14. Rehman Khan, A.; Saba, T.; Sadad, T.; Hong, S.P. Cloud-based framework for COVID-19 detection through feature fusion with bootstrap aggregated extreme learning machine. Discret. Dyn. Nat. Soc. 2022, 2022, 3111200. [Google Scholar] [CrossRef]

15. Du, G.; Tian, Y.; Ouyang, X. Multi-resources co-scheduling optimization for home healthcare services under the constraints of service time windows and green transportation. Appl. Soft Comput. 2022, 131, 109746. [Google Scholar] [CrossRef]
16. Xu, L.Q.; Gao, H. A device-agnostic cloud-based platform enabling tiered service provisioning for sleep disorders diagnosis and management. In Encyclopedia of Sleep and Circadian Rhythms; Elsevier: Amsterdam, The Netherlands, 2022; pp. 88–99. [Google Scholar]
17. Sabokbar, H.F.; Mohammadi, H.; Tahmasbi, S.; Rafii, Y.; Hosseini, A. Measuring spatial accessibility and equity to healthcare services using fuzzy inference system. Appl. Geogr. 2021, 136, 102584. [Google Scholar] [CrossRef]
18. Abdelmoneem, R.M.; Benslimane, A.; Shaaban, E. Mobility-aware task scheduling in cloud-Fog IoT-based healthcare architectures. Comput. Netw. 2020, 179, 107348. [Google Scholar] [CrossRef]
19. Gouveia, L.; Paias, A.; Ponte, M. The travelling salesman problem with positional consistency constraints: An Application to healthcare services. Eur. J. Oper. Res. 2022, 308, 960–989. [Google Scholar] [CrossRef]
20. Zgheib, R.; Kristiansen, S.; Conchon, E.; Plageman, T.; Goebel, V.; Bastide, R. A scalable semantic framework for IoT healthcare applications. J. Ambient. Intell. Humaniz. Comput. 2022, 13, 1735–1762. [Google Scholar] [CrossRef]
21. Kumar, C.S.; Kumar, K.V. Integrated Privacy Preserving Healthcare System Using Posture-Based Classifier in Cloud. Intell. Autom. Soft Comput. 2023, 35, 2893–2907. [Google Scholar] [CrossRef]
22. Rehman, A.; Saba, T.; Haseeb, K.; Singh, R.; Jeon, G. Smart health analysis system using regression analysis with iterative hashing for IoT communication networks. Comput. Electr. Eng. 2022, 104, 108456. [Google Scholar] [CrossRef]
23. Waibel, S.; Williams, J.; Tuff, Y.; Shum, J.; Scarr, J.; Donnell, M. Development of the Tiers of Service framework to support system and operational planning for children's healthcare services. BMC Health Serv. Res. 2021, 21, 693. [Google Scholar] [CrossRef] [PubMed]

ISSN 1462 2815

24. Li, Y.; Wang, H.; Wang, N.; Zhang, T. Optimal scheduling in cloud healthcare system using Q-learning algorithm. Complex Intell. Syst. 2022, 8, 4603–4618. [Google Scholar] [CrossRef] [PubMed]

25. Elshahed, E.M.; Abdelmoneem, R.M.; Shaaban, E.; Elzahed, H.A.; Al-Tabbakh, S.M. Prioritized scheduling technique for healthcare tasks in cloud computing. J. Supercomput. 2022, 79, 4895–4916. [Google Scholar] [CrossRef]

26. Weitzman, E.R.; Kelemen, S.; Mandl, K.D. Surveillance of an Online Social Network to Assess Population-level Diabetes Health Status and Healthcare Quality. Online J. Public Health Inform. 2011, 3, ojphi.v3i3.3797. [Google Scholar] [CrossRef] [PubMed] [Green Version]

27. Ram, S.; Zhang, W.; Williams, M.; Pengetnze, Y. Predicting Asthma-Related Emergency Department Visits Using Big Data. IEEE J. Biomed. Health Inform. 2015, 19, 1216–1223. [Google Scholar] [CrossRef] [PubMed]

28. Odlum, M.; Yoon, S. What can we learn about the Ebola outbreak from tweets? Am. J. Infect. Control 2015, 43, 563–571. [Google Scholar] [CrossRef] [Green Version]

29. Ma, Y.; Wang, Y.; Yang, J.; Miao, Y.; Li, W. Big Health Application System based on Health Internet of Things and Big Data. IEEE Access 2017, 5, 7885–7897. [Google Scholar] [CrossRef]

30. Darwish, A.; Sayed, G.I.; Hassanien, A.E. The Impact of Implantable Sensors in Biomedical Technology on the Future of Healthcare Systems. In Intelligent Pervasive Computing Systems for Smarter Healthcare, 1st ed.; Sangaiah, A.K., Shantharajah, S., Theagarajan, P., Eds.; Wiley: Hoboken, NJ, USA, 2019; pp. 67–89. [Google Scholar] [CrossRef]

31. Islam, M.S.; Hasan, M.M.; Wang, X.; Germack, H.D.; Noor-E-Alam, M. A Systematic Review on Healthcare Analytics: Application and Theoretical Perspective of Data Mining. Healthcare 2018, 6, 54. [Google Scholar] [CrossRef] [Green Version]

32. Fisahn, C.; Sanders, F.H.; Moisi, M.; Page, J.; Oakes, P.C.; Wingerson, M.; Dettori, J.; Tubbs, R.S.; Chamiraju, P.; Nora, P.; et al. Descriptive analysis of unplanned readmission and reoperation rates after intradural spinal tumor resection. J. Clin. Neurosci. 2017, 38, 32–36. [Google Scholar] [CrossRef]

33. Yu, Y.; Li, M.; Liu, L.; Li, Y.; Wang, J. Clinical big data and deep learning: Applications, challenges, and future outlooks. Big Data Min. Anal. 2019, 2, 288–305. [Google Scholar] [CrossRef] [Green Version]
34. Simpao, A.F.; Ahumada, L.M.; Gálvez, J.A.; Rehman, M.A. A review of analytics and clinical informatics in health care. J. Med. Syst. 2014, 38, 45. [Google Scholar] [CrossRef]
35. Khalifa, M. Health Analytics Types, Functions and Levels: A Review of Literature. Stud. Health Technol. Inform. 2018, 251, 137–140. [Google Scholar]
36. Alharthi, H. Healthcare predictive analytics: An overview with a focus on Saudi Arabia. J. Infect. Public Health 2018, 11, 749–756. [Google Scholar] [CrossRef]
37. Mosavi, N.S.; Santos, M.F. How Prescriptive Analytics Influences Decision Making in Precision Medicine. Procedia Comput. Sci. 2020, 177, 528–533. [Google Scholar] [CrossRef]
38. Dicuonzo, G.; Galeone, G.; Shini, M.; Massari, A. Towards the Use of Big Data in Healthcare: A Literature Review. Healthcare 2022, 10, 1232. [Google Scholar] [CrossRef]
39. Khan, P.; Kader, F.; Islam, S.M.R.; Rahman, A.B.; Kamal, S.; Toha, M.U.; Kwak, K.-S. Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances. IEEE Access 2021, 9, 37622–37655. [Google Scholar] [CrossRef]
40. Chauhan, N.K.; Singh, K. A Review on Conventional Machine Learning vs. Deep Learning. In Proceedings of the 2018 International Conference on Computing, Power and Communication Technologies (GUCON), Greater Noida, India, 28–29 September 2018; pp. 347–352. [Google Scholar] [CrossRef]
41. Xing, W.; Bei, Y. Medical Health Big Data Classification Based on KNN Classification Algorithm. IEEE Access 2020, 8, 28808–28819. [Google Scholar] [CrossRef]
42. Wang, L.; Liu, J.; Zhu, S.; Gao, Y. Prediction of Linear B-Cell Epitopes Using AAT Scale. In Proceedings of the 2009 3rd International Conference on Bioinformatics and Biomedical Engineering, Beijing, China, 11–13 June 2009; pp. 1–4. [Google Scholar] [CrossRef]
43. Venkatesan, C.; Karthigaikumar, P.; Paul, A.; Satheeskumaran, S.; Kumar, R. ECG Signal Preprocessing and SVM Classifier-Based Abnormality Detection in Remote Healthcare Applications. IEEE Access 2018, 6, 9767–9773. [Google Scholar] [CrossRef]
44. Li, Y.; Wu, H. A Clustering Method Based on K-Means Algorithm. Phys. Procedia 2012, 25, 1104–1109. [Google Scholar] [CrossRef] [Green Version]

45. Hasson, U.; Nastase, S.A.; Goldstein, A. Direct Fit to Nature: An Evolutionary Perspective on Biological and Artificial Neural Networks. Neuron 2020, 105, 416–434. [Google Scholar] [CrossRef]
46. Thapa, S.; Adhikari, S.; Ghimire, A.; Aditya, A. Feature Selection Based Twin-Support Vector Machine for the Diagnosis of Parkinson’s Disease. In Proceedings of the 2020 IEEE 8th R10 Humanitarian Technology Conference (R10-HTC), Kuching, Malaysia, 1–3 December 2020; pp. 1–6. [Google Scholar] [CrossRef]
47. Xu, L.; Liang, G.; Liao, C.; Chen, G.-D.; Chang, C.-C. An Efficient Classifier for Alzheimer’s Disease Genes Identification. Molecules 2018, 23, 3140. [Google Scholar] [CrossRef] [Green Version]
48. Ahmed, U.; Issa, G.F.; Khan, M.A.; Aftab, S.; Said, R.A.T.; Ghazal, T.M.; Ahmad, M. Prediction of Diabetes Empowered with Fused Machine Learning. IEEE Access 2022, 10, 8529–8538. [Google Scholar] [CrossRef]
49. Wang, W.; Bu, F.; Lin, Z.; Zhai, S. Learning Methods of Convolutional Neural Network Combined with Image Feature Extraction in Brain Tumor Detection. IEEE Access 2020, 8, 152659–152668. [Google Scholar] [CrossRef]
50. Chintala, S. (2019). IoT and Cloud Computing: Enhancing Connectivity. International Journal of New Media Studies (IJNMS), 6(1), 18-25. ISSN: 2394-4331. https://ijnms.com/index.php/ijnms/article/view/208/172
51. Chintala, S. (2018). Evaluating the Impact of AI on Mental Health Assessments and Therapies. EDUZONE: International Peer Reviewed/Refereed Multidisciplinary Journal (EIPRMJ), 7(2), 120-128. ISSN: 2319-5045. Available online at: www.eduzonejournal.com
52. Chintala, S. (2024). AI in Personalized Medicine: Tailoring Treatment Based on Genetic Information. Community Practitioner, 21(1), 141-149. doi: ISSN 1462-2815
53. Chintala, S. K., et al. (2022). AI in public health: Modeling disease spread and management strategies. NeuroQuantology, 20(8), 10830-10838. doi:10.48047/nq.2022.20.8.nq221111
54. Chintala, S. K., et al. (2021). Explore the impact of emerging technologies such as AI, machine learning, and blockchain on transforming retail marketing strategies. Webology, 18(1), 2361-2375.http://www.webology.org

55. Chintala, S. (2022). Data Privacy and Security Challenges in AI-Driven Healthcare Systems in India. Journal of Data Acquisition and Processing, 37(5), 2769-2778. https://sjcjycl.cn/DOI: 10.5281/zenodo.7766