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ADVANCES IN RISK ASSESSMENT

Basics of Artificial Intelligence (AI) Modeling

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AI with machine learning and its subset deep learning are revolutionizing research into the morbidity and mortality of diseases and conditions. The major models of AI are discussed, with an attempt to simplify what many acknowledge as agnostic processing of vast amounts of data to arrive at a conclusion or diagnosis. Such models include convolutional neural networks, artificial neural networks, recurrent neural networks, generative adversarial networks, local interpretable model-agnostic explanations, shapley additive explanations, counterfactual explanations, multi-armed bandit models, deep-Q-learning models, fusion models, federated learning, predictive modeling, and disease outbreak prediction. Topics are well-referenced for further research.
Methodology: A key-word search of artificial intelligence, artificial intelligence in medicine, and artificial intelligence models was done in PubMed and Google Scholar yielded more than 100 articles that were reviewed for summation in this article.

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INTRODUCTION

New technologies are transforming medicine, and this revolution starts with data: health data, clinical images, genome sequences, data on prescribed therapies and results obtained, and any other sources of data that can be imagined. The origins of AI originated with Alan Turing and John Haugland in their epic *The Turing Test: Verbal Behavior as the Hallmark of Intelligence* in 1950. The huge size of computers and cost of storage limited initial rapid growth of this field, but with time and technological advances, **machine learning (ML)**, where a computer program's performance improves with experience with respect to some class of tasks and performance measures, incrementally increased.

ML's capacity to deal with data allows computer scientists to develop algorithms and models that learn from data – to analyze, evaluate, and make predictions or decisions based on learning and data characteristics.[1] The capacity of such systems for advanced problem solving is generally termed **artificial intelligence (AI)**.

A subset of ML is **deep learning (DL)**, which differs from the larger class of ML by mimicking the functioning of the human brain, particularly the neural networks responsible for processing and interpreting information. DL does this by utilizing artificial neurons in a computer neural network. DL finds weights for each artificial neuron that connects to each from one layer to another layer. Once the number of layers is high (i.e., deep), more complex relationships between input and output can be modeled.[2] This enables the network to acquire more intricate representations of the data as it learns. The utilization of a hierarchical approach enables DL models to autonomously extract features from the data, as opposed to depending on human-engineered features as is customary in conventional ML

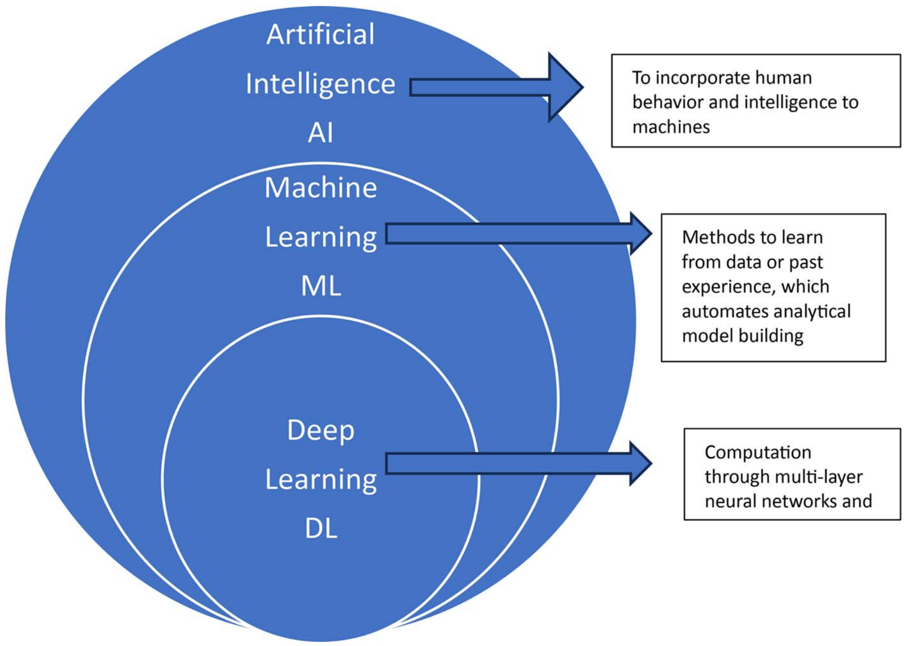

Figure 1. *Subsets of Artificial Intelligence (AI).*

models. DL is therefore a highly specialized form of ML that is ideally modified for tasks involving unstructured data, where the features in the data may be learnable, and exploration of non-linear associations in the data can be possible (Figure 1).[3,4]

The main difference between ML and DL lies in the complexity of the models and the size of the datasets they can handle. ML algorithms can be effective for a wide range of tasks and can be relatively simple to train and deploy.[5–7] DL algorithms, on the other hand, require much larger datasets and more complex models but can achieve exceptional performance on tasks that involve high-dimensional, complex data. Unlike classical ML, which requires pre-defined elements of interest to analyze the data and infer a decision, DL can automatically identify which aspects are significant. Each neuron in DL architectures (i.e., **artificial neural networks** – **ANN**) has a non-linear activation function that helps it learn complex features representative of the provided data samples.[8] Convolutional Neural Networks (**CNN**) specializes in image tasks, using convolutional layers, while ANN is a general neural network term for various tasks. They are mimicking the way that biological neurons signal one another. CNN, Recurrent Neural Networks (**RNN**) and ANN are different types of neural networks that have different strengths and weaknesses depending on the data and the task. CNNs are good for images or spatial data, because they can capture local features and reduce the dimensionality of the data.

ML and its subset DL algorithms can be categorized as either supervised, unsupervised, or reinforcement learning based on the input-output relationship. For example, if output labels (outcome) are fully available, the algorithm is called "supervised" (supervised learning = input data is labelled [matched to a known output] with other words input data is labelled for a particular output), while unsupervised algorithms explore the data without their reference standards/outcomes/labels in the output.[9]. In terms of applications, both DL and ML may be used for tasks such as classification, regression, and clustering.

DL methods' success depends on the availability of large-scale data, new optimization algorithms, and the availability of Graphics Processing Units (GPUs). These algorithms are designed to autonomously learn and develop as they gain experience, just as

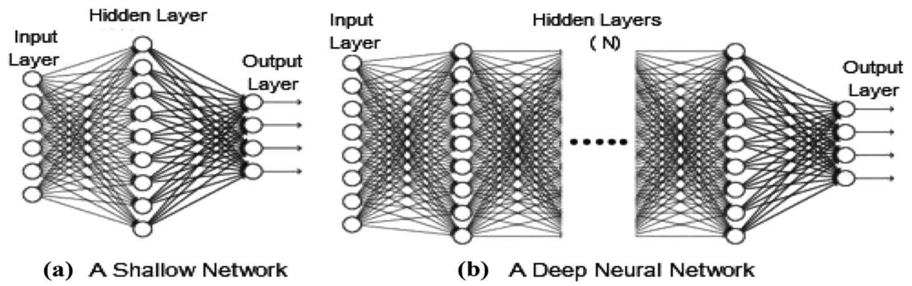

Figure 2. *Convolutional Neural Networks (CNNs) 'shallow' versus 'deep'.*

humans do. As a result of DL's powerful representation of the data, it is considered today's most improved ML method, providing drastic changes in all fields of medicine and technology, and is the driving force behind virtually all progress in AI today.[10] Multiple hidden layers, including unhidden input and output layers, make up a typical deep neural network. Figure 2 shows a general structure of a deep neural network (*hidden layer* = N and N ≥ 2) compared with a shallow network (*hidden layer* = 1).[11]

Convolutional Neural Networks (CNNs) are predominantly employed for tasks related to computer vision and signal processing. CNNs can handle tasks requiring spatial relationships where the columns and rows are fixed, such as imaging data. CNN architecture encompasses a sequence of phases (layers) that facilitate the acquisition of hierarchical features. Initial phases (layers) extract more local features such as corners, edges, and lines. Later phases (layers) extract more global features. Features are propagated from one layer to another layer, and feature representation becomes richer. During feature propagation from one layer to another layer, features are added to certain nonlinearities and regularizations to make the functional modeling of input-output more generalizable. Once features become extremely large, there are operations within the network architecture to reduce the feature size without losing much information, called "pooling" operations. The auto-generated and propagated features are then utilized at the end of the network architecture for prediction purposes (segmentation, detection, or classification). The following is a general architecture of a convolutional neural network (CNN) (Figure 3)[12]:

There are various types of AI that include analytical, functional, interactive, textual, and visual types.

- *Analytical AI* has the capability of extracting insights from vast amounts of data to ultimately produce recommendations and thus contribute to data-driven decision-making. Today this is primarily in the domain of business intelligence.
- *Functional AI* works similarly to analytical AI because it also explores massive quantities of data for patterns and dependencies, like analytical AI, but it executes

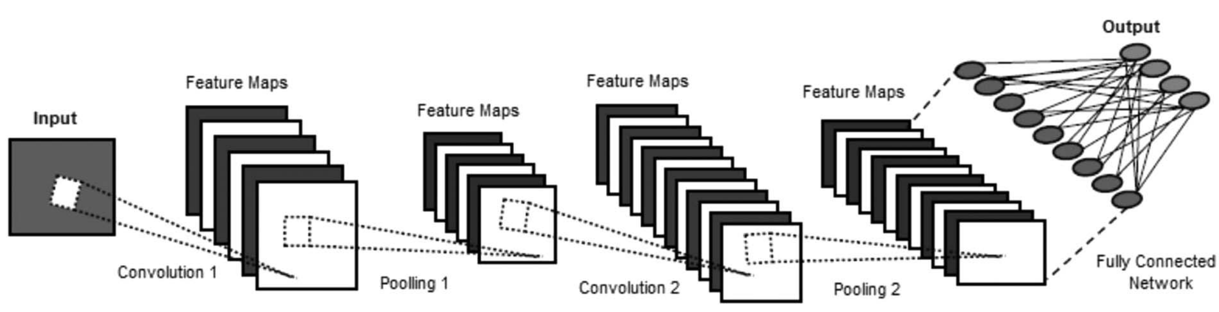

Figure 3. *'Pooling' of information in propagated convolutions.*

actions rather than making recommendations. For instance, a functional AI model could be useful in robotics to take immediate actions.

- *Interactive AI* enables efficient and interactive communication automation, essential in building chatbots and smart personal assistants.
- *Textual AI* typically covers textual analytics or natural language processing through which businesses can enjoy text recognition, speech-to-text conversion, machine translation as well as content generation capabilities.
- *Visual AI* is capable of recognizing, classifying, and sorting items, as well as converting images and videos into insights. Visual AI can be considered as a branch of computer science that trains machines to learn images and visual data in the same manner that humans do. This sort of AI is often used in fields such as computer vision and augmented reality.

Turning to the specific issue of how AI models will revolutionize morbidity and mortality research:

1. **Deep Learning for Identifying Morbidity and Mortality Risk Factors:**
   - Convolutional Neural Networks (**CNNs**): CNNs excel at analyzing medical images like X-rays, CT scans, histology slides, and ECGs. Trained on vast datasets, they can identify subtle abnormalities associated with increased morbidity and mortality risk, leading to earlier diagnoses and interventions.[13]
   - Recurrent Neural Networks (**RNNs**): RNNs excel at analyzing temporal data like electronic health records (EHRs). By analyzing longitudinal data points like lab results, medication use, and clinical notes, RNNs can identify patterns indicative of future health decline and predict morbidity and mortality risk with high accuracy.[14]
   - Generative Adversarial Networks (**GANs**): GANs can generate synthetic data that closely resembles real-world data. This opens doors for creating realistic simulations of disease progression and testing potential interventions in a virtual environment without risking patient safety.[15]
2. **Explainable AI (XAI) for Unveiling Underlying Mechanisms:**
   - Local Interpretable Model-agnostic Explanations (**LIME)**: LIME helps explain the "black box" nature of complex deep learning models, providing insights into how they arrive at their predictions. This is crucial for understanding the mechanisms underlying identified risk factors and developing effective prevention and treatment strategies.[16]
   - SHapley Additive exPlanations (**SHAP)**: SHAP quantifies the contribution of individual features to a model's prediction. This allows researchers to pinpoint the most important risk factors and prioritize them for further investigation.[17]
   - **Counterfactual Explanations:** These explanations explore alternative scenarios to understand how different factors might have influenced the predicted outcome. This helps identify potential interventions and assess their likely impact on morbidity and mortality.[18]
3. **Reinforcement Learning for Optimizing Treatment Strategies:**
   - Multi-armed Bandit (**MAB**) algorithms: MABs can guide treatment decisions by dynamically adapting to patient data in real-time. By constantly learning from treatment outcomes, MAB algorithms can optimize treatment plans for individual patients, improving their chances of survival and reducing morbidity.[19]
   - **Deep Q-learning:** This technique can be used to train AI agents to navigate complex clinical decision-making scenarios, considering various factors like patient characteristics, available resources, and

potential risks and benefits of different treatment options. This can help healthcare providers make informed decisions and personalize treatment plans for optimal outcomes.[20]

4. **Multimodal AI for Integrating Diverse Data Sources:**
   - **Fusion Models:** These models combine data from diverse sources like EHRs, medical images, genomics, and wearable devices. By integrating this multifaceted information, fusion models can provide a more comprehensive understanding of disease progression and identify previously unknown risk factors and therapeutic targets.[21]
   - **Federated Learning:** This decentralized approach allows for the training of AI models across multiple institutions without sharing patient data. This facilitates collaboration and knowledge sharing while protecting patient privacy, thereby accelerating research advancements without compromising ethical considerations.[22]

5. **AI for Population Health Management:**
   - **Predictive Modeling:** AI models can predict the future health of populations based on demographics, social determinants of health, and other risk factors or development of a condition in an individual. This information can guide public health interventions, resource allocation, and the development of targeted prevention programs to reduce overall morbidity and mortality rates.[23]
   - **Disease Outbreak Prediction:** AI models can analyze real-time data from various sources, including social media, travel patterns, and environmental factors, to predict the emergence and spread of infectious diseases. This allows for early warning systems and timely interventions to mitigate potential outbreaks and save lives.[24]

Finally, on the strictly clinical side, Large Language Models (**LLMs**) are presenting new opportunities for physicians in arriving at a differential diagnosis in difficult clinical scenarios. The most recent LLM for differential diagnosis exhibited standalone performance that exceeded that of unassisted clinicians (top-10 accuracy 59.1% vs. 33.6%). Use of the LLM comparing physicians with assistance from search engines and standard medical resources continued to yield a benefit (44.4%) ($p = 0.03$). Furthermore, clinicians assisted by this LLM arrived at more comprehensive differential lists than those without its assistance.[25]

CONCLUSION

AI models are poised to revolutionize research in morbidity and mortality, enabling researchers to uncover hidden patterns, predict future health risks, and personalize treatment strategies. By leveraging the power of deep learning, explainable AI, reinforcement learning, multimodal AI, and population health management, we can accelerate scientific progress, improve healthcare outcomes, and allow underwriters and medical directors to better assess the risks of applicants with health issues.

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REFERENCES

1. Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. *Elect Markets* 2021;31:685–695. https://doi.org/10.1007/s12525-021-00475-2
2. Piccialli F, Somma VD, Gaimpaoio F, Cuoma S, and Fortino G. A survey on deep learning in medicine: Why, how, and when? *Information Fusion* 2021;66:111–137. https://doi.org/10.1016/j.inffus.2020.09.006
3. Sarker IH. Deep Learning: a comprehensive overview on techniques, taxonomy, applications, and research directions. *SN Comput Sci.* 2021:2:420. https://doi.org/10.1007/s42979-022-01043e-x
4. Elif Keles, Ulas Bagci. The past, Current, and

future of neonatal intensive care units with artificial intelligence: a systemic review. *Digital Medicine* 2023;6:220. https://doi.org/10.1038/s41746-023-00941-5

5. Beam AL and Kohane IS. Big data and machine learning in health care. *JAMA* 2018;319:1317–1318. https://doi.org/10.1016/j.amjmed.2018.05.038
6. Muehlematter U, Daniore P, Vokinger K. Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015-20): a comparative analysis. *Lancet dig.health* 2021;3:e195–e203. https://doi.org/10.1016/S2589-7500(20)30292-2
7. LaCun Y, Bengia Y, and Hinton G. Deep learning. *Nature* 2015;521:436–444. https://doi.org/10.1038/nature14539
8. Beam, ibid.
9. Wiens J, Suchi S, Sendak M, et al. *Nat Med* 2019; 25:1337–1340. https://doi.org/10.1038/s41591-019-0548-6
10. Futoma J, Simmons M, Panch T, Doshi-Velez F, and Celi, LA. The myth of generalizability in clinical research and machine learning in health care. *Lancet Digit Health* 2020;2:e489-3492. https://doi.org/10.1016/S2589-7500(20)30186-2
11. Sarker, I.H. AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN COMPUT. SCI*. 2022;3:158. https://doi.org/10.1007/s42979-022-01043-x
12. Sarker, ibid.
13. S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network," *2017 International Conference on Engineering and Technology (ICET)*, Antalya, Turkey, 2017, pp. 1–6. https://doi.org/10.1109/ICEngTechnol.2017.8308186
14. Arras, L., Osman, A., Müller, K., & Samek, W. (2019). Evaluating Recurrent Neural Network Explanations. *ArXiv*. /abs/1904.11829. https://doi.org/10.48550/arXiv.1904.11829
15. Gui J, Sun Z, Wen Y, Tao D, Ye J. A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications. *J LATEX Class Files*. 2015;14.
16. Aditya, P. S., & Pal, M. (2022). Local Interpretable Model Agnostic Shap Explanations for machine learning models. *ArXiv*. /abs/2210.04533. https://doi.org/10.48559/arXiv.2210.04533
17. Lundberg, S., & Lee, S. 2017. A Unified Approach to Interpreting Model Predictions. *ArXiv*. 2017; 1705.07874. https://doi.org/10.48550/arXiv.1705.07874
18. Verma, S., Boonsanong, V., Hoang, M., Hines, K. E., Dickerson, J. P., & Shah, C. Counterfactual Explanations and Algorithmic Recourses for Machine Learning: A Review. *ArXiv*. 2020/abs/2010.10596. https://doi.org/10.48550/arXiv.2010.10596
19. Christian Hubbs. Multi-Armed Bandits and Reinforcement Learning. Dec 29, 2019. Published in *Towards Data Science*.
20. van Hasselt H, Guez A, Silver D. Deep Reinforcement Learning with Double Q-Learning. *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence* (AAAI-16).
21. Basiri ME, Abdar M, Cifci M, Nemati S, Acharya UR. A novel method for sentiment classifications of drug reviews using fusion of deep and machine learning techniques. *Knowledge-Based Systems* 2020;198:105949. https://doi.org/10.48550/arXiv.2010.10596
22. Li T, Sahu AK, Talwalkar A, Smith V. Federated Learning: Challenges, Methods, and Future Directions. *arXiv* 2019; 19008:07873. https://doi.org/10.48550/arXiv.1908.07873
23. Parish, E. J., & Duraisamy, K. (2016). A paradigm for data-driven predictive modeling using field inversion and machine learning. *Journal of Computational Physics*, 2016; 305:758–774. https://doi.org/10.1016/j.jcp.2015.11.012
24. Kim, J., & Ahn, I. (2021). Infectious disease outbreak prediction using media articles with machine learning models. *Scientific Reports*, 11(1), 113. https://doi.org/10.1038/s41598-021-83926-2
25. McDuff D, Schaekermann M, Tu T, Palepu A, et al. Towards Accurate Differential Diagnosis with Large Language Models. *arXiv*.2312.00164 [cs. CY]. https://doi.org/10.48550/arXiv.2312.00164