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Artificial Intelligence and the Evaluation and Treatment of Stroke

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Abstract

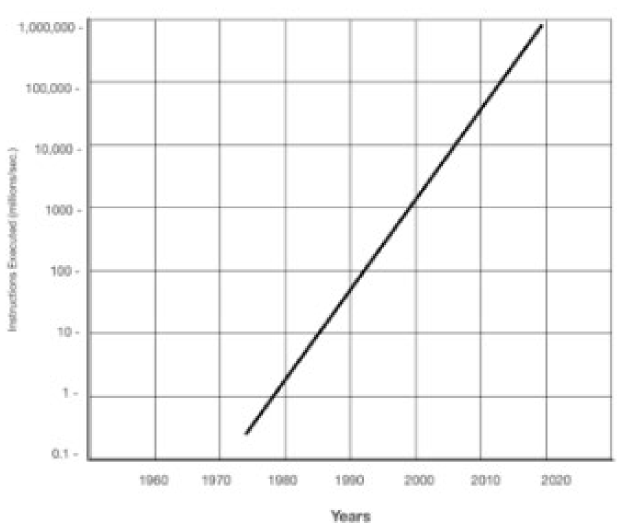
Stroke affects close to 800,000 Americans every year and is a major cause of disability and mortality. Prompt, accurate diagnosis and treatment of stroke is of critical importance in minimizing these deleterious effects. Recent advances in computer technology have allowed the development artificial intelligence technology that can be applied to the diagnosis, treatment and rehabilitation of victims of stroke.

Introduction

In 2021, more than 795,000 people in the United States suffered a stroke. About 610,000 (77%) of those were first time strokes. The annual stroke related costs were nearly $56.5 billion, and this included the costs of health care services, medicine and missed days of work. Stroke is a leading cause of disability and reduced mobility.[1] Over the past decade, improvements in technology have enabled the application of artificial intelligence (AI) in medicine and specifically to the evaluation and treatment of stroke.

Computer technology has long been applied in medicine but originally was quite limited by slow speeds and high costs. In the 1950s computers were large and slow. The IBM Model 350 Disk File had a storage capacity of only 5 megabytes. In 1980 IBM introduced Model 3380 with a hard drive size of more than 1 gigabyte, but it was the size of a refrigerator, weighed 550 pounds and cost $100,000. Since then the speed of computers has increased exponentially (Figure 1) and the prices have markedly decreased.[2]

Figure 1. Advances in Computer Speed Over Time



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AI is a generic term that refers to the simulation of thought processes by computer systems, enabling them to perform tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, solving problems, and making decisions. While AI has not achieved human intelligence (at least, not yet), the capacity to learn from data increases the amount and sophistication of tasks that can be tackled by machine learning systems.[3] Currently we are exposed to AI daily when using virtual assistants such as Siri and Alexa, speech and image recognition on our smartphones, and personalized recommendations on streaming platforms.[4]

Machine learning (ML) is a subfield of AI that consists of a set of algorithms that use data to make predictions or decisions without being explicitly programmed. There are three primary subdivisions of ML: supervised learning, unsupervised learning, and reinforcement learning.[5,6]

Supervised Learning

Supervised learning starts with labelled "training" data and predicts labels for new "test" data.

Algorithms

Regression methods including LASSO (Least Absolute Shrinkage and Selection Operator), Classification Trees, Random Forests, Gradient Boosting algorithms (like XGBoost and LightGBM), Support Vector Machines, and Artificial Neural Networks (more on this below).

Example

In an algorithm to distinguish spam emails from non-spam (ham) emails, a large number of emails, both spam and ham, are analyzed for different features, such as keywords and presence of exclamation marks. These features are input variables and the label of the email, spam or ham, is the target variable. Seventy to eighty percent of the emails are used as the training set. A supervised learning algorithm, such as logistic regression, is fed the training data. The algorithm learns the patterns and relationships between the input features and the target variable (spam/ham) during the training process. Once the model is trained, the remaining 20-30% of the emails, the test data, is provided to the model. If the predicted labels are close in accuracy to the actual labels in the test set, then the model can be used to make spam versus ham predictions on new, unseen emails.

Unsupervised Learning

Unsupervised learning starts with unlabeled training data and identifies patterns and clusters.

Algorithms

K-means Clustering and Principal Component Analysis (PCA)

Example

Analyzing customers of an online store to help tailor marketing campaigns. The customers do not have any specific labels, but the clustering algorithm would help assign them to certain clusters or labels based on known data about the customers. Then marketing campaigns could be devised to target the specific characteristics of each cluster (label).

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Reinforcement Learning

Reinforcement learning is learning from experience. An agent communicates with its environment, and is given a reward function that it tries to optimize. The purpose of the agent is to understand the effect of its decisions and discover the best strategies for maximizing its rewards during the training and learning procedure.

Algorithms

Q-Learning, State-Action-Reward-State-Action (SARSA) and Deep Q Networks (DQNs)*Algorithms:* Q-Learning, SARSA (State-Action-Reward-State-Action), and Deep Q Networks (DQNs).

Example

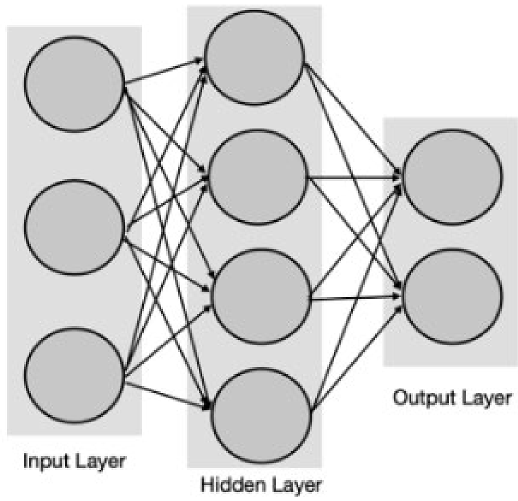
Training a robot in a maze to find the exit as quickly as possible. Rewards and penalties are assigned to guide the robot's behavior. Each time the robot takes a step closer to the exit, it receives a positive reward. If the robot hits a wall, it receives a negative penalty. Reaching the exit gives the robot the highest positive reward. Through trial and error, the robot (agent) learns to associate actions with higher rewards and, over time, converges on an optimal policy to solve the maze navigation problem.[3]

Deep Learning

Deep Learning (DL) is relatively new type of supervised learning that deserves special mention. It attempts to replicate the workings of the human brain by using artificial neural networks (ANN). DL employs a range of algorithms that use neural-type networks with many (i.e., deep) layers. It is a sophisticated approach to building intelligent systems that can learn and make decisions based on a vast amount of data. DL enables the system to perform complex tasks such as image recognition. This has been utilized for the analysis of computerized tomography (CT) and magnetic resonance imaging (MRI) to help quickly and accurately detect abnormalities, such as acute cerebral ischemia or hemorrhage.[3,6,7]

ANNs are composed of multiple connected nodes or "neurons." A typical network consists of an input layer connected to hidden layers which are eventually connected to an output layer (Figure 2). The hidden layers covertly process information between the input and output layers. This is analogous to the human visual system instantly recognizing three lines forming a triangle. We are not consciously aware of the mental processing involved with recognizing three lines (input) as a triangle (output).[7] Object recognition software such as that employed in self-driving cars to detect pedestrians and obstacles may use upwards of 150 hidden (deep) layers.[7]

Figure 2. Model of an Artificial Neural Network



Radiology

The management of stroke is highly dependent on the interpretation of imaging studies. Automated imaging analysis could greatly speed up CT and MRI interpretation.

DL methods of image analysis could also be valuable in areas where neuroradiologists are not immediately available. CT perfusion is utilized in acute cerebral infarctions to detect brain tissue at risk and to help clinicians decide which patients are good candidates for thrombolytic and neuro-interventional therapy, such as mechanically extracting blood clots from large cerebral vessels. ANNs can be used to "de-noise" perfusion images to give clearer pictures. They can also reduce radiation dose for CT scans.[6] Amazingly, DL methods do not require *a priori* assumptions of what image features are important. The network can *learn* on its own to identify them.

AI is well suited to be employed in radiology since it excels in image analysis. Radiology has an established digital workflow that makes it easy to integrate AI. It can rapidly detect and flag intracranial hemorrhage and large vessel occlusion. This could expedite the decision to use thrombolytic or neuro-interventional therapy for the acute treatment of cerebral ischemia.

In ANN the term "weights" represents the strength of the connection between the two nodes it connects. The sizes of networks used to interpret data is staggering. AI models consisting of networks with billions of weights can train on a large amount of data. These models can evaluate clinical data and radiographic data to generate suggestions for therapy, follow up and additional testing.[7]

Outcomes

By analyzing and combining clinical, laboratory, and imaging information, AI can give individualized recommendations for the best therapy to treat stroke and provide prognostic information for functional outcomes. This technology is also being used to assist with stroke rehabilitation. Robotic devices using AI can analyze a patient's movement patterns and provide guidance to help improve motor and gait function. It likely also can assist in developing programs to help with the treatment of speech, language and vision problems.[8] By analyzing clinical and imaging data, AI may also be able to predict which patients will suffer from depression and cognitive dysfunction after strokes.[8]

Dysphagia is a common complication of stroke. This can lead to malnutrition, pneumonia and possibly death. Video-fluoroscopic swallow studies (VFSS) are the standard tool to evaluate swallowing function after stroke. Researchers have employed AI to evaluate the VFSS images of 190 stroke patients.[9] The model developed was very accurate in distinguishing normal swallowing, penetration of swallowed food and liquid into the upper airway, and frank aspiration. It is emphasized that using a high-quality dataset is a prerequisite for obtaining excellent learning and analysis results when using image data.[6] The old adage regarding computers of "garbage in, garbage out" is equally applicable to AI.

Limitations

Besides the necessity for high quality data, there are some other limiting factors to the use of AI in stroke. It is not clear for many of the machine learning algorithms how and why a decision has been cast. This is particularly true of the most popular deep neural network approaches currently in use. This is termed the "black box problem." Concern regarding this opacity has lead the governments of the United States and United Kingdom, as well as the European Union, to call for measures to make AI intelligible.[3] Confidence in AI systems can be hindered by this lack of transparency. Also, if models are not updated to reflect factors such as changes in disease prevalence, their accuracy can decrease.[6]

Despite these limitations, AI holds tremendous potential to assist medical professionals in the care of stroke patients. It likely will become progressively more accurate in the diagnosis and evaluation of stroke and its sequelae. It therefore will become increasingly more helpful in assisting with optimizing treatment and rehabilitation to limit damage to the brain and help stroke patients recover faster and more completely.

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References

1. Tsao, C. W., Aday, A. W., Almarzooq, Z. I., Anderson, C. A. M., Arora, P., Avery, C. L., ... Martin, S. S., & the American Heart Association Council on Epidemiology and Prevention Statistics Committee and Stroke Statistics Subcommittee. (2023, February 21). Heart disease and stroke statistics—2023 update: A report from the American Heart Association. *Circulation, 147*(8), e93–e621. https://doi.org/10.1161/CIR.0000000000001123 PubMed

2. Haug, C. J., & Drazen, J. M. (2023, March 30). artificial intelligence and machine learning in clinical medicine, 2023. *The New England Journal of Medicine*, *388*(13), 1201–1208. https://doi.org/10.1056/NEJMra2302038 PubMed

3. Yang, G., Ye, Q., & Xia, J. (2022, January). Unbox the black-box for the medical explainable AI via multi-modal and multi-centre data fusion: A mini-review, two showcases and beyond. *Information Fusion*, *77*, 29–52. https://doi.org/10.1016/j.inffus.2021.07.016 PubMed

4. Cohen, F. (2023, May). The role of artificial intelligence in headache medicine: Potential and peril. *Headache*, *63*(5), 694–696. https://doi.org/10.1111/head.14495 PubMed

Doi: 10.32481/djph.2023.08.014

5. Theobald, O. (2021). Machine Learning for Absolute Beginners: A Plain English Introduction (Third Edition).

6. Rajpurkar, P., & Lungren, M. P. (2023, May 25). The current and future state of ai interpretation of medical images. *The New England Journal of Medicine*, *388*(21), 1981–1990. https://doi.org/10.1056/NEJMra2301725 PubMed

7. Mouridsen, K., Thurner, P., & Zaharchuk, G. (2020, August). Artificial intelligence applications in stroke. *Stroke*, *51*(8), 2573–2579. https://doi.org/10.1161/STROKEAHA.119.027479 PubMed

8. Choo, Y. J., & Chang, M. C. (2022, October 31). Use of machine learning in stroke rehabilitation: A narrative review. *Brain & Neurorehabilitation*, *15*(3), e26. https://doi.org/10.12786/bn.2022.15.e26 PubMed

9. Kim, J. K., Choo, Y. J., Choi, G. S., Shin, H., Chang, M. C., & Park, D. (2022, February 14). Deep learning analysis to automatically detect the presence of penetration or aspiration in videofluoroscopic swallowing study. *Journal of Korean Medical Science*, *37*(6), e42. https://doi.org/10.3346/jkms.2022.37.e42 PubMed