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A Critical Analysis of Artificial Intelligence Integration in Healthcare

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Abstract: *Recent years have seen fast development in AI software algorithms, hardware implementation, and applications in many fields. We cover the newest AI applications in biomedicine, including illness diagnosis, living assistance, biomedical information processing, and research. This review tracks new scientific achievements, understands technology availability, appreciates AI's promise in biomedicine, and inspires associated researchers. AI in biomedicine, like AI itself, is still developing. New innovations will push the boundary and expand AI application, and quick advancements are expected. Epileptic seizure prediction and urine bladder filling are shown in two case studies.*

Keywords: AI in Healthcare, Healthcare Analytics

I. INTRODUCTION

AI is mechanical intelligence, not human or animal intelligence [1,2]. AI also studies "intelligent agents"—anything that can perceive and comprehend its surroundings and act to maximize its objectives [3]. AI lets machines learn, analyze, and solve problems like people. The intelligence is machine learning (ML) [4]. AI systems are usually software and hardware. AI software uses algorithms. Artificial neural networks (ANNs) underpin AI algorithms [5]. It has weighted neuronal communication channels like the brain [6]. The network may adapt to external inputs and react to numerous nearby neuron stimuli [7]. The neural network (NN) may react to environmental inputs and outputs like the brain. Many configurations exist for layered NNs. Unsupervised learning involves learning from unlabeled, classified, or categorized test data to identify common features and react based on their presence or absence. NNs get "deeper," meaning they have more neurons to model a human brain and learn, as computing power grows. Combining feature extraction and classification techniques into a deep network is called "deep learning" [9,10].

AI hardware implements NN algorithms on physical computers. NN algorithm implementation on a general-purpose CPU in multithread or multicore mode is easy [7]. Large-scale NNs perform better on GPUs than CPUs due to convolutional computations [11]. CPU-GPU co-processing spikes NNs faster than CPU alone [12,13]. FPGAs and ASICs may implement NNs for specialized applications more efficiently in computation, power, and form size [14]. More power-efficient and smaller than GPU and CPU platforms, these platforms may be customized for an application. Edge devices like cellular phones and IoT sensor nodes need better power efficiency and form factor to use AI. AI algorithms are built using analog ICs, spintronics, and memristors [15–20]. New platforms like memristor crossbar circuits [21] may merge computation and memory, circumventing the von Neumann "memory wall" problem. Access is needed to update parameters. Researchers are reducing data representation bits to improve AI implementation. When data representation is lowered from 32 or 16 bits to 8 bits, calculation accuracy is maintained. Faster computation, reduced power, and smaller form factor [22]. However, "memory wall" limits persist. ANN performance relies on proper training methods, balanced datasets, sufficient data, and constant availability. AI is widely used in IoT, machine vision, autonomous driving, natural language processing, and robotics due to rapid software and hardware development. Most intriguingly, biomedical researchers are employing AI to improve analysis, therapy, and healthcare sector efficacy [35–37]. The number of publications in this field from 1999 to 2018 is shown in Fig. 1. Interest has surged in the last five years and is anticipated to continue. A few decades ago, AI was predicted to enhance medicine [38]. Biological engineering AI is reviewed [36,37]. Advances in AI and healthcare are recent.

Recent AI developments in biomedical engineering and healthcare are discussed here.

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AI can make healthcare more personal, predictive, preventative, and interactive. The enhancements made to AI should help it become a viable biomedical tool. Rest of article covers main AI Applications. Section 2 addresses information processing and algorithm implementation, whereas Section 3 provides disease diagnosis and prognosis. Two case studies of medical sickness prediction are in Section 4. Final results are in Section 5.

Information processing and algorithm implementation

AI in biomedicine has four primary uses. The first three categories in this section are designed to efficiently handle huge data and enable rapid access to data to address healthcare challenges. These applications include natural language processing, elderly and handicapped living aid, and basic research. Section 3 will examine the last AI application category, illness diagnosis and prediction.

AI for living assistance

AI applications and smart robotic devices are improving life quality in assisted living for the elderly and handicapped. An overview of smart

Recent publications include home functions and tools for individuals with loss of autonomy (PLA) and intelligent solution models based on wireless sensor networks, data mining, and AI [39]. NNs may learn to interpret face emotions as instructions via image processing. Facial expression analysis-based human–machine interfaces (HMIs) enable disabled persons to operate wheelchairs and robot support vehicles without joysticks or sensors [40].

RUDO, a "ambient intelligent system," helps blind individuals live alongside sighted people and engage in informatics and electronics [41]. Blind people may utilize this intelligent assistant's various functions via one interface. In important pregnancy phases, an AI-based "smart assistant" may provide nutritional and other advise. It can provide "advanced" recommendations using its intelligence and "cloud-based communication media between all parties." [42].

A sparse Bayesian classifier and radar Doppler time–frequency signature fall-detection system may minimize elder fall risks and problems [43]. In fact, "smart communication architecture" systems for "ambient assisted living" (AAL) allow AI processing information from different communication channels or technologies to determine network events and elderly people's assistance needs [44]. Smart homes' "ambient intelligence" may help older people age in place by providing activity awareness and support. The activity-aware screening of activity limitation and safety awareness (SALSA) intelligent agent may assist seniors with medication [45]. ML in motion analysis and gait studies may detect dangerous acts and prompt prevention [46,47]. Figure 2 [39] depicts the AAL model.

In this scenario, sensors gather environmental and human behavior data for cloud computing or edge intelligence to examine. After deciding what to do, alarms or precautionary measures are activated. An AI-based expert system combined with mobile devices and PDAs may enable people with permanent memory impairment achieve independent daily functioning [48]. This greatly expands the expert system for memory rehabilitation (ES-MR) for non-experts.

AI in biomedical information processing

Natural language processing for biomedical applications has advanced. The goal of biological question answering (BioQA) is to quickly and accurately answer user-formulated queries from documents and databases. Thus, natural language-processing methods should find useful responses [49]. First, biological questions must be categorized to get useful information from the answers. Biomedical queries may be classified into four kinds by ML with around 90% accuracy [50]. Next, an intelligent biomedical document retrieval system may quickly find parts of texts that may answer biomedical inquiries [51]. The yes-or-no response generator, derived from word sentiment analysis, may effectively extract information from binary replies [52].

Clinical information merging, comparison, and dispute resolution may dominate biomedical information acquired from several sources across time [53]. These have long been laborious, time-consuming, and unsatisfactory human occupations. AI has been shown to do these jobs with professional evaluator accuracy to enhance efficiency and accuracy [54]. Natural language processing of medical narrative data is essential to release people from the challenge of tracking temporal occurrences while retaining structures and explanations [55]. ML can handle high-complexity clinical data (e.g., text and connected biological data), include logic reasoning, and apply the obtained knowledge for many reasons [56].

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AI in biomedical research

As a "eDoctor" AI can diagnose, cure, and prognose sickness and is underused in biomedical research [57]. AI accelerates worldwide biological research and innovation book scanning and indexing [58,59]. Recent research topics include tumor-suppressor processes [60], protein–protein interaction information extraction [61], genetic association of the human genome to help healthcare genome discoveries [62], and others. Semantic graph-based AI helps biomedical researchers quickly summarize relevant material [63]. When there are too many publications to read, AI can help biomedical researchers find and rank useful content. Biomedical research requires solid scientific theories. AI may help researchers choose and rank figures in the expanding literature [64] to test ideas.

Biomedical researchers may explore "conscious" smart medical devices [65,66]. The computational modeling assistant (CMA) helps biomedical researchers generate "executable" simulation models from conceptual models [67]. Fig. 3 depicts CMA-human researcher interactions [67]. CMAs gain skills, methods, and databases. Biological models of the researcher hypothesis are sent to CMA. The CMA's intelligence combines this data and models to simulate researchers' ideas. The researcher choose the best models, and the CMA writes simulation algorithms. Thus, the CMA increases output and research. In addition, smart robots may lead biomedical imaging, oral, and plastic surgery investigations [68,69]. Human-machine consciousness and biomedical engineering explain this development [70].

In addition to the above applications, AI can assist standard

Decision support systems (DSSs) to enhance diagnosis accuracy and illness management to minimize staff load. AI is applied in integrated cancer management, tropical disease diagnosis and treatment, cardiovascular disease diagnosis and management, and diagnostic decision-making. These applications show that AI can accurately diagnose, manage, and predict illnesses and patient states. Examples of two case studies follow.

Healthcare

AI is being used in several healthcare applications. It has been employed for signal and image processing and function change predictions in urinary bladder control, epileptic seizures, and stroke. These bladder volume and epileptic seizure case studies are common.

Bladder volume prediction

If the bladder's storage and urine functions fail due to spinal cord damage, other neurological disorders, health conditions, or aging, health complications occur. Implantable brain stimulators can partially restore drug-resistant bladder function. In conditional neurostimulation, a bladder sensor detects stored urine to provide electrical stimulation only when needed to enhance neuroprostheses' efficiency and safety. The sensor may also alert persons with impaired feelings to empty their bladders or if post-micturition volume is too high.

We proposed new methods and built a digital signal processor (DSP) to sense urine pressure and fullness using afferent neural activity from the bladder's natural neural roots (mechanoreceptors) that show filling changes.

Smart neuroprostheses are implanted and worn. Modules wirelessly transmit data and insert power. The internal unit records brain impulses, analyzes sensory inputs on-chip (to varying degrees depending on the application), neurostimulates appropriate nerves via FES, logically governs implanted unit operations, and interfaces with the external unit. Once the internal unit provides the recorded signal, the remote unit performs complex algorithms and sends neurostimulation commands. Size, power consumption, temperature rise, electromagnetic radiation, and other factors make implantation undesirable. For adaptability, the external base station provides implant–user and implant–computer interfaces.

This section designs a neuroprosthesis pee bladder volume and pressure sensor. In persons with the above disorders and conditions, conditional neurostimulation may restore bladder function or detect bladder fullness. The implanted unit's enhanced DSP decoded bladder pressure and volume in real time for bladder neuroprosthetic patients. This strategy strongly affected the best prediction algorithm selections below.

Afferent neural activity from bladder wall stretching mechanoreceptors was decoded by qualitative and quantitative ML algorithms. These approaches need real-time implanted unit brain activity detection, classification, and decoding. The suggested qualitative technique rates bladder fullness low, medium, or high. Lower activity decreases hardware and power use. Advanced algorithms calculate bladder capacity or pressure to feedback the closed-loop neurostimulation system, yet implanted hardware optimizes it for minimal power consumption.

Real-time offline training starts qualitative and quantitative monitoring methods. Sensors learn real-time monitoring parameters here. Learning is done offline on a computer linked to the implant via the external unit, so we may pick the optimal algorithms regardless of complexity or execution time. Learning offloads complexity and hardware strain to offline processing, enabling real-time monitoring with better prediction algorithms and power management. For learning, digital data conditioning utilizes non-causal linear-phase FIR band-pass filtering. Determine which afferent neuronal activity best matches bladder volume/pressure (Fig. 4: Unit 1). Spearman's rank correlation coefficient (q) was employed to evaluate a monotonic dependency instead of Pearson's (linear) coefficient, making our estimation technique more robust. We evaluated Spear-man's rank correlation coefficient using Eq. (1): low volume (pleasant), medium volume (within a given period), and large volume (urinary leakage danger). Setpoints are 0.25, 0.5, and 1.0 times bladder capacity. Our linear-regression-based learning algorithms calculated BIR0.25, BIR0.5, and BIR1.0 for these three fullness levels. Finally, the real-time calculated BIR with the lowest difference from the reference values (BIR0.25, BIR0.5, and BIR1.0) qualitatively predicted volume or pressure. This system gave bins one of three fullness degrees. Bins quantified volume curves, calculated BIR, and projected bladder volume or pressure using two approaches. Brief descriptions of both algorithms follow.

The qualitative volume or pressure prediction method predicts low, medium, and high bladder fullness. Regression was used to estimate volume and pressure using little hardware. shown in Eq. (3):

$$\rho_k = \frac{\sum_{i=1}^{n}\left(FR_{i,k} - \bar{FR}_k\right)\left(V_{i,k} - \bar{V}_k\right)}{\sqrt{\sum_{i=1}^{n}\left(FR_{i,k} - \bar{FR}_k\right)^2 \sum_{i=1}^{n}\left(V_{i,k} - \bar{V}_k\right)^2}}$$

where V is estimated volume and ci is regression model coefficients. The bisquare robust fitting approach was utilized to calculate ci and reduce outliers. Simulated trials using animal model brain recordings determined the regression model's optimum order (N) in Eq. (3). After multiple simulations, we chose the smallest N and shortest BW with the lowest estimate error.

Epileptic seizure prediction

One of the most common neurological diseases, epilepsy, causes spontaneous, unexpected, and repeated seizures. First-line treatment is long-term medication, although over 30% of patients are refractory.

However, epilepsy surgery is still rare owing to poor success rates and fear of complications. Predicting seizures might be fascinating study. Although seizure-forecasting research began in the 1970s, the few seizure episodes,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(V_i - \hat{V}_i\right)^2}{n}}$$

The real-time monitoring phase runs the following steps:

Digital non-causal filtering

On-the-fly spike classification

BIR calculating using optimum BW

Comparing BIR to baseline and setting volume to 0 for lower values

If BIR is higher, use Eq. (3) to calculate bladder volume or pressure. As demonstrated in Fig. 5, our methods were tested and validated many times.

II. CONCLUSION

We explored the newest AI applications in biology, including illness diagnosis and prediction, living aid, biomedical information processing, and research. AI is useful in many other biological fields. AI is becoming more relevant in biomedicine due to its constant advancement and the inherent complexity of biological issues and AI's capacity to tackle them. New AI capabilities provide biomedicine solutions, and biomedicine development need new AI skills. This combination of supply and demand and combined improvements will allow both sectors to grow greatly in the near future, improving the quality of life of those in need.

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