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Many Fields Benefit from Artificial Intelligence; An Overview of AI Medical Applications

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Abstract— ***The widespread use of AI in many aspects of our lives has improved the quality of people's lives. Thanks to AI, the percentage of patients recovering has increased, and accuracy and rapidity of tasks have been provided for physicians, technicians, and agriculturalists. In this review, studies demonstrating AI contributions in various medical disciplines, including ophthalmology, anesthesiology, cancer, sleep medicine, and cardiac intensive care have been summarized.***

Keywords: AI anesthesiology cancer sleep medicine cardiac intensive care.

I. INTRODUCTION

AI refers to any approach that allows machines to imitate human actions and replicate or outperform human decision-making in order to complete complicated tasks autonomously or with minimum human intervention [1]. As such, it deals with a wide range of key issues, such as representation of information, thinking, learning, organizing, understanding, and communication, and relates to a wide range of tools and procedures [2]. AI, machine learning (ML), deep learning (DL), and artificial neural network families (ANNs) are all interconnected but distinct concepts [3]. ML refers to the achievement of a computer program increasing with experience in relation to a set of goals and performance metrics [4]. As such, it seeks to automate the work of developing analytical models in order to execute mental tasks that include object identification and natural language translation [5]. This is accomplished by employing algorithms that learn repeatedly from problem-specific data used for training, allowing computers to discover hidden information and complicated trends without being directly programmed. The neural network is a more advanced type of machine learning that has been accessible since the 1960s and has been well established in healthcare research for several decades [6]. Deep neural networks beat shallow ML techniques in most applications that require the processing of text, picture, video, voice, and audio data because DL is particularly helpful in domains with big and high-dimensional information [7]. However, with low-dimensional data input, particularly when training data is scarce, ML may provide superior outcomes, which are often more interpretable than those produced by deep neural networks [8]. Furthermore, DL capability may be superhuman for issues requiring strong AI skills, such as literal comprehension and intentionality, that remain unsolved [9]. ANNs have been employed in a variety of uses, such as approximation of functions [10, 11] categorization [12, 13], selecting features [14, 15] healthcare picture registration [16, 17] identifying patterns [18, 19], mining data [20], signal analysis [21], nonlinear systems recognition [22, 23] analyzing speech [24], and so on. Several DL approaches have been applied in a variety of applications such as, classification [25], forecasting [26], phoneme identification [27], and hand-written digit identification [28, 29]. AI algorithms have been developed for application in several fields of medicine, including cardiac intensive care [30], cancer imaging, prognosis, and diagnosis [31, 32] anesthesiology [33], and respiratory medicine [34], with promising accuracy and clinical application. The integration of AI into the plasma medicine field has resulted in significant advancements in different areas. These include real-time diagnostics, plasma tar refining processes, time investigation, species transitions, optimum parameters, defect categorization, energy efficiency, antimicrobial activity, antimicrobial inactivation levels, the discharge type, working gas, and discharge characteristics [35].

II. METHODS

The studies in this review have been collected by searching for keywords such as, ' artificial intelligence,' OR 'AI' AND 'cancer', 'AI' AND keratoconus, 'AI' AND ' glaucoma, 'AI' AND diabetic' retinopathy', 'AI' AND 'pain', 'AI' AND "anesthesia',' 'AI' AND sleep medicine, 'AI' AND ' cardiac intensive care', and' AI' AND 'opthalmacology' in databases and websites like Elsevier, Springer, Wiley Online Library, Google Scholar, Refseek, and MDPI.

A. Cardiac intensive care

Several AI techniques have been integrated into the field of Cardiac intensive care.

Among these techniques, ML algorithms, in particular the random forest algorithm, have been used to precisely identify the risk of acute kidney injury (AKI) in patients with acute myocardial infarction (AMI), with an AUC obtained from an external validation cohort, ranging from 0.71 to 0.78, and have optimized the precision of risk stratification for AKI in AMI patients [36]. Tehrany et al. demonstrated how ML algorithms, such as LR and RF, might calculate the risk of pressure injury by determining physical activities, suggesting that ML can be used as a useful platform for developing AI strategies for detecting, prognosticating, and managing pressure injury in hospital units [37]. In another study, the lightGBM model had the most effective efficiency for single model forecasting among machine learning algorithm models used to predict the death rates in hospitals of critically ill lung tumor patients. Other models also performed well in this regard [32]. A model analyzed by Kessler et al. to predict readmissions using recurring neural networks, showed that the long short-term memory (LSTM)-based deep learning model performs better than all other models with respect to the area under the receiver's operating characteristics curve. Additionally, in terms of the area under the accuracy-recall curve, LSTM performed the best [38]. AI-ECG algorithms have been used in electrocardiograms to predict the likelihood of various clinically relevant applications, such as left ventricular systolic disorders [39], underlying atrial fibrillation [40], heart amyloidosis [41], hyper-aortic stenosis [42], and trophic cardiomyopathy [43]. In echocardiography, AI has shown promise in imaging processes, including image acquisition [44] and incorporation into clinical evaluation [45] for diagnostic and prognostic purposes [46]. Hunter et al reviewed AI uses in trauma treatment, such as injury prediction, patient triage, ED sizing, and outcomes. The findings showed that Algorithms are used to forecast the severity of car accidents from the moment of injury. The artificial intelligence that emerges at the scene of an accident can assist rescue workers in remote patient selection, showing the site and urgency of the transfer. Therefore, these methods can be used to predict injuries in the receiving hospital. Following the patient's arrival at the hospital, these algorithms can not only estimate the severity of an injury, which can assist in decision-making, but they are also able to forecast patient outcomes to assist trauma teams in anticipating the patient's trajectory [47]. Zheng et al. developed a model basing on the XGBoost Algorithm to predict 28-day mortality for septic shock patients in a training and independent evaluation cohort. AUROC of the model was 0.9161 by the 5-fold cross-validation in the training cohort. The model showed AUROC of 0.9027 in the independent evaluation cohort [48]. Kim et al. developed and validated two deep-learning-based models using real-world ICU data to predict sepsis and septic shock. The models achieved an AUROC of 0.7888 for sepsis and 0.8494 for septic shock, which are superior to other traditional models. In addition, the model of septic shock exhibited the highest AUROC (0.9346) at the time of the onset of sepsis and septic shock, indicating the outperformance of these models [49].

B. Cancer

Through the use of AI techniques, clinicians are now able to gain a synthetic and thorough understanding of tumors by mining deep-level data from radiomics, transcr- itomics, proteomics, genomics, digital pathology images, and other sources. Furthermore, AI can use data to identify novel biomarkers that can assist in treating, detecting, diagnosing, screening, predicting tumors [50]. Govindan et al performed an overview of AI techniques utilized to evaluate the practical use of multi functional magnetic nanostructures for cancer diagnosis and treatment. The hybrid magnetic sy- stems used as cancer therapy utilizing AI models have also been reviewed. The finding exhibited that AI can be used in several ways to enhance the delivery of anti- cancer drugs to patients. It can also aid in recognizing the indicators that may predict the probability of adverse effects that occur during treatment. The synthesis and delivery of magnetic nanoparticles for anticancer drug delivery can be improved with the aid of AI algorithms. AI-aided algorithms can forecasts the ideal conditions for synthesizing nanoparticles that precisely direct the molecules to the intended cells. In addition, it tracks the MNPs, surveils the drug toxicity during delivery, and identifies nanoparticles at the tumor [51]. AI-based algorithms combined with several big data sets from medical imaging assist in improving the early diagnosis and detection rate of colorectal cancer (CRC). as well as the early and systematic patient assessment. It also strengthens patients' prognosis monitoring by enhancing the effectiveness of adjuvant therapy, such as NCRT and specific therapy. Furthermore, deep learning provides a new therapy alternative, owing to its contributions in gene sequencing research [52]. According to [53], AI has good potential for predicting urological cancers outcomes, including kidney cancer, bladder cancer, and prostate cancer. The advancements of AI in prediction, reaction to treatment, recurring, metastasis, assessment of staging, genotype, and segmentation with rectal cancer have been summarized [54].

C. Ophthalmology

Artificial intelligence algorithms have been used in the field of ophthalmology, esp-ecially in eye conditions, such as macular edema, glaucoma, age-related macular deg-eneration, stargardt disease, epigastric membrane, and referrable diabetic retinopathy.

A study by Abràmof, et al. exhibited that convolutional neural networks can be used to identify referrable diabetic retinopathy. The improved deep learning algorithm performs considerably better than in previously studies. Sensitivity, specificity, negative predictive value, and the AUC were 96.8%, 87.0%. 99.0%, and 0.980 [55]. Lee et al. created a CNN that can identify macular edema using manually segmented macular optical coherence tomography (OCT) images (with a cross-validation Dice coefficient of 0.911). Ultra-widefield (UWF) imaging enables up to 200° of fundus vision, perhaps detecting diabetic-related peripheral disorders at 200° [56]. Nagasawa et al. showed that a CNN has a high sensitivity (94.7%) and specificity (97. 2%) in identifying proliferative DR on UWF pictures [57]. DL can predict retinal function by micrometrics in patients with stargardt disease-based structural OCT evaluation [58]. DL can also predict demographic information such as age, sex, and cardiac risk factors such as SBP, the state of smoking, significant external cardiac adverse events, and the diagnosis of the eye [59]. Masumoto et al. constructed a neural network to evaluate conjunctival hyperemia using the Japanese eye allergy association classification. This method assesses the severity of hypertension with remarkable accuracy [60]. AI has been integrated into the bionic eye field, resulting in several advancements, including enhancing the quality of the images, creating innovations in wireless communication, minimizing implants, incorporating AI, and creating multi-modal sensory prostheses. [61]. Lauren et al. performed a comprehensive review on AI-enabled glaucoma identification systems producing and utilizing segmented fundus images (optic cup, optic disc, and neuroretinal rim). The systems focused on two steps: the automatic detection of optic cup and disc contours and the visual explanation of the steps that occur between the diagnosis and the raw image. The systems achieved high accuracy, ranging from 85.1% to 100% [62].

D. Sleep medicine

Maniaci et al. developed a support vector machine (SVM) model to identify obstructed sleep apnea severity. The sensitivity and specificity of the SVM model were 0.93 and 0.80 and had a precision of 0.86 [63]. Different models to ameliorate AI sleep scoring have been investigated; for instance, a neural network model to recognize breathing disorders during sleep events was iteratively refined with the use of a supervised approach [64]. Studies utilizing ML algorithms for stages of sleep and respiratory scoring exhibited improved performance to varying degrees [65]. AI contributions in improving phenotyping, endotyping, drug response prediction in sleep disordered breathing, circadian rhythm sleep-wake disorders lp, REM sleep behavior disorder, population health-predicting morbidity and mortality, and the status of patients with insomnia and hypersomnia have been reviewed [65].

E. Anesthesiology

A mature computer-aided diagnostic (CAD) system has been constructed in a recent study by Xu et al. CAD has been shown to improve patient satisfaction during sedat-ion-aided endoscopic procedure [66]. According to [67], ML is more effective in ma- managing, classifying, showing, and diagnosing pain in contrast to conventional sta-tistical strategies. The usefulness of AI in offering personalized activity suggestions for every patient with back or neck pain has shown in one study [68]. ML ach- ieved an accuracy rate over than 80%, with outcomes that range from 82.73% to 95.- 33%, when interpreting EEG data and predicting various states of pain [69].

III. CONCLUSION

In summary, AI aids in identifying the risk of acute kidney injury, calculating the risk of pressure injury, and predicting sepsis, septic shock readmissions and the severity of car accidents. In addition, AI can be used in the diagnosis and treatment of colorectal, rectal, and urological cancers. DL can predict demographic information. AI has good potential for identifying referrable diabetic retinopathy, diabetic-related peripheral di- sorders, and glaucoma with high accuracy. AI has been shown to improve patient sati- sfaction and predict different states of pain with a high accuracy rate.

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