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A Review on the Integration of Artificial Intelligence for Clinical and Laboratory Diagnosis

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ABSTRACT

Background: The advancement of artificial intelligence (AI) in medicine is associated with applications meant to support physicians in diagnosing patients, selecting treatments, and forecasting their results. Thanks to the quick advancement of analytical tools and the growing availability of healthcare data, it is revolutionizing the healthcare industry. Modern deep learning (DL) and machine learning approaches for structured data, such as neural networks and classical support vector machines, as well as natural language processing for unstructured data, are examples of artificial intelligence techniques. **Methodology**: More than 60 articles were reviewed, and 45 were selected. The literature review was conducted using the databases PubMed, Embase, Google Scholar, and Scopus. **Review**: Laboratory medicine uses modern technology to improve clinical decision-making, disease monitoring, and patient safety. Artificial intelligence is increasingly used in clinical microbiology informatics. Genomic data from isolated bacteria, metagenomic microbiological results from original specimens, mass spectra recorded from growing bacterial isolates, and huge digital images are all examples of massive datasets in clinical microbiology that can be used to develop AI diagnoses. **Conclusion**: Healthcare technological innovation is accelerating and becoming more integrated into our daily lives and medical practices, such as smart health trackers and diagnostic algorithms.

Key Words: *AI, laboratory medicine, infectious diseases, clinical diagnosis, artificial intelligence.*

INTRODUCTION:

Medical artificial intelligence refers to the creation of AI programs that assist clinicians in making diagnoses, making therapeutic decisions, and forecasting outcomes. These systems include artificial neural networks (ANN), fuzzy expert systems, hybrid intelligent systems, and evolutionary computation. The advancement of intelligent medical technologies has enabled the emergence of a new medical field: augmented medicine. Other digital tools that enable augmented medicine include surgical navigation systems for computer-assisted surgery and virtuality-reality continuum tools for surgery, pain management, and psychotic disorders. AccuVein is an example. The handheld device employs laser technology to "see" through your skin and into your veins. It is designed to make it easier for doctors, nurses, and others to locate a vein to take blood or insert an IV device. The augmented reality device includes a headset with a display that allows doctors to look through to the patient. It enabled them to project images from X-rays or computed tomography (CT) scans, for example, onto the body and view both at the same time. As long as the images are perfectly aligned, surgeons appear to have X-ray vision. Artificial intelligence seeks to replicate human cognitive functions. It is delivering a paradigm shift in healthcare, driven by the increased availability of healthcare data (1).

Machine learning methods for structured data, such as the classical support vector machine and neural network, as well as current deep learning, are examples of artificial intelligence approaches. Natural language processing is also used for unstructured data. Cancer, neurology, medicine, and cardiology are among the most common applications of AI tools (1). Machine learning is the most common sort of artificial intelligence utilized in medicine. The most advanced types of machine learning are neural networks and deep learning, which use multiple levels of characteristics or variables to predict outcomes. Deep learning is frequently used in healthcare to detect potentially dangerous tumors in radiographic images. Machine learning methods for structured data, such as the classical support vector machine and neural network, as well as current deep learning, are examples of artificial intelligence approaches. Natural language processing is also used for unstructured data. Cancer, neurology, medicine, and cardiology are among the most common applications of AI tools (1). Machine learning is the most common sort of artificial intelligence utilized in medicine. The most advanced types of machine learning are neural networks and deep learning, which use multiple levels of characteristics or variables to predict outcomes. Deep learning is frequently used in healthcare to detect potentially dangerous tumors in radiographic images. (2)

Another form, known as natural language processing (NLP), comprises speech recognition, text analysis, translation, and other language-related tasks. There are two main methods to it: statistical and semantic NLP. The primary uses of NLP in healthcare are the generation, comprehension, and classification of clinical documentation and published research. Natural language processing systems can evaluate unstructured clinical notes on patients, create reports (such as radiological examinations), transcribe patient discussions, and perform conversational AI. Robotic process automation is used in healthcare to automate repetitive tasks such as prior authorization, updating patient information, and billing. Since the 1970s, when MYCIN was developed at Stanford to diagnose blood-borne bacterial infections, artificial intelligence has been focused on disease diagnosis and therapy. Artificial intelligence is the process of collecting data, interpreting it, and learning how to produce the intended result (3).

METHODOLOGY;

More than 60 articles were reviewed, of which 45 were shortlisted. The review was based on a literature search in Pubmed, Embase, Google Scholar, and Scopus databases.

REVIEW:

Laboratory medicine is always incorporating new technology to aid clinical decision-making, disease monitoring, and patient safety. Innovation can alter healthcare systems and laboratory medicine by providing healthcare workers with the knowledge and tools they need to give better care to more patients while using less resources. Artificial intelligence can transform present diagnostic, disease preventive, and control techniques, dramatically improving patient safety and treatment quality. To enhance workflow and personnel utilization, labs now employ software to automate sample, operation, and outcome management. Rule-based auto verification, for example, compares patient outcomes to many factors to validate and expedite reporting or reactive actions. Simultaneously, sophisticated systems monitor activities to identify bottlenecks and warn of possible problems, such as STAT sample delays or reagent expiry. Healthcare systems rely on digitalization to manage hundreds or thousands of point-of-care (POC) testing devices and their data outside of the central lab. These rule-based programs conduct activities and calculations directly as they are programmed, following predetermined logic. Artificial intelligence is the next phase in the evolution of laboratory software. Awareness of AI and its applications is still an ongoing debate amongst treating physicians, but it has shown accuracies in the radiological and laboratory diagnosis of infectious diseases. Infectious diseases are characterized by rapid transmission and harmful effects, so researchers must explore and foresee the location and future intensity of an epidemic. Mathematicians have been able to use machine learning algorithms not only to estimate the size and location of the epidemic but also to investigate the infection relationship. The COVID-19 pandemic has recently catalyzed AI and innovation. Kaur et al discussed the results of AI models and showed that human-driven control methods had a major influence on the screening, analysis, prediction, and tracking of infected persons. They also compared AI and non-AI-based ways to identify COVID-19 symptoms and highlighted AI as a crucial instrument in infectious disease management as well as its current deployment in the COVID-19 pandemic, to reduce time, cost, and human effort, together with providing efficient and dependable solutions in the pandemic (4).

Lin et al conducted a retrospective study in which they used a deep learning model – COVNet is a COVID-19 detection neural network that was created to extract visual information from volumetric chest CT scans for COVID-19 detection; CT scans of community-acquired pneumonia (CAP) and other non-pneumonia abnormalities were included to test the robustness of the model. The authors discovered that in the independent test set, the per-scan sensitivity and specificity for identifying CAP were 87% (152 of 175 scans) and 92% (239 of 259 scans), respectively, with an area under the receiver operating characteristic curve of 0.95 (95% CI: 0.93-0.97). They demonstrated that a deep learning algorithm could detect coronavirus 2019 and distinguish it from community-acquired pneumonia and other lung diseases (5).

Another implementation of AI in the COVID-19 pandemic is treatment surveillance, which allows for automatic prediction of virus spread, and diseased individuals and keeping the public informed about the pandemic situation as well as contact tracing of individuals by identifying "hot spots" to trace the infection and predict the future course and chances of remission. Airport testing is one of the numerous precautions used to prevent the spread of a contagious disease. Various machine learning parameters, including Matlab, nested one versus one (OVO) support vector machine (SVM), leave one out cross-validation (LOOCV), and SVM learning method, have been used in combination in diagnostics by separating genetic sequences from bacteria (6). Also, AI assists in the creation of vaccines and medications by speeding up drug development methodologies, diagnosing processes, and clinical trial management (7).

Chatbots have been also developed by several healthcare-ganisations to improve mental health services, telehealth as well as patient engagement and well-being. Moreover, numerous researchers have highlighted the influence and role of emerging healthcare platforms and electronic mediums such as mobile health, 5G, telemedicine, internet of things, AI,and others in the fight against pandemics by acting as advanced weapons to prevent further spread of infection (8-10). Clinical microbiology informatics is progressively using AI. Genomic information from isolated bacteria, metagenomic microbial results from original specimens, mass spectra recorded from grown bacterial isolates, and huge digital photographs are all examples of enormous data sets in clinical microbiology that may be used to build AI diagnoses (11). Microscopy for traditional Gram stains, ova, parasite production, and histopathology slides might be revolutionized by machine-learning-based image analysis. For instance, a neural network could classify Gram stains from positive blood cultures into Gram positives/negatives and cocci/rods with amazing accuracy (12).

Mathison et al offer a computer vision validation for a novel application: protozoa identification in trichrome-stained fecal smears. It is a complete validation of the computer vision program, including studies of accuracy, precision, and detection limit (13).

A systematic review documented that machine learning was used for species identification and antibiotic susceptibility testing. Support vector machines, genetic algorithms, artificial neural networks, and fast classifiers were among the most extensively utilized machine learning approaches (14). Deep learning is particularly significant for omic analysis because it allows the combination and interpretation of image-based data with – omic information, allowing this data to be used to generate new and more trustworthy knowledge (15). Recently, infectious disorders such as malaria, which have time-consuming diagnosis criteria and need many health services, have been diagnosed using machine learning techniques. The use of digital in-line holographic microscopy (DIHM) data processing to detect infected RBCs in the blood of malaria patients is a suitable and cost-effective technology. Furthermore, for training and testing groups, various machine-learning techniques are effective and accurate in distinguishing healthy cells from infected ones. Artificial intelligence approaches based on DIHM do not need extensive blood sample processing (16). Infectious outbreaks such as Ebola have necessitated the use of technologically-based approaches such as logistic regression (LR), SVM classifiers (with good accuracy profiles), single-layer artificial neural networks (ANN), and decision tree (DT), which have proven as a successful set of indicators to be used for various Ebola-related data configurations (17). To allow a better response, technology techniques should also integrate socioeconomic aspects to support a consistent approach to infection diagnosis and treatment (18). Artificial intelligence, which employs convolutional networks, is predicted to play a significant role in cancer outcome prediction. A study conducted by Lee Su-In et al demonstrated a promising approach to identifying robust molecular markers for the targeted treatment of acute myeloid leukemia (AML) by introducing data from 30 AML patients including genome-wide gene expression profiles and in vitro sensitivity to 160 chemotherapy drugs, a computational method to identify reliable gene expression markers for drug sensitivity by incorporating multi-omic prior information relevant to each gene’s potential to drive cancer. They also showed that their method outperformed several state-of-the-art approaches in identifying molecular markers replicated invalidation data and predicting drug sensitivity accurately (4).

Hirasawa et al built a system that could process a large number of stored endoscopic pictures in a short amount of time with clinically meaningful diagnostic capabilities, which may be used in everyday clinical practice to relieve endoscopists' workload (19). Gulshan et al designed an algorithm for identifying referable diabetic retinopathy and macular edema with excellent sensitivity and specificity (20). Lee et al developed a deep learning-based computer-aided diagnosis approach for detecting cervical lymph node metastases by CT scan in thyroid cancer patients (21). Early lung cancer chest CT scans with AI-assisted automated learning showed good specificity and sensitivity for early lung cancer detection and could be beneficial in the future in assisting doctors in the early diagnosis of microscopic lung cancer nodules (22).

Mobedarsany et al showed that AI was proven to be more accurate than surgical pathologists in predicting patient outcomes. This study gives light on the application of deep learning in medicine as well as the integration of histology and genetic data, and ways for dealing with challenges such as intratumoral heterogeneity (23). Muneer et al, on the other hand, employed AI approaches to identify glioma grade and their findings were good, with better than 90% accuracy (24).

Yala et al created a big database by using a machine-learning algorithm to identify important tumor features from breast pathology reports (25). The algorithm-based smartphone software "Skinvision" may assist a user by performing frequent self-checks for skin cancer using a phone and a snapshot of a skin spot. The algorithm, like a doctor, can determine the texture, color, and form of the lesions. Users get an instant risk assessment for skin lesions in 30 seconds, and the algorithm has been shown to detect 95% of skin cancer at an early stage (26).

IBM's Watson has recently received a lot of attention for its focus on precision medicine, particularly cancer detection and treatment. Watson employs a mix of machine learning and natural language processing techniques. Users discovered how difficult it was to train Watson how to handle certain forms of cancer and integrate it into care procedures and systems, thus initial excitement for this implementation of the technology diminished (27, 28).

Recently, Google has been working with healthcare delivery networks to develop big-data prediction algorithms that will alert physicians to high-risk illnesses like sepsis and heart failure (29). Nvidia, a renowned international technology firm located in the United States, has revealed its ambition to create an AI supercomputer for medical research and medicine delivery in November 2020 (30, 31). In recent years, the demand for automated laboratory recommendation systems has risen in order to provide more accurate and faster diagnoses. By incorporating image analysis and machine learning into ordinary surgical pathology, the digital revolution is revolutionizing the practice of diagnostic surgical pathology. An automated recommendation might help save healthcare resources by improving the accuracy and efficiency of test requests. In a study, it was shown that with limited variables from EHR, the DL model had the greatest discriminating ability for all diagnostic laboratory tests, with a mean AUROC micro of 0.98 and AUROC macro of 0.94, respectively (32). WSI scanners can now capture and store slides in the form of digital pictures, allowing for automated study of histology slides. This scanning, along with deep learning algorithms, enables the automated detection of lesions based on previously confirmed regions of interest (33). In a simulated setting, machine learning algorithms produced potentially quicker and more accurate diagnoses than 11 pathologists, according to new research (15). The future laboratory will be more automated and dominated by robotics, as well as more networked to make use of benefits provided by AI and the Internet of Things (34).

Artificial intelligence has also several administrative applications in healthcare. These are required in healthcare since a typical US nurse, for instance, spends 25% of her time on administrative and regulatory tasks. RPA is the technology that would be most likely to apply to this goal. It has a wide range of healthcare applications, including billing process, claims processing, and clinical documentation management Based on the DL NHS 111 algorithm, the AI-based clinical assessment service "National Health Service"- NHS 24 is in the clinical testing phase in Scotland to assist people with minor health concerns at home through telephonic contact (36). Likewise, another virtual care company, "Babylon Health," uses semantic web technology to deliver complementary digital services to improve clinical results. The semantic web aims to make internet data machine-readable. Develop a clinical LDG (Linked Data Graph) to integrate various bioinformatics-based biomedical data banks in a way that is understandable to the average individual who uses AI-based medical services (37). Before AI may become widespread in medicine, the issue of legal accountability must be settled, particularly in imaging disciplines such as radiology and pathology. The lack of clarity and misunderstanding around important concerns such as the processing of sensitive personal information and data gathering, consent, transparency, storage, and other difficulties further complicates and obscures the question of legal accountability for AI-based judgments in medicine. According to a recent study, depending too much on decision support systems in radiology led to a higher rate of false negative diagnoses than when the computer-aided diagnostic system was unavailable to the same group of radiologists (38).

In a simulated setting, machine learning algorithms produced potentially quicker Maedica A Journal of Clinical Medicine, Volume 17, No. 2, 2022 425 and more accurate diagnoses than 11 pathologists according to a new study (15). Similarly, bringing AI to clinical decision-making also comes with a slew of difficulties. One such challenge is equitable decision-making that does not discriminate based on biases contained in datasets and methodologies used to construct the system. Some AI models lack transparency, which can have no cognitive similarity to the problem they are tackling and might exacerbate these problems. Understanding the reasons behind a model's choice or suggestion is frequently a difficult task. For instance, if a decision-support tool suggests that a patient's total knee arthroplasty surgery be postponed, the patient and his/her care team might appreciate knowing the variables that led to that conclusion (39, 40). The future laboratory is expected to be increasingly automated and dominated by robotics as well as more networked with the use of AI and the benefits of the Internet of Things (34). Artificial intelligence can be applied across any stream of medical field, including and not limited to clinical and laboratory diagnosis only. One such example is MetaPathwhich can be used to prioritize novel drug targets. Such methods can identify combinations of genetic variants or abnormalities that cause disease, including cases where causal genes are either known or unknown. The progress in data integration combined with novel AI/ML algorithms and disease causality modeling will probably shift the paradigm and establish unbiased ways for target selection and prioritization (41).

CONCLUSION:

Healthcare technological innovation is accelerating and becoming more integrated into both our daily lives and medical practice, with examples including smart health trackers and diagnostic algorithms. Deep learning is increasingly being utilized to fulfill an increasing variety of specialized roles in medicine. According to the studies mentioned above, using algorithms can improve not only the sensitivity and accuracy of diagnoses but also the turnaround time.

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