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The Transformative Impact of Artificial Intelligence and Big Data on Enhancing Health Security and Pandemic Surveillance in Modern Healthcare Systems: Review

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Abstract

Background: The integration of Artificial Intelligence (AI) and Big Data has revolutionized the healthcare sector, particularly in enhancing health security and pandemic surveillance. AI applications are crucial for analyzing vast datasets to improve decision-making, diagnosis, and treatment outcomes.

Methods: This review synthesizes existing literature on AI and Big Data applications in healthcare. It explores the efficacy of machine learning (ML) algorithms, data privacy concerns, and safety implications. The analysis includes various AI technologies, such as virtual and physical AI, and their roles in diagnostic processes, patient triage, and real-time decision support.

Results: Findings indicate that AI significantly improves disease prediction and diagnosis, operational efficiency, and patient management. For instance, machine learning algorithms demonstrated high accuracy in predicting health crises, such as chronic obstructive pulmonary disease flare-ups. However, challenges persist, including data privacy issues, bias in AI algorithms, and the need for comprehensive validation to ensure patient safety.

Conclusion: While AI and Big Data hold transformative potential for healthcare, their integration requires careful consideration of ethical, legal, and safety standards. Enhancing AI systems for practical application in healthcare settings is paramount to leverage their benefits effectively. Future research should focus on developing robust frameworks for AI implementation, addressing biases, and ensuring data security.

Keywords: Artificial Intelligence, Big Data, Healthcare, Machine Learning, Patient Safety.

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1. Introduction

Artificial intelligence (AI) is transforming healthcare. The primary objective of AI applications in healthcare is to examine the correlations between preventive or therapeutic strategies and patient outcomes. AI applications may save costs and time in the diagnosis and treatment of diseases, hence enhancing the effectiveness and efficiency of healthcare. AI facilitates rapid and thorough analysis of large data sets to enhance decision-making with efficiency and precision. Artificial intelligence is primarily categorized into two types: virtual and physical [1]. Virtual AI encompasses informatics derived from deep learning applications, including electronic health records (EHRs) and image processing, to aid doctors in diagnosing and managing illness conditions. Physical AI encompasses mechanical innovations, including robots used in surgical procedures and physical rehabilitation. Algorithms have been developed to train data sets for statistical applications, facilitating precise data processing. These principles form the foundation of machine learning (ML), allowing computers to make accurate predictions based on prior experiences. While both AI and ML can facilitate these advancements, such technologies may also pose safety concerns, potentially leading to significant issues for patients and other healthcare stakeholders [2,3].

Data privacy and security is a significant problem, since most AI systems depend on vast amounts of data to enhance decision-making. Moreover, machine learning systems often use data—frequently personal and sensitive information—to enhance their learning and performance. This increases their vulnerability to significant problems such as identity theft and data breaches. AI may potentially be linked to diminished forecast accuracy, hence raising safety issues. For example, convolutional neural networks (CNNs) are trained and validated with data sets in clinical environments, which may not generalize effectively to a broader population; in one study, the monitoring of skin lesions for skin cancer detection may exhibit greater diversity in the general populace [4]. Consequently, such an AI system may yield erroneous or imprecise predictions. The study provides an overview of the implications of AI and ML for healthcare safety to address possible difficulties. The team examines the potential and problems associated with the development and secure use of AI in healthcare.

2. Artificial Intelligence in Healthcare

In healthcare, AI is characterized as the replication of human cognitive processes by computers. AI draws inspiration from the operation of biological neurons and encompasses fundamental aspects of perception, recognition, and object identification, allowing machines to perform at least as well as, or beyond, human capabilities [5]. Nonetheless, because to its intrinsic deficiency in articulation and insight production, AI cannot replace doctors in healthcare. In the absence of universally applicable guidelines, AI must often be augmented by the judgment of physicians. A comprehensive linkage of historical and clinical data is essential for the diagnosis or monitoring of any illness condition. The physician–patient connection is shaped by associative and lateral thinking, which might impact management choices. Furthermore, the impact of several elements (e.g., psychological, emotional) on illness outcomes is outside the purview of AI [6,7].

Machines exhibit more precision, reliability, and comprehensiveness, with a comparatively reduced danger of bias; yet they remain deficient in trust and empathy. There is an increasing apprehension that AI systems, via experiential learning and repeated training, may surpass human performance. Artificial intelligence has a potential future in healthcare, contingent upon its diligent use for appropriate objectives [7].

3. Artificial Intelligence and Safety

Safety in healthcare denotes the reduction or minimizing of risks and uncertainties associated with adverse occurrences. The aspects of safety are evolving with the integration of AI in healthcare. Artificial Intelligence and Machine Learning, with a little probability of anticipated and unanticipated detriments, have been used to enhance safety. Minimizing risk is essential for AI-based applications [8].

Machine learning applications are primarily categorized into type A (e.g., medical diagnosis) and type B applications (e.g., voice transcription systems), based on safety and risk mitigation considerations. While safety is of utmost significance in type A applications, risk reduction is the primary concern in type B applications. Epistemic uncertainty, the scientific uncertainty inherent in the model, is much lower in type B applications. Errors are few in type B applications, resulting in less safety concerns. Additionally, the expenses associated with adverse outcomes are considered a criterion for evaluating negative results [9].

Machine learning has become significant in the prevention, diagnosis, and treatment of several medical diseases. The safety of these innovative techniques has been delineated in abstract metrics based on the illness domain and anticipated results. Swaminathan et al. developed a machine learning algorithm to predict flare-ups and offer at-home decision support for patients with chronic obstructive pulmonary disease. The algorithm demonstrated high accuracy in triaging patients and prioritized patient safety in a validation study (n = 101). The algorithm consistently identified all patients requiring referral to a physician and undertriaged individuals for emergency department visits in less than 14% of instances. In contrast, doctors undertriaged patients in 22% and 30% of the instances for the same judgments. This model was developed with data sets identified by physicians. The model's performance was assessed by juxtaposing its conclusions with the consensus decisions of a panel of clinicians, using an out-of-sample representative patient cohort. [10]

4. Opportunities and Challenges of Artificial Intelligence in the Healthcare Safety Context

Artificial intelligence significantly enhances understanding and optimizes results in healthcare. Artificial Intelligence (AI) has extensive applications in disease prediction and diagnosis, management of substantial data volumes, synthesis of insights, and enhancement of efficiency and outcomes in medical disease management [11]. The advantages of AI have been documented across various diseases and outcomes; for instance, in predicting sepsis in intensive care and diagnosing and classifying malignant lesions, retinal disorders, and pneumonia, among others. AI principles have been utilized in precision medicine to develop accurate, safe, and targeted therapies [12-16].

The use of AI in healthcare offers substantial advantages. Artificial intelligence may significantly enhance normal healthcare treatment and research. The primary advantages of AI are rapid and effortless access to information, enhanced outreach, and a decrease in diagnostic and treatment mistakes for diseases [17]. AI has significantly enhanced predictive diagnosis, precision medicine, and the administration of tailored treatments. Virtual follow-ups and consultations enhance efficiency for both expenses and time. AI-driven telemedicine systems enhance treatment quality while minimizing wait times and the risk of hospital-acquired infections for patients. This eventually leads to elevated patient satisfaction during treatment [18,19].

Artificial intelligence has several uses in diagnostic processes and decision-making assistance. Artificial Intelligence empowers decision-makers to obtain accurate and current information, facilitating improved real-time decision-making [20]. The implementation of AI has instigated a transformative shift in radiological diagnosis by enhancing the efficacy and precision of image analysis. Deep learning architectures have facilitated digital image analysis for the early identification of breast pathologies with high accuracy. Additionally, a machine learning software library has been developed to identify alterations in Parkinson's disease through DaTscan image analysis. This resource may serve as a valuable supplement to clinical diagnosis [21-24].

Artificial intelligence is used in patient triage. Wearable gadgets are designed for the remote monitoring and analysis of vital signs and awareness levels. Algorithms have been developed to categorize illness conditions according to severity. Models have been established to triage patients and forecast survival in the pre-hospital setting. Electronic triage (e-triage) demonstrates efficacy in emergency departments [25]. In a multicenter, retrospective, cross-sectional analysis of 172,726 emergency visits across urban and community emergency departments, e-triage exhibited superior accuracy compared to the Emergency Severity Index (ESI) for triage purposes. In comparison to ESI, e-triage detected over 10% (14,326 patients) of ESI level 3 patients requiring critical care or an emergency operation, with a higher up-triage rate (6.2% e-triage vs 1.7% ESI) and a greater hospitalization need (45.4% e-triage vs 18.9% ESI) [26].

Nevertheless, despite these advantages, several constraints hinder the effective acceptance and smooth application of AI. There is a scarcity of evidence-based research about the usefulness and safety of AI in healthcare. Clinicians often exhibit resistance and reluctance towards the integration of AI in medical practice. Furthermore, the implementation of AI-enabled systems in medical practices and research raises concerns regarding privacy, anonymity, ethics, and medicolegal issues. The machine executes tasks based on explicit instructions; however, it progressively adapts to diverse situations by utilizing newly acquired data. This generates a growing need for the collecting and exchange of private and public data, compromising user privacy [27].

Medical ethics, including an individual's right to privacy, may be compromised by AI and big data capabilities due to the aggregation and retention of data from many sources. Moreover, the confidentiality and safety of critical information may be jeopardized by the exploitation of medicolegal algorithms by hackers to create autonomous methods. To avoid such problems, AI research must adhere to established norms and ethical standards [28].

AI algorithms may include intrinsic errors, potentially resulting in inequitable and detrimental results influenced by race and socioeconomic position. Moreover, contextual interpretation and ambiguous ethical norms lead to significant challenges in the coding of AI systems. Any direct or indirect effects of AI on patients or doctors should be mitigated by preventative and precautionary measures. The use of AI and ML without comprehensive validation may jeopardize patient safety and undermine professionals' confidence in technology [29].

Machine learning may generate out-of-sample predictions and pose safety issues. This may arise because to changes in illness patterns and features, training and performance datasets, and their application to diverse populations. Generally, CNNs are trained and verified using datasets in clinical environments. These applications may not exhibit the same level of accuracy when implemented on broader population-based samples. For instance, in the use of machine learning for the monitoring of skin lesions to identify skin cancer, the variability of skin lesion appearances and patient characteristics in the general population may exceed that present in the training dataset. Confidence in an AI system may be diminished about forecast accuracy when the system lacks enough knowledge to make a conclusion. Unsafe AI decision-support systems may inaccurately anticipate low or high illness risk, rendering the predictions untrustworthy [8].

High-quality datasets are essential for training AI systems in healthcare. Data must be accurately labeled for the relevant outcomes to enable systems to identify a "ground truth" for learning relationships. If this is not achieved, AI applications will exhibit inadequate repeatability. Lacunae are documented in training datasets, even inside high-performing AI systems [14]. CheXNet, a 121-layer convolutional neural network, surpassed the diagnostic capabilities of four radiologists in pneumonia identification, having been trained only on frontal radiography pictures. Despite the significance of lateral imaging and fever history in diagnosing pneumonia within clinical environments, both elements were excluded from the algorithm's training [30,31].

Training and operational datasets are seldom identical in the use of machine learning in medicine. Training data sets may exhibit shortcomings, whereas operational data sets may include outliers and unexpected anomalies. This is known as the "frame problem" in AI within the medical field, indicating inadequacies in modifying inputs to represent the environment for autonomous agents [32].

Machine learning algorithms are taught on balanced datasets for cases and controls. Nonetheless, this may not be applicable to trial and real-world contexts, where the figures for cases and controls may differ. unbalanced datasets might lead to incorrect overdiagnosis or underdiagnosis of an illness. Data sampling-based boosting frameworks can be used on unbalanced datasets to facilitate precise diagnostic outcomes [3-35]].

AI systems may lack sensitivity to consequences. These systems may neglect to consider false-positive and false-negative predictions in the therapeutic environment. Li et al. [36] employed a deep learning method to identify referable diabetic retinopathy in a dataset of 71,043 retinal pictures. This investigation demonstrated that the algorithms had a sensitivity of 92.5% and a specificity of 98.5%. The misclassification of mild or severe diabetic retinopathy constituted 85.6% of false-positive instances, whereas undiscovered intraretinal microvascular abnormalities represented 77.3% of all false-negative occurrences. To get more accuracy and eliminate errors, systems must recognize outliers and alter their diagnostic confidence appropriately.

Efforts are concentrated on building efficient algorithms to facilitate precise diagnosis of medical disorders [37]. Ongoing prospective research is examining the use of AI for detecting diabetic retinopathy in primary care. AI computer-aided detection systems, including convolutional neural networks and automated hierarchical learning, are being used to reduce false-positive rates in breast cancer screening [38].

The explainability and interpretability of AI and ML algorithms pose significant challenges. Only interpretable models can be articulated, and elucidation is crucial for the acceptance of any system in medical decision-making [39]. Artificial intelligence has generated apprehensions over opaque medical decision-making processes. This indicates that the system's predictions remain unknown until the ultimate result is realized [40,41]. Although training datasets may be inadequate, it is impossible to ascertain the influence of the dataset on the prediction of the disease state. This characteristic will only become apparent after prolonged and repeated practical use. The incapacity to evaluate machine knowledge will persist; nevertheless, openness in development processes and algorithm sharing may foster trust in the adoption of these technologies [42].

Conversely, the safety of AI in healthcare may be jeopardized by automation complacency. With frequent use, clinicians may see AI as infallible and put unwarranted reliance in it. Automation complacency, seen in both novice and experienced doctors, arises when automated activities vie for the physician's attention alongside manual duties. Physicians may unconsciously refrain from considering potential alternatives when an AI system consistently corroborates their diagnosis. The quality of AI systems may be characterized by interpretable forecasts accompanied with a confidence estimate. Understanding the reliability of predictions may assist physicians in reducing automated bias [43,44].

5. Unanticipated Conduct and Non-Scalable Supervision

The conduct of AI is challenging to anticipate and regulate. Calibration drifts often occur in regression and machine learning models for individualized risk assessments. Instances of these drifts encompass models for acute renal damage and inpatient mortality [45,46]. AI is an independent system that perpetually learns and may exhibit unanticipated behaviors in its application of acquired knowledge. This may occur due to the phenomena of "wireheading." Machine learning algorithms may emulate previous judgments. This may result in many issues. A prevalent occurrence of unforeseen conduct is the use of automation in heparin dosage. The system's ongoing learning may result in an elevated dosage of heparin, thereby increasing the incidence of adverse events [47]. This necessitates the implementation of training methods to prevent hazardous overdose. The mechanical systems may prioritize drug delivery without regard for long-term effects. Signal processing algorithms in mechanical ventilators can attain optimal oxygenation regardless of potential long-term lung damage [48,49]. The learning phase of these systems may be challenging to quantify and anticipate. This may result in unmanageable supervision necessitating cumbersome and costly assessments to monitor hemorrhaging. Another example is an autonomous insulin pump that requires comprehensive data on food consumption to ascertain the appropriate insulin regimen for optimum blood glucose regulation. These represent fundamental issues of "reinforcement learning" in automated systems, which possess an intrinsic capacity to optimize a specified reward. The ongoing availability of data for the continual training of AI systems may also prove to be a constraint [50].

6. Prejudice, Morality, and Confidentiality

Artificial intelligence, an endeavor to replicate biological intelligence, is susceptible to prejudice. AI reflects its training, and any bias present in the training datasets might lead the AI application to include bias in the operational dataset [51]. Human-like biases are a documented and acknowledged element of automated systems. These inadvertent biases might jeopardize the safety of AI systems. AI applications may produce erroneous decisions, like as in the interpretation of radiological imaging [52].

Ethics are a fundamental problem in healthcare, and artificial intelligence is no exception. The adoption of AI, its use in research, its effects on results, and its vulnerability to bias are increasingly pressing issues as AI is being utilized more extensively in medicine and healthcare. Artificial Intelligence and Machine Learning have not yet reached full maturity to adhere to fundamental biomedical concepts of autonomy, beneficence, justice, and non-maleficence. Clinicians and medical researchers, although not being the primary creators of AI-based systems, must guarantee that these values are upheld. The responsibility rests exclusively with people, not AI systems [53].

The privacy and anonymity of AI systems provide a prevalent concern. Patient data of a sensitive nature are increasingly used in digital format and integrated into networked systems. The security levels of these systems are often ambiguous. An evaluation of the security and privacy of electronic health records (n = 49 papers) indicated that role-based access control is the most favored access control paradigm. Digital signatures, together with logins and passwords, constituted alternative authentication methods. The authors indicated a relative deficiency in training regarding security and privacy for healthcare personnel and system users [53]. The security and privacy of data are significant considerations when using AI in a medical context. Numerous systematic literature reviews underscore the need of safeguarding data security and privacy. Certain studies have identified the entities responsible for granting access to EHR data. A recent investigation outlined essential aspects critical to the security and privacy of EHRs, including access control and adherence to security regulations, among others [54].

Another possible concern is the loss, leakage, and manipulation of information, which may indicate concerns linked with AI-driven mobile health apps. Aggregated consumer data exchanged across applications presents hazards to individual privacy and security. The interconnected app families, spanning other sectors outside healthcare, may pose data privacy issues. It is essential for developers of AI-driven mobile medical applications to ensure the security of user data [55].

Advancements in telemedicine technology may lead to malpractice concerns, requiring the procurement of relevant licenses and sufficient training and certifications. This might increase the expenses associated with adopting telemedicine and may foster distrust in these systems [56].

7. Methods for Ensuring Safety in Artificial Intelligence

The precision of predictions, the causal relationships in predictive models, the human labor required for labeling out-of-sample instances, and the reinforcement and learning of systems all enhance the safety of applications in healthcare. Four fundamental principles of safety engineering pertain to the safety of AI in healthcare: safe design, safety reserves, safe fail, and procedural safeguards. Inherently safe design denotes the exclusion of possible risks rather than their simple containment inside systems. Health care systems may be rendered secure by ensuring that training data sets are not derived from the test data sets. While this may enhance system accuracy, variations in data domains remain a significant barrier. AI applications should have safety reserves to facilitate the identification of uncertainty in training and testing systems, as well as to manage both average and maximum test mistakes. The systems must be designed to provide safe failure, meaning they should maintain safety even during operational failures. The model must be taught to assertively decline when it is unable to provide a desired forecast. In instances of such rejections, human interventions may be used to enhance forecasts. Procedural protections include user experience design that assists users in configuring and using the program, hence enhancing safety. Open data and open-source software are said to enhance safety [8].

The illogical extrapolation of machine learning algorithms must be circumvented. Algorithms developed using readily accessible patient samples may compromise patient safety when used in broader and more heterogeneous populations. Algorithms must be developed and taught to assess illness severity and progression. Establishing ethical norms will facilitate the broader use of AI and alleviate concerns over its potential to surpass human talents. Societal advantages of AI will materialize if AI technologies are rendered open source, user-friendly, and have established therapeutic efficacy and economic worth [57,58].

The implementation of AI in healthcare lacks enough regulation. The evaluation of the effectiveness and safety of AI applications must be standardized. The US Food and Drug Administration (FDA) and the European Medicines Agency have established working groups to develop and validate technological and digital applications in healthcare. Furthermore, the European Patent Office has recently issued guidance for patent applications concerning AI-based devices and machine learning [59]. The inaugural deep learning clinical platform, Arterys' medical imaging platform, received FDA approval in 2017. The FDA endorses the use of real-world evidence and adaptive design in clinical trials to evaluate the efficacy and functionality of AI in healthcare. Regulatory changes are necessary to facilitate a more efficient and secure interchange and sharing of data [60].

8. Conclusions

Strategies for ensuring the safety of AI and ML in healthcare are in a state of evolution and remain underdeveloped. The current emphasis on AI safety in healthcare pertains to forecasts and the resultant consequences derived from such predictions. Systems and applications with significant and little safety must be managed according to established protocols. Models for individualized risk assessments must be well calibrated and efficient, with effective update methods established. Cost, risk, and uncertainty must be delineated for all potential uses. Automated systems and algorithms must be capable of adapting to and addressing uncertainty and unpredictability. Efforts should focus on reducing epistemic ambiguity.

A limited number of test samples before to deployment is a prevalent difficulty in AI-driven learning systems. Training samples may not consistently reflect the characteristics of test samples. The "frame problem" may be mitigated by including a human element into AI applications, which includes ongoing system calibration based on human input, clinician evaluation of anomalous data sets, and the integration of various demographics in training datasets.

Training is essential not only for AI-based systems but also for clinicians, who can be cultivated as information specialists to enhance the development of precise and reliable AI solutions. AI-augmented clinicians should exhibit increased efficiency and confidence, alleviating the uncertainties associated with technological advancements in medicine. Physicians must comprehend, cultivate, implement, and use AI to enhance patient care.

Efforts must be undertaken to optimize the advantages of AI in healthcare. Experts advocate four essential elements: quantifying benefits for measurement, fostering trust for AI adoption, developing and augmenting technical skills, and establishing a governance framework. Data protection legislation must be formulated and reinforced for the collection and processing of data in clinical research. Through objective and verifiable safety, AI may facilitate value-based and patient-centered healthcare. Quality requirements for AI applications in medicine must be explicitly delineated to enhance value, precision, efficiency, and satisfaction in healthcare.

The expenses and distribution of results in AI-based systems remain uncertain. Extensive feasibility studies and cost-effectiveness evaluations may enhance the integration of AI in healthcare. The privacy, sharing, and disclosure of safety data about AI applications should be enhanced. Stringent criteria must be established for the validation of AI and ML applications in healthcare. Protocols, rules, and methodologies must be established to facilitate the secure and efficient development and integration of AI and ML in healthcare. Trust and training will facilitate the comprehensive integration of AI into healthcare research and practice.

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التأثير التحويلي للذكاء الاصطناعي والبيانات الضخمة على تعزيز الأمن الصحي ومراقبة الأوبئة في أنظمة الرعاية الصحية الحديثة: مراجعة

الملخص

الخلفية :أحدث دمج الذكاء الاصطناعي (AI) والبيانات الضخمة ثورة في قطاع الرعاية الصحية، خاصة في تعزيز الأمن الصحي ومراقبة الأوبئة. تُعد تطبيقات الذكاء الاصطناعي أساسية لتحليل مجموعات البيانات الضخمة لتحسين اتخاذ القرارات، والتشخيص، ونتائج العلاج.

المنهجيات :تستعرض هذه المراجعة الأدبيات الحالية حول تطبيقات الذكاء الاصطناعي والبيانات الضخمة في الرعاية الصحية. كما تستكشف كفاءة خوارزميات التعلم الآلي(ML) ، وقضايا خصوصية البيانات، وآثار السلامة. تشمل التحليلات تقنيات الذكاء الاصطناعي المختلفة، مثل الذكاء الاصطناعي الافتراضي والمادي، ودورها في عمليات التشخيص، وتقييم المرضى، ودعم اتخاذ القرارات في الوقت الحقيقي.

النتائج :تشير النتائج إلى أن الذكاء الاصطناعي يُحسن بشكل كبير التنبؤ بالأمراض وتشخيصها، والكفاءة التشغيلية، وإدارة المرضى. على سبيل المثال، أظهرت خوارزميات التعلم الآلي دقة عالية في التنبؤ بالأزمات الصحية، مثل تفاقم مرض الانسداد الرئوي المزمن. ومع ذلك، لا تزال هناك تحديات، بما في ذلك قضايا خصوصية البيانات، والتحيز في خوارزميات الذكاء الاصطناعي، والحاجة إلى التحقق الشامل لضمان سلامة المرضى.

الخلاصة :رغم الإمكانات التحويلية للذكاء الاصطناعي والبيانات الضخمة في الرعاية الصحية، فإن دمجهما يتطلب مراعاة دقيقة للمعايير الأخلاقية والقانونية ومعايير السلامة. يُعد تحسين أنظمة الذكاء الاصطناعي للتطبيق العملي في بيئات الرعاية الصحية أمرًا بالغ الأهمية للاستفادة الفعالة من مزاياها. يجب أن تركز الأبحاث المستقبلية على تطوير أطر قوية لتطبيق الذكاء الاصطناعي، ومعالجة التحيزات، وضمان أمان البيانات.

الكلمات المفتاحية :الذكاء الاصطناعي، البيانات الضخمة، الرعاية الصحية، التعلم الآلي، سلامة المرضى.