



Role of Artificial Intelligence, Machine Learning, and Deep Learning in Transforming Public Health Services: Opportunities, Challenges, and Future Directions

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ABSTRACT

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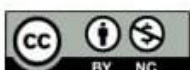
Artificial Intelligence, Machine Learning, Deep Learning, Public Health Services, Data Science, Neural Networks, Predictive Analytics, Healthcare Optimization, Computer Science.

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Advanced public health services are leveraging Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) to revolutionize their functions by harnessing complex data for analysis, forecasting of disease outbreaks, and making intelligent decisions. They are covered in this review and used in epidemiological surveillance, disease prevention, population health management and optimization of healthcare resources. It delves into computational methods like neural networks, predictive modeling, and the structures of deep learning, as well as cutting-edge technologies like generative AI and federated learning. Some of the major obstacles are data privacy, algorithmic bias, model interpretability, and infrastructure constraints. Future research priorities are identified in this review and include an increased focus on explainable AI, ethical governance, reliable validation and equitable implementation to drive better public health outcomes globally.

INTRODUCTION

Public health services are an essential component of the prevention of disease, promotion of health, minimization of health disparities and overall health and wellbeing of populations. Previously, most public health systems have been based on epidemiological investigations, statistical analysis, clinical



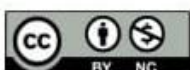


records, and population-based surveys for the discovery of health risks and their prevention [1]. In recent years, however, the complexity of health problems, the growth of population, the emergence of new infectious diseases, chronic health conditions, and the uneven distribution of access to health care have made it even more important to think about using more sophisticated and efficient, data-driven methods [2]. The advancements of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and data science have brought new possibilities for revolutionizing public health services by leveraging intelligent data analysis, predictive modeling, automated surveillance, and evidence-based decision-making [3].

Artificial Intelligence (AI) are computation techniques that can be used to make decisions or provide predictions that are typically performed by humans. One of the key areas in AI, Machine Learning enables computational systems to learn patterns from past data and make predictions without having to be explicitly programmed with rules for each task [4]. The application of decision trees, random forests, support vector machines and gradient boosting to disease prediction, population health risk assessment, and epidemiological surveillance has taken center stage in recent years. These capabilities are further expanded with Deep Learning, a technique that involves using multilayer neural networks to learn complex representations from large and diverse sets of data, such as medical images, electronic health records, genomic information, environmental measurements and time-series health data [5].

The use of these technologies with computer science and data science can be used to enable better public health planning and service delivery. AI-powered prediction models can be used to target populations at high risk for contracting a disease, to predict potential outbreaks of infectious disease, to allocate healthcare resources effectively, and to facilitate early-warning systems, for instance [6]. Likewise, NLP can be used to pull out meaningful data from unstructured health records and geospatial machine learning can detect geospatial trends in disease spreading and environmental health hazards. These capabilities can enhance the timeliness and accuracy of public health responses, especially when combined with trusted public health surveillance and people [7]. When combined with trusted public health surveillance and people, these capabilities can enhance the timeliness and accuracy of public health responses.

While these possibilities are available, there are also obstacles in implementing AI in public health such as incomplete or biased data sets, privacy and cybersecurity concerns, the lack of interpretability, inadequate computational resources, and unequal access to digital technologies. Additionally, the accuracy of the predictions is not enough to ensure better population health outcomes [8]: AI-based systems must be carefully validated, supervised, transparent and evaluated in real-life contexts. Thus,





the implementation of AI, ML, and DL in public health care services should be done responsibly to ensure technology advances are helping to provide equitable, safe, and sustainable health care delivery [9].

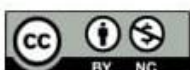
This review focuses on the potential of Artificial Intelligence, Machine Learning and Deep Learning in reaping the transformative power of public health services, especially with respect to computational techniques, applications, new opportunities, implementation hurdles and future research directions. It also examines how the fields of computer science, neural networks, and data analytics can help create more intelligent, predictive, and resilient public health systems.

ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND DEEP LEARNING

The fields of Artificial Intelligence, Machine Learning, and Deep Learning are closely related areas of computation that are increasingly aiding data-driven innovation in public health services. By combining their features, researchers and public health professionals can gain valuable insights from large datasets, detect patterns that may not have been apparent, forecast health risks, and make better decisions [10]. Increased availability of the electronic health record, disease surveillance reports, disease environmental measures, genomic data, wearable device data and population health surveys has made computational methods that can handle complex and heterogeneous information increasingly important [11]. The key concepts, algorithms and connections between these technologies must be understood to assess their effectiveness and limitations in public health applications.

Artificial Intelligence: It is the ability of computational systems to carry out tasks that normally need human cognitive powers, including learning, reasoning, pattern recognition, language processing and decision support. AI can help in public health by automating disease surveillance, pinpointing vulnerable groups, interpreting health data, and aiding in resource allocation [12]. Data from various sources can be fused together using AI-based decision support systems to aid in the detection of emerging health threats and in the evaluation of preventive actions. AI-driven recommendations should be considered alongside expert medical and public health advice and not in place of it [13].

Machine Learning is actually a subdomain of AI that allows algorithms to discover statistical designs in data and utilize these patterns to forecast or decide. Supervised learning is used to build classifiers or regressors, for example, to predict disease risk or to forecast hospital demand, based on a set of labeled examples [14]. Unsupervised learning finds structures in unlabeled data using dimensionality reduction, clustering and other techniques that can help to identify population subgroups with similar health characteristics. The reinforcement learning branch of computer science addresses the learning of decision strategies from the feedback received from an environment and could be applicable to



resource allocation and intervention planning [15].

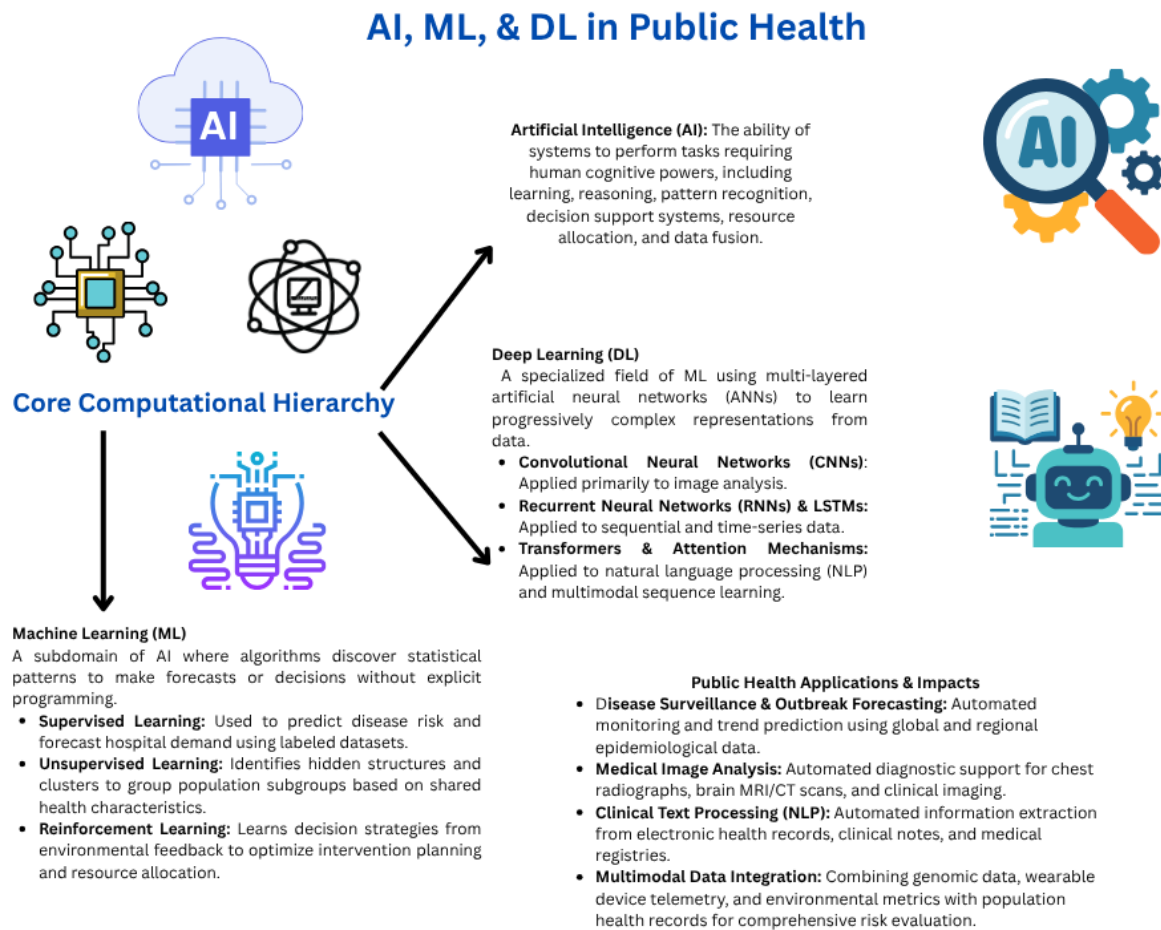


Figure 1. AI, ML, & DL in Public Health

A specialized field of ML is Deep Learning, which refers to neural networks having multiple layers of processing to learn progressively more complex representations from data. The artificial neural network is made of interconnected computational units that learn weights and activation functions to transform information in the input [16]. CNNs are known for their use in image analysis and RNNs and LSTMs have been applied to sequential and time-series data. Attention architectures have been applied to work with long sequences of information, making transformers possible, and have been shown to be useful for NLP and multimodal learning [17]. These architectures can be used in the field of public health for medical image analysis, outbreak forecasting, automated information extraction from clinical text, and the integration of a variety of health data sources.

DATA SOURCES AND COMPUTATIONAL INFRASTRUCTURE FOR PUBLIC HEALTH

AI

High-quality, reliable data and computational infrastructure are essential to implementing Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in public health services. Public

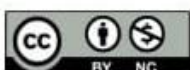


health systems (PHSS) collect a vast amount of information, such as from environmental monitoring, population-based surveys, wearable devices, laboratories, epidemiological surveillance programs, and hospitals [18]. These data sources can be useful for identifying disease patterns, predicting health risks, monitoring disease outbreaks, and evidence-based public health planning. But, the effectiveness of AI-based systems relies on data integrity, its completeness, representativeness, and interoperability, as well as computational resources [19]. Combining data from multiple sources and sophisticated computing techniques can enhance the effectiveness and efficiency of the public health decision-making process.

One key source of health-related data for AI applications is the Electronic Health Records (EHRs) or Electronic Medical Records (EMRs). They can include patient information such as their demographics, medical history, diagnoses, lab results, medications, clinical observations, and treatment outcomes. These data can be used to detect who is at risk, foresee hospital admissions, forecast the course of the disease, and aid preventive healthcare measures, among other functions, with the help of machine learning algorithms [20]. Deep learning and NLP can also be used to identify relevant information in unstructured clinical notes. However, inconsistencies in documentation, missing data and poor data transfer between healthcare organizations can impact on the performance of the models and generalizability [21].

Public health surveillance systems gather data on disease occurrence, transmission pattern, mortality and health indicator data at population level. Important functions of these datasets include the ability to keep track of infectious diseases, provide a tool for detecting anomalies in reported cases, and evaluate the success of public health measures [23]. Historical surveillance data can be analysed using an AI-based model to predict disease patterns and early-warning systems. For instance, time-series forecasting and recurrent neural networks could be used to predict shifts in the influenza-like illness or other communicable diseases [24]. Uncertainties can still arise, however, due to delayed reporting of cases, underdiagnoses, variable case definitions, and incomplete surveillance coverage.

AI-supported disease detection and population health monitoring can also be achieved through medical imaging and laboratory information. Radiological images, microscopy data, pathology images, and laboratory test results can be analyzed using machine learning and deep learning techniques. For instance, convolutional neural networks have been explored for medical image analysis and disease diagnosis, where they can help classify abnormalities in medical images [25]. Laboratory data can also be used to help inform predictive models to determine infection risk and track disease progression. There are potential advantages in the use of these applications to accelerate the analysis, but they need to be properly validated, standardized in the data collected and evaluated





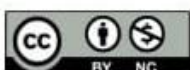
in various populations and healthcare environments [26].

These devices, with the help of mobile health apps, can make continuous or frequent measurements of physical activity, heart rate, sleep patterns, environmental exposures, and other health metrics, all of which can be collected through wearable devices, smartphones, mobile health applications, and Internet of Things (IoT) sensors [27]. These data can be used in the remote health monitoring, health promotion, and early detection of potential health risks. Changes in behavioural pattern can be identified by ML algorithms and deep learning models can analyse sequential sensor measurements. It may also be possible for mobile technologies to support health education, remind people to get vaccinated, and provide communication between public health officials and communities [28]. Access to digital devices, errors in measurement, consent of users, and privacy of data, however, are important considerations.

AI, MACHINE LEARNING, AND DEEP LEARNING IN PUBLIC HEALTH SERVICES

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are becoming more and more of a focus to enhance public health services using predictive analytics, automated surveillance, risk assessment, and data-driven decision-making. The accumulation of data on health in hospitals, laboratories, epidemiological surveillance networks, environmental monitoring networks, and wearable devices has opened the door for the creation of computational models with the ability to uncover patterns that are difficult to observe with traditional analytical techniques alone [29]. AI-driven solutions can help public health workers make sense of the spread of disease, pinpoint the population at risk, predict health threats, and leverage preventive actions. However, their effectiveness relies on accurate data, correct model validation and implementation within a healthcare system [30].

These algorithms are able to predict the likelihood of developing specific diseases by using demographic, clinical, behavioral and environmental data. Random forests, support vector machines, gradient boosting, and neural networks are among the models that have been explored for predicting health conditions like diabetes, cardiovascular diseases, respiratory diseases, and so on [31]. Early identification of these at-risk persons could facilitate screening, preventive counseling and clinical evaluation. Another advantage of deep learning is its ability to analyze complex and high-dimensional data, looking for patterns related to disease progression [32]. However, prediction models need to be tested in other populations to make sure that the results are accurate and not exacerbating current health disparities.



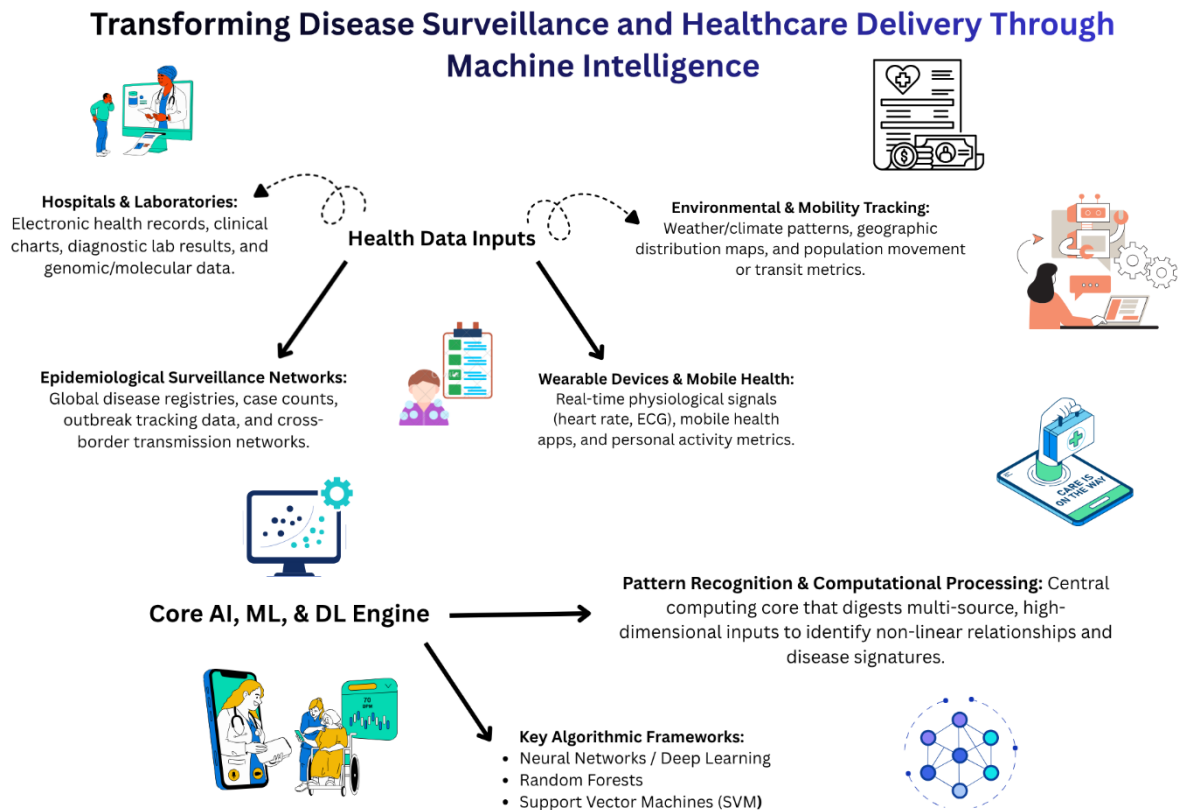


Figure 2. Transforming Disease Surveillance and Healthcare Delivery through Machine Intelligence

AI can support public health surveillance by analyzing disease notifications, laboratory reports, historical disease counts, mobility patterns and environmental indicators. Time-series forecasting models and recurrent neural networks can be used to forecast changes in disease incidence and to highlight abnormal patterns in disease incidence that may require further investigation [33]. These techniques can be used to help early-warning systems and aid decision-makers in planning for future outbreaks. Reporting inaccuracies, slow data reporting and a changing pattern of disease transmission can lower predictive performance, however. Hence, the use of computation-based predictions should be combined with the epidemiological monitoring and expert judgment [34].

Machine learning and deep learning are potential aids to the prevention of infectious diseases by recognizing the patterns of transmission, forecasting disease outbreaks and estimating the effects of preventive measures. AI models have been examined for various diseases including the flu, tuberculosis, malaria and the COVID-19 [35]. These systems can facilitate geographical identification of potential high-risk areas, assist in screening strategies, and assist in resource allocation decisions about testing. They are only reliable if they are based on representative surveillance data, appropriate



validation, and consideration of changes in the pathogen characteristics and population behavior [36].

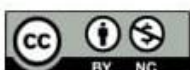
MACHINE LEARNING TECHNIQUES FOR PUBLIC HEALTH ANALYTICS

Machine Learning (ML) is a significant field of Artificial Intelligence (AI) which helps computer systems learn from data patterns and make predictions or decisions without needing to be explicitly programmed for each specific purpose. In the context of public health services, machine learning technologies are increasingly being employed to analyze large-scale data, uncover patterns in disease risk factors, predict disease trends, and optimize health resource distribution [37]. These techniques can analyze data from EHRs, disease surveillance systems, lab reports, population surveys, wearable devices and environmental monitoring systems. ML can be used to assist with making evidence-based decisions, detecting disease outbreaks early and focusing public health measures appropriately [38]. But these methods will only be useful if the data quality is good and suitable modelling techniques are used and results are validated and interpreted well.

Supervised learning is one of the machine learning techniques where algorithms are trained from labeled data sets that have input variables and known outputs. Classification models predict discrete categories (e.g., belongs to high risk disease group), whereas regression models estimate continuous values (e.g., expected incidence of disease, demand for healthcare) [39]. Population health risk prediction can be carried out using algorithms such as logistic regression, decision trees, random forests and support vector machines. These could be useful to identify vulnerable groups, assist in screening strategies and aid in better planning of prevention. Their performance should be evaluated by appropriate metrics, such as sensitivity, specificity, precision, recall or calibration, depending on the prediction task [40].

Unsupervised learning is a type of learning in which the structures of a set of data are discovered without any outcome labels. Clustering methods, such as k-means and hierarchical clustering, can be used to categorize populations based on health attributes, environmental exposures, or health care use. Dimensionality reduction techniques, like principal component analysis, can be used to reduce the dimensionality of a dataset and facilitate exploratory analysis [41]. In public health, these methods can be used for the detection of disease clusters, characterization of population sub-groups, and health inequalities investigation [42]. However, patterns that are discovered need to be interpreted epidemiologically and independently validated before being applied to inform public health action.

Ensemble learning is used to generate prediction by fusing predictions from several prediction models in order to enhance the predictive performance or robustness. Random Forest creates several decision trees and combines their results; gradient boosting does successive models that fix errors from previous models [43]. The gradient-boosted decision tree is a popular machine learning algorithm for





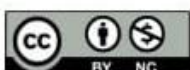
predictive modeling that is efficiently implemented in XGBoost. These can be used to examine complicated relationships between demographic, clinical, behavioral and environmental variables [44]. They are potentially useful in disease risk prediction, hospital demand forecasting, and identification of target groups in need of targeted preventive services. Input tuning, representative training data and validation on independent data sets, however, are important for their performance [45].

DEEP LEARNING AND NEURAL NETWORK ARCHITECTURES IN PUBLIC HEALTH

Deep Learning (DL), an advanced machine learning (ML) technique, employs a multi-layered artificial neural network to detect more intricate patterns in huge and complex datasets. It has been a significant focus of public health research due to its capability to handle both structured and unstructured data, such as electronic health records, medical images, lab results, genomic data, environmental data, and epidemiological time series. Deep learning can extract informative representations from data, whereas many traditional machine learning methods require manually engineered features. These capacities enable disease prediction, outbreak forecasting, health risk assessment and population level surveillance [46]. But the challenges of data availability, computational resources, model transparency, and systematic validation for other populations have to be met to be successful.

Artificial Neural Networks (ANNs) are computational techniques that are modeled after the interconnections of biological neural networks. They have input, hidden and output layers of computational units called neurons. In training, the network adjusts its parameters to minimise the prediction errors [47]. Public health applications of ANNs include disease risk prediction, mortality prediction, identification of high-risk populations and healthcare demand prediction. They can be useful when several demographic, behavioural, clinical, and environmental factors interact, as they are able to model nonlinear relationships [48]. However, ANNs can be hard to interpret, and they need a lot of training data for them to work well.

One type of deep learning architectures that is especially useful for analyzing image-based information is Convolutional Neural Networks (CNNs). They rely on convolutional operations for the extraction of features, like shapes, textures, and spatial patterns. In the field of public health and medical research, CNNs have been studied for analyzing radiological images, microscopy images, pathology slides, etc [49]. Such models can be used for detecting abnormalities associated with tuberculosis, for categorising skin lesions and for recognising imaging features associated with the disease. They could also be used in population-level screening programs in conjunction with suitable clinical workflows [50]. But for reliable implementation, training sets must be representative,





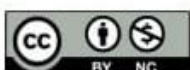
independent validation is required and the performance of the system needs to be assessed on different imaging devices and different population groups [51].

Recurrent Neural Networks (RNNs) are suitable for processing sequences, which are also applicable to health data over time. A variant of the RNN, the Long Short-Term Memory (LSTM) networks have been introduced to better model long-term dependencies in sequences [52]. In the public health sector, these architectures can be employed for infectious disease forecasting, longitudinal health records analysis, tracking health indicators and predicting the need for healthcare services. For instance, historical disease surveillance data can be used to model the seasonal pattern and to estimate the number of cases in the future [53]. Forecasting accuracy can be less reliable if there is a change in reporting practices, data are incomplete, or an unforeseen event occurs that changes historical trends. In the transformer architecture, attention is applied to find relationships between the elements of sequences and/or other structured inputs. They have made significant progress in natural language processing and are being increasingly explored for use in analyzing health-related data. Transformer-based models have the potential to assist in information retrieval from clinical documents, scientific literature analysis, summarization of surveillance reports, and combining several health data sources, in the context of public health [54]. Meta LLM can also be used to help with the creation of health communications and structuring public health data. But outputs generated may have inaccuracies or claims which are not supported, which means that expert verification, protection of privacy and suitable safeguards are needed [55].

OPPORTUNITIES AND BENEFITS OF AI-ENABLED PUBLIC HEALTH SERVICES

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) hold great promise for enhancing the effectiveness, efficiency, and access of public health services. These technologies will be able to gain insights from vast amounts of health information, detect disease trends, forecast health risks, facilitate preventative health measures, and guide policy makers in evidence-based policy-making [56]. They can enhance disease surveillance, make better use of health care resources and help manage the health of a population when combined with data science and computer science.

Epidemiological, clinical, and environment parameters can be fed into AI predictive models to detect population groups at higher risk of disease. Machine learning can be used to aid in early disease detection and predict the likelihood of outbreaks, giving public health officials the time to take steps to prevent the spread of the disease. AI can be used to automate the analysis of surveillance reports, laboratory results, and other health information to reveal unusual disease patterns [57]. Monitors changing trends in diseases and issues early warning using deep learning and time-series. These capabilities can aid in making timely decisions in the event of an outbreak of infectious diseases and



in a public health emergency [58].

AI can assist public health agencies in distributing resources such as human resources, diagnostic tools, vaccines, and other medical supplies based on their expected needs. By forecasting inefficiencies, predictive analytics can help optimize plans and minimize unnecessary expenses, leading to more efficient service provisioning. But cost-effectiveness must be demonstrated by using proper real world evaluations [59]. By examining a variety of factors such as demographics, behaviors, environments, and health outcomes, machine learning can reveal disparities in disease risk among populations. Such knowledge can be used to design community-specific screening and prevention programs and health education efforts [60]. Mobile apps, telehealth services, and digital decision-support tools powered by AI can help enhance access to health information and services in remote or underserved areas. These technologies, if designed inclusively, can help to identify gaps in services, and serve to facilitate more equitable distribution of resources [61].

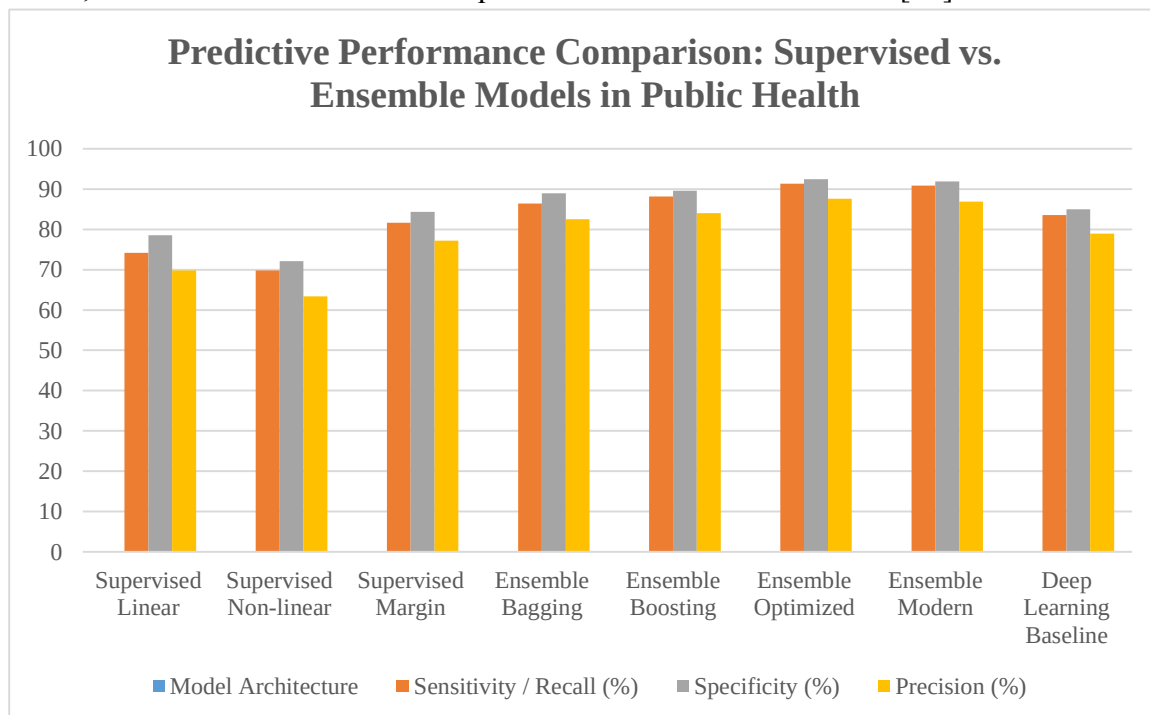


Figure 3. Predictive Performance Comparison: Supervised vs. Ensemble Models in Public Health

CHALLENGES AND LIMITATIONS OF AI IN PUBLIC HEALTH

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have potential to enhance public health care services, but present technical, ethical, organizational and financial challenges. AI systems have to be reliable and accurate, driven by high-quality data, capable of integration with the vast and complex nature of healthcare systems, and capable of delivering accurate predictions [62]. Awareness of these constraints will help to ensure that AI technologies will be safe,



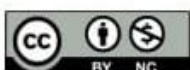
fair, transparent, and of benefit to all populations.

High-quality data are essential for developing reliable AI models. Public health information can be incomplete, include missing fields, have incorrect or inconsistent information, and have population coverage that is incomplete. These restrictions may impact the model's accuracy and lead to inaccurate predictions. In addition, data gathered at particular hospitals or areas may not be representative of other populations [63]. Data cleaning, data standardization, and data external validation are therefore needed. When trained on biased or unrepresentative datasets, AI models can perpetuate or exacerbate existing health disparities. Some socioeconomic minority communities, rural communities, or un-served populations might be under-represented in training data. As a result, predictive models can have different performance across demographic groups [64]. Researchers are encouraged to consider fairness, to measure subgroup performance, and to consider representative datasets to minimise discriminatory outcomes.

Public health information is often personal and health-related information that is sensitive. The risks of collecting, storing and analyzing these data include unauthorized access, data breaches and inappropriate disclosure. The use of strong encryption, access controls, data minimization, informed consent if applicable, and privacy-preserving techniques is critical for safeguarding individuals and public trust [65]. There are many models in deep learning that are complex and cannot be explained. The lack of transparency can also make it difficult for public health professionals to grasp the rationale behind the designation of a population as high-risk [66]. While explanations are useful, they demand careful validation, and can be used to identify influential variables and to communicate model behavior, with explainable AI techniques.

It is possible for a model to do well on the training set and to do badly on the test set if the test set comes from a different region, population, or healthcare system. The accuracy of predictions can be influenced by changes in disease prevalence, in data collection procedures, in environmental setting, and in population characteristics [67]. Before widespread implementation, external validation and continuous monitoring are needed. Implementing AI solutions within existing public health services is challenging due to systems integration, legacy systems, staff buy-in, and operational complexity [68].

The adoption process depends on the interoperability of technologies, involvement of stakeholders, sufficient resources and testing of real-world effectiveness. Issues surrounding AI use in public health are not limited to performance, but lie in other areas such as privacy, fairness, transparency, and infrastructure and organization readiness [69]. To overcome these challenges, it is crucial to establish responsible governance frameworks, ensure the availability of representative datasets, validate these





datasets with professional rigor, and use human oversight in training AI systems to build reliable and equitable public health services [70].

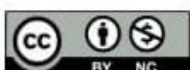
FUTURE DIRECTIONS AND EMERGING RESEARCH TRENDS

Prominent developments in computational intelligence, data science, neural networks, and computer science are likely to influence the future of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in public health services. New technologies are opening up the possibilities of better monitoring, forecasting health crises, enhancing prevention measures and assisting in evidence-based policymaking [71]. In the future, more and more studies will concentrate on multimodal data integration, the creation of reliable AI-driven systems, and the enhancement of AI model explain ability and equity in the provision of intelligent public health services. But this progress should be backed up by intensive assessment, ethical oversight, and real-world proof of better population health [72].

Generative AI and Large Language Models (LLMs) can analyse and create human-readable texts, extract and summarise information from scientific literature, support health communication and interpret text information from public health reports. The technologies could assist practitioners in creating educational content, analyzing surveillance reports and disseminating health advice in various languages [73]. But the accuracy of facts, the skewing of information, and the risk of privacy violations require verification by an expert and appropriate protection measures.

Federated learning is an approach where several institutions can federate together to train a machine learning model without regularly sending their raw data to a central server. This can work to facilitate cooperation among hospitals, lab and public health systems and mitigate some of the risks of data sharing. However, certain updates to the model could still expose sensitive information, adding another layer of privacy and security checks might be necessary [74]. One differentiator of causal machine learning from traditional prediction-oriented work is the ability to study causal relations. These approaches could be applied in future studies to assess the impacts of health education campaigns, environmental policies, preventive measures and vaccination programs [75]. To draw valid causal inferences, appropriate study designs, controlling for confounding variables and appropriate assumptions are essential.

The foundation models are trained with huge data sets and can then be customized for other tasks. Multimodal models are models which use information from clinical records, medical images, laboratory measurements, and environmental data. Such methods could offer better overall picture of population health risks [76]. But they do need to be carefully validated, have computational power and be guarded against being biased and making poor predictions. By combining these factors—





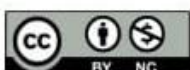
epidemiological surveillance, movement data, laboratory results, and environmental conditions—AI can enhance the capabilities of epidemic response. Emerging threat identification, healthcare resource estimation and emergency resource planning could be aided by predictive systems [77]. Future systems should be based not only on historical patterns, but on uncertainty and changing dynamics of the disease.

CONCLUSION

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are reshaping public health by providing cutting-edge computational tools for disease prediction, epidemiological monitoring, health risk estimation, and evidence-based decision-making. The combination of these technologies with data science, neural networks and computer science offers the potential to analyze and interpret large and complex datasets, uncovering hidden patterns, and to create predictive models for helping manage population health. This review focuses on the increasing significance of intelligent computational systems as means to reinforce disease prevention; optimize the allocation of healthcare resources; manage environmental health risks; and inform public health policy-making. Structured health data can be used to uncover relationships using machine learning algorithms, such as Random Forest, Support Vector Machines, Gradient Boosting, and XGBoost, and make predictions for various public health uses. Other architectures like Artificial Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, Transformers, and Graph Neural Networks can be applied to other medical imaging tasks, sequential data, textual reports, and connected population health data. In addition, new technologies, such as generative AI, federated learning, geospatial intelligence and multimodal learning, could help increase the capacity of public health systems to meet complex and changing health challenges.

However, there are some challenges that need to be overcome before AI solutions can be used at scale. They can be limited by poor data quality, algorithmic bias, lack of interpretability, privacy issues, cyber security risks, inadequate computation resources and lack of expertise. Furthermore, good predictive performance does not necessarily mean better health outcomes. AI-based models need to be comprehensively validated internally and externally, tested for fairness, and tested in the real world to ensure reliability, generalizability and usefulness. It is critical that there is transparent governance and regulatory compliance as well as appropriate human oversight to ensure responsible implementation.

Going forward, it is important to develop explainable, privacy-preserving, computation efficient, and equitable AI systems. Communication and interaction between computer scientists, epidemiologists, biostatisticians, health professionals, policy makers and the community are needed to turn





technological innovation into effective public health solutions. Local availability of datasets, low-cost infrastructure, multi-lingual applications and sustainable implementation plans are particularly relevant in resource-constrained contexts.

AI, ML and DL should be used alongside, not in place of, public health professionals and good professional practice and judgment. They can be integrated in a responsible way to strengthen disease surveillance, support preventive measures, aid in the process of resource planning and evidence-based policymaking. Public health institutions can leverage intelligent computational technologies to their best effect and at the lowest possible risk by responding to technical, ethical and organizational issues. The future of AI in public health system services, and their impact on population health outcomes, will depend on interdisciplinary innovation, data management and governance, and ongoing evaluation.

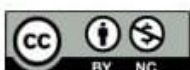
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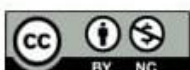


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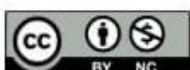


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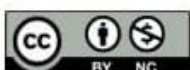


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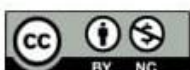


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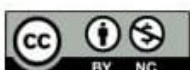


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