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Advancement in public health through machine learning: a narrative review of opportunities and ethical considerations

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Abstract

This narrative review presents a comprehensive and state-of-the-art synthesis of how machine learning (ML) is transforming public health through enhanced prediction, personalized treatment, real-time surveillance, and intelligent resource optimization. Drawing from 170 peer-reviewed studies published up to 2024/2025, this work uniquely integrates cross-domain insights spanning disease outbreak forecasting, genomic data analysis, personalized medicine, mental health monitoring, and public health infrastructure planning. The novelty of this review lies in its multidimensionality. It merges technical efficacy, ethical challenges, and future trends into a unified narrative. Our findings show substantial performance gains across domains: for example, ML models such as LightGBM, GRU neural networks, and LSTM achieved disease prediction accuracies ranging from 88 to 95%. In genomics, ML methods enabled nuanced disease subtype discovery and improved the accuracy of cancer risk assessment and pharmacogenomic modeling. Mental health prediction systems based on NLP and wearable data delivered up to 91% accuracy in stress and depression detection, while hospital resource forecasting models using deep learning minimized errors in predicting emergency admissions. Ethically, this review surfaces critical issues, including algorithmic bias, data privacy concerns in mental health analytics, and the interpretability of black-box models used in outbreak surveillance. A forward-looking discussion identifies future priorities such as the integration of multi-omics data, deployment of explainable AI, and equitable data inclusion frameworks. This review stands out by not only cataloguing applications but also offering a systems-level perspective on how ML can equitably and ethically scale to support public health strategies globally. It is among the first narrative reviews to concurrently evaluate ML's predictive power, ethical constraints, and domain-specific improvements across all core pillars of public health.

Keywords: Public health, Machine learning, Artificial intelligence, Personalized medicine, Mental health, Resource allocation and optimization, Genomic data analysis

Introduction

Public Health is the main pillar on which the edifice of the well-being of society stands. It uses organized efforts to suppress diseases, improve life expectancy, and make society healthier. Therefore, it plays an important role in the growth of a nation. "Public health can be defined as the science and practice of safeguarding, advancing, and enhancing the health of populations via coordinated initiatives and informed decisions made by society, organizations, communities, and individuals." [1] Public health is a comprehensive domain that includes multiple facets aimed at safeguarding the health and welfare of populations.

Public health encompasses various pillars, including epidemiology, biostatistics, environmental health, health policy and management, social and behavioral sciences, global health, infectious disease control, chronic disease prevention, health equity and social justice, maternal and child health, nutrition and food safety, occupational health, and disaster preparedness. These elements are crucial for societal well-being, addressing disease trends, promoting health education, addressing global health challenges, and ensuring universal healthcare access [1–4]. Figure 1 depicts these elements.

Public health contributes to society through disease prevention, control, mental health promotion, cost savings, health equity, policy development, health education, preparedness, environmental health, and emergency preparedness. It also helps

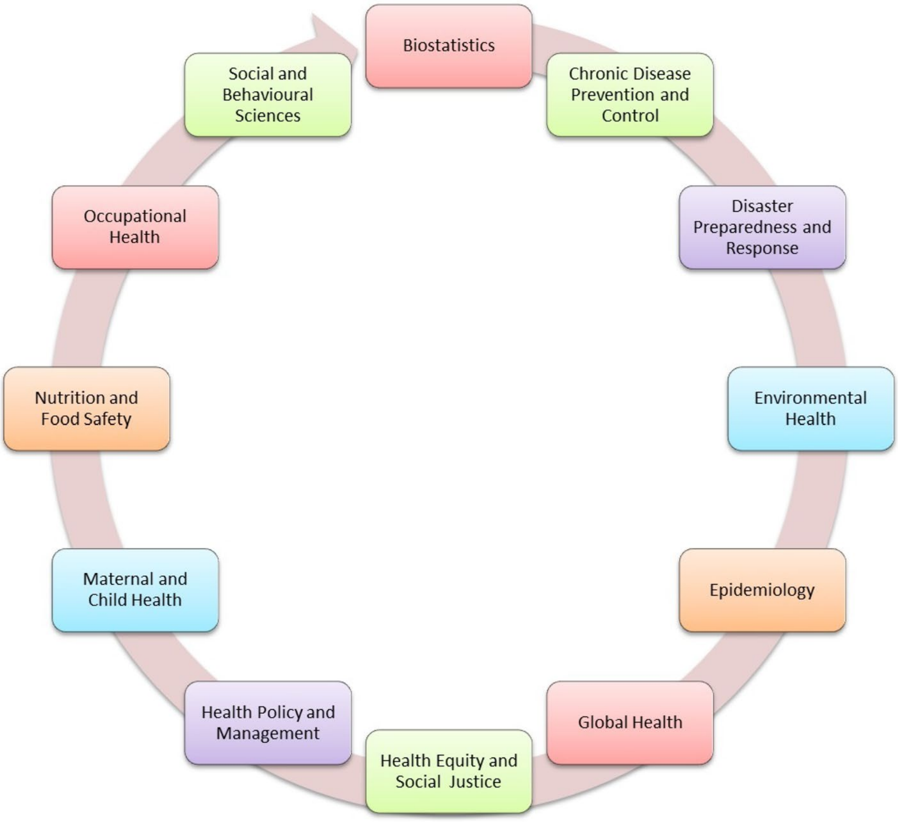

Fig. 1 Different Aspects of Public Health [1–4]

in environmental health and aims for population well-being, promoting continuous efforts through technological developments.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as effective solutions to various societal problems, improving existing methods and resulting in innovative solutions in the Public Health domain, as discussed in Related Work. AI and ML are interconnected, with AI emulating human intelligence for unique solutions, and ML enabling machines to learn from data to identify patterns and make predictions. Advanced algorithms and large datasets have improved public health response, predicting disease outbreaks, refining treatment methods, and improving resource allocation. ML's ability to analyse diverse datasets enables sophisticated models for individual health outcomes [4, 5]. The relationship has been presented in Fig. 2. It also identifies their respective applications. Machine learning classifiers are used to predict infectious disease spread, identify high-risk populations, and evaluate public health interventions. They also aid in disease detection and remediation, particularly in managing chronic diseases like diabetes and cardiovascular diseases, ensuring timely interventions and precise patient treatment [6–9].

This paper reviews over 170 research papers, published till 2025, on the use of machine learning in public health, focusing on the post-COVID-19 era. The review highlights the need for scalable, data-driven solutions to manage vast datasets. It evaluates how ML improves predictive accuracy, treatment personalization, and interfaces with issues like data privacy, algorithmic fairness, and institutional readiness. The review synthesizes advances across outbreak surveillance, personalized medicine, genomic analytics, and mental health monitoring, highlighting model accuracy improvements (up to 95%) and resource optimization outcomes. It provides a unique perspective on ML's role in building resilient, equitable, and explainable public health infrastructures.

The contributions of this study are as follows:

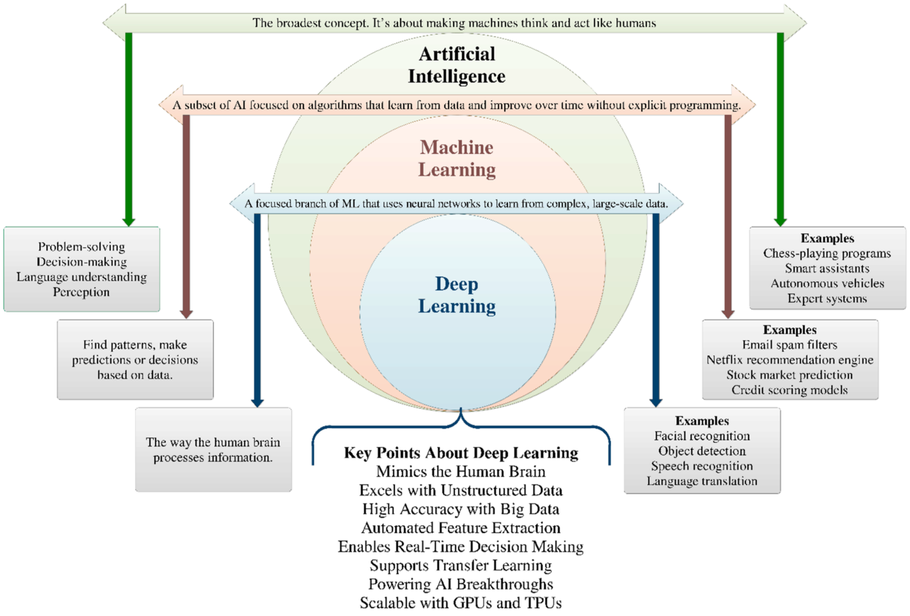

Fig. 2 Relationship between AI and ML

- A comprehensive narrative review of the state-of-the-art machine learning methodologies employed in public health prediction systems has been presented. In this work, focus has also been given to *ethical and practical implementation challenges without restricting itself to technical advancements.*
- It evaluates each domain employing tailored machine learning techniques, incorporating aspects such as advantages, challenges, datasets, and security considerations;
- This review draws from 170 peer-reviewed studies published up to 2024/2025. It uniquely integrates cross-domain insights spanning disease outbreak forecasting, genomic data analysis, personalized medicine, mental health monitoring, and public health infrastructure planning.

Research methodology, research questions, and paper selection process

The primary aims of the research are to discover, assess, and differentiate the significant publications in the domain of machine learning applications in public health. To attain these objectives, a narrative review (NR) has been utilized to meticulously analyze the elements and characteristics of methodologies applied in this context. Furthermore, this narrative review facilitates a comprehensive grasp of the principal issues and complexities inherent in this domain. The subsequent paragraph details many research inquiries.

Research Questions:

- This paper investigates the applications of machine learning in public health with the following key research questions:
- What are the major public health domains utilizing ML (e.g., disease prediction, mental health, resource optimization)?
- How do ML techniques improve public health outcomes?
- What are the emerging trends and future directions in ML for public health?
- How can ML techniques be utilized to monitor and forecast disease outbreaks?
- What are the potential impacts of ML on personalized medicine, genomic data analysis, and mental health?
- What ethical and technical challenges arise when integrating ML into public health systems?

Methods: literature search process, selection criteria, and data extraction and synthesis methods

PRISMA (preferred reporting items for systematic reviews and meta-analyses)

A PRISMA-style flowchart in Fig. 3 was used for the document identification, screening, and inclusion process, ensuring a replicable and structured review process.

i. *Identification:* Studies were identified through database searches using predefined search terms (e.g., “machine learning for public health,” “disease forecasting,” “genomic data personalized medicine”).
ii. *Screening:*

  - Titles and abstracts were screened for relevance.

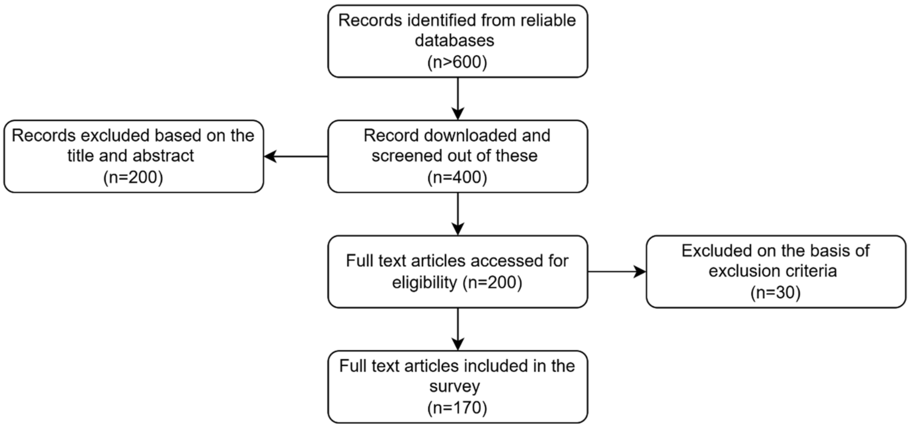

Fig. 3 Flow chart for the article selection method

- Duplicates and irrelevant studies were removed.

iii. *Eligibility:*

- Full-text articles were assessed for eligibility based on inclusion/exclusion criteria.
- Studies without substantial experimental data or those focused on non-public health domains were excluded.

iv. *Inclusion:*

- Only those studies meeting all inclusion criteria were retained for synthesis.

To the best of our knowledge, we have not kept any bias towards certain ML algorithms, geographies, or diseases. The main concern was to find the interventions that have resulted in sufficient enhancements. Therefore, to select appropriate literature, the following inclusion and exclusion criteria have been utilized:

- *Inclusion Criteria:*
  - Studies focusing strictly on the applications of ML in public health, including disease prediction, genomic data analysis, resource allocation, and mental health, were included
  - Peer-reviewed articles published in English were used for review.
  - Research presenting empirical results or systematic reviews that provide *substantial improvements in public health interventions* by utilizing ML.
- *Exclusion Criteria:*
  - Articles unrelated to public health or ML. Like some articles, though using AI, but not strictly related to Public Health, or vice versa, were removed
  - Opinion pieces, editorials, or non-peer-reviewed publications have been excluded.
  - Some articles that were not in English were also omitted.
  - Studies with inadequate methodological transparency, small improvement in results, or insufficient data were also removed.

Literature search process

The authors conducted an extensive literature review to identify the applications of machine learning in public health. The search was performed across multiple databases, including PubMed, ScienceDirect, BMC, IEEE Xplore, and Google Scholar, covering publications up to 2024. To ensure comprehensive coverage of both technical and clinical literature relevant to machine learning in public health, a strategic selection of multidisciplinary databases was employed. PubMed was chosen for its extensive repository of peer-reviewed biomedical and public health research, making it ideal for sourcing studies on disease prediction, epidemiology, genomics, and mental health interventions. IEEE Xplore was selected to capture cutting-edge developments in machine learning algorithms, data-driven healthcare technologies, and engineering-based implementations relevant to digital public health systems. ScienceDirect and BMC were included to access a broad spectrum of interdisciplinary studies combining health sciences with computational modeling, particularly those emphasizing ML applications in real-world healthcare settings. Google Scholar was utilized to capture additional gray literature, recent preprints, and cross-disciplinary works not indexed in traditional databases, thereby enhancing the inclusivity and currency of the review. Together, these databases provided a well-rounded, high-quality literature base aligned with the narrative review's dual focus on technical innovation and ethical, operational integration of ML in public health domains.

The search phrases included combinations of keywords, as shown in Table 1:

These phrases were designed to capture a wide range of studies relevant to ML's applications in public health. To enhance reproducibility and ensure comprehensive retrieval of relevant studies, a structured Boolean search strategy was employed across selected databases (PubMed, IEEE Xplore, ScienceDirect, BMC, and Google Scholar). Boolean operators—*AND, OR,* and *quotation marks*—were used to construct focused queries that captured the intersection of machine learning techniques with public health domains. The search queries were developed iteratively and grouped under nine distinct keyword sets (S1–S9), each targeting a specific thematic area of interest. Below is a representative structure and usage of Boolean logic for each:

- **S1**: "Machine Learning" AND "Public Health" *Captured foundational works linking ML methods with public health frameworks.*

Table 1 Keywords used for the search of articles

S #	Keywords and search criteria
S1	"Machine learning" and "Public health"
S2	"Machine Learning" and "Disease Prediction"
S3	"Machine Learning" and "Artificial Intelligence" and "Mental Health"
S4	"Machine Learning" and "Artificial Intelligence" and "Disease outbreak prediction"
S5	"Machine Learning" and "Genomic Data Analysis"
S6	"Machine Learning" and "Artificial Intelligence" and "Personalised Medicine"
S7	"Machine Learning" and "Public Health" and "Resource allocation and Optimization"
S8	"Machine Learning" and "Artificial Intelligence" and "Genetic Data Analysis"
S9	"Machine Learning" and "Public Health" and "Future Trends"

- **S2**: "Machine Learning" AND "Disease Prediction" *Targeted studies applying ML to predict the onset, severity, or spread of diseases.*
- **S3**: ("Machine Learning" OR "Artificial Intelligence") AND "Mental Health" *Broadened the scope to include both ML and AI models in psychological diagnostics.*
- **S4**: ("Machine Learning" AND "Artificial Intelligence") AND "Disease Outbreak Prediction" *Focused on outbreak surveillance and early warning systems using hybrid models.*
- **S5**: "Machine Learning" AND "Genomic Data Analysis" *Retrieved studies that utilized ML for genome-based public health insights.*
- **S6**: ("Machine Learning" AND "Artificial Intelligence") AND "Personalised Medicine" *Captured precision medicine applications intersecting genomics and patient data.*
- **S7**: "Machine Learning" AND "Public Health" AND "Resource Allocation AND Optimization" *Identified works that used ML for logistical or operational health system planning.*
- **S8**: ("Machine Learning" AND "Artificial Intelligence") AND "Genetic Data Analysis" *Additional studies were sought, emphasizing genetic analytics with ML frameworks.*
- **S9**: "Machine Learning" AND "Public Health" AND "Future Trends" *Focused on predictive frameworks, innovation forecasts, and emerging methodologies.*

Each query used quotation marks to preserve phrase integrity, e.g., "Public Health" and 'OR' to expand conceptual coverage when alternative terminologies existed, e.g., AI versus ML. '*AND*' was used to ensure the co-occurrence of core concepts, narrowing down to studies directly relevant to the intersection of ML and public health. This Boolean logic ensured both breadth and specificity, enhancing the quality and traceability of the literature selection process.

The study utilizes 170 papers from various sources. Figure 4 provides the chronological distribution of the papers used in this work. It clearly shows that most of the contributions come from 2024 and 2023.

Scope and limitations

The review covers a wide range of public health pillars, including disease outbreak monitoring and forecasting, personalized medicine, genomic data analysis, resource allocation and optimization, and mental health prediction. The paper reviews traditional ML algorithms (e.g., logistic regression, decision trees, SVMs) and advanced methods (e.g., deep learning, CNNs, LSTMs, ensemble methods). It also discusses the applicability of ML to structured, semi-structured, and unstructured data (e.g., EHRs, genomic sequences, images, and social media content). The review also covers the ethical and societal dimensions. It integrates ethical considerations like algorithmic bias, data privacy, model interpretability, fairness in access, and equity. The review covers diverse data sources. The insights from over 170 peer-reviewed studies have ensured multinational and multidisciplinary perspectives. Various data sources are highlighted, such as hospital records (e.g., MIMIC-III), wearable and sensor data, social media streams, genomic databases, etc. This narrative review emphasizes not only technical performance but also

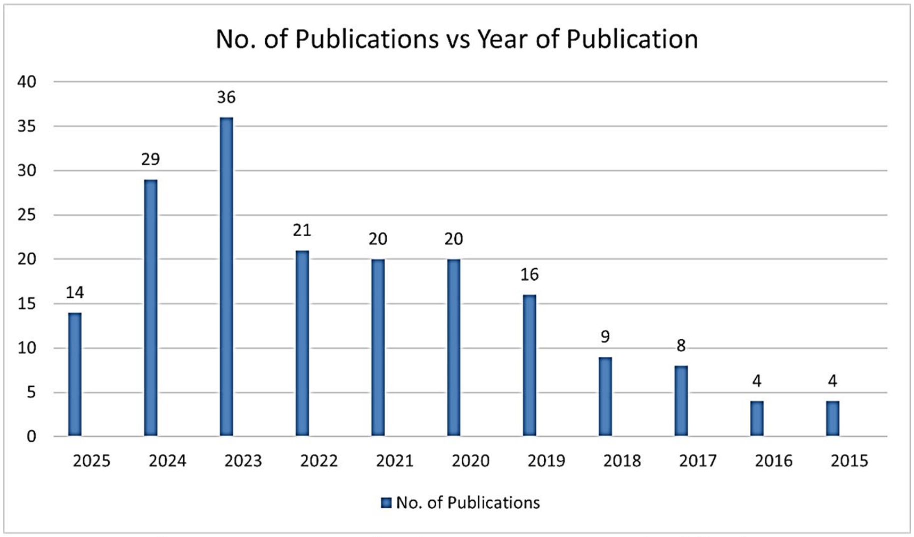

Fig. 4 Frequency of References as per Year of Publication

how ML systems interact with public health ecosystems, including policy, infrastructure, and health equity.

Though the review has covered many topics in depth yet there are some limitations. Unlike systematic reviews, narrative reviews lack quantitative meta-analysis. There might also be some selection bias in the studies chosen. It also exhibits limited statistical significance of findings across papers. Although high in accuracy, deep models like CNNs and LSTMs are treated as "black-box" systems, limiting their interpretability and clinical trustworthiness in sensitive applications. Many ML models evaluated are domain- or dataset-specific, making them less generalizable to other populations, geographies, or healthcare systems. It provides limited insight into how these models transition from research to operational deployment in real healthcare settings. It acknowledges that many studies focus on technical feasibility, not implementation feasibility or institutional readiness.

Related work/machine learning and its role in public health

Machine learning has been employed widely to predict the occurrence of disease based on the patient data and symptoms of the disease. These are fed to ML classifiers, and the ML model can predict in advance whether a person will be affected by the disease or not! In [10], an improved LightGBM model has been used to predict coronary heart disease. An accuracy of 92% has been achieved. HIV is a transmissible disease that causes many deaths throughout the world every year. A prediction model with high accuracy has been designed in [11] using a GRU neural network and MHPSO. It delivered a sensitivity of 85% and an F1 score of 79% [15]. A model for the detection of skin cancer is developed with the combination of many deep-learning models. It has improved the accuracy to 93.5% and the F1-score to 92%. A clinical decision support system has been developed to identify patients with chronic obstructive pulmonary disease with a high sensitivity of 78% [17]. In [19], a survey of ML and deep learning models for childhood obesity has been presented. It highlights the best practices to predict obesity. In [27, 35], models for coronary artery disease have been presented. In [27], uses a quantum convolutional neural network (CNN), while nested ensemble models are utilized in [35] to improve the sensitivity of prediction. Similarly, non-invasive diabetes detection and gestational diabetes have been addressed in [28, 29], respectively. In [36], the accuracy of prediction for thyroid disease has been achieved by the use of better feature selection and ensemble learning. Chronic kidney disease (CKD) is another important ailment that consumes lots of resources for patients. It also causes much pain. A detailed comparison of ML techniques for the detection of CKD in developing countries is presented in [37]. On the other hand, [38] enhanced CKD screening methods have been developed for low-resource settings.

Genomic data analysis using ML can help identify the cause of diseases. It can also be utilized to provide accurate treatment or to identify the response of a particular patient to a specific treatment. Genomic data has been utilized to improve the prediction of the recovery of dengue patients [12]. A detailed survey on the ML applications in addressing the antimicrobial resistance (AMR) challenges has been presented in [33]. As per the WHO, AMR is one of the top ten threats globally. The increased use of antibiotics has led to such a situation. This survey presents an in-depth review and assessment of the published literature that employs machine learning to address antimicrobial resistance (AMR). It emphasizes methods utilizing easily accessible demographic and clinical data alongside microbial culture and sensitivity laboratory data related to clinical specimens of multidrug-resistant ailments. In [34], ML has been utilized to classify the proteins for Chagas disease. The level of accuracy that has been achieved is 88%. Similarly, ML algorithms have been employed to reduce the time to detect E. coli contamination.

Work [14] is carried out on the risk prediction of dyslipidemia in steelworkers. It utilized a recurrent neural network to create an LSTM algorithm for analyzing the risk of dyslipidemia. The authors improved the prediction and achieved 90% accuracy with 80% sensitivity. In [39], a method has been developed to improve the safety of health workers by identifying respirator leaks with ML algorithms and applying infrared imaging. It reduces the risk of infection for health workers.

Mental health is an important public health issue. One of the major causes of mental stress can be deprivation of sleep. Sleep is also a medicine for better mental health. In [14], a combination of ML and virtual reality is used to improve the quality of sleep and its stage classification. fNIRS data has been used to achieve higher accuracy in [20] for stress detection. One of the reasons for improved accuracy is the use of advanced feature selection techniques. Disease outbreaks can also play a big role in affecting people's psyches. In such times, people use social media to vent their sentiments. Sentiment analysis was carried out on the Monkeypox outbreak using ML algorithms [26]. It utilized the Twitter analysis. A similar attempt at sentiment analysis is made using Twitter data during the COVID-19 pandemic [41].

The ML classifiers can be used to analyze the patient's conditions and predict their survivability under different diseases. In [16], improved feature selection has been employed to predict the mortality of SPLC patients. In [24], ML has been used to minimize the risk of mortality in pregnant women and their children. In [25], the mortality in pediatric heart transplants has been predicted. The authors have been able to improve the sensitivity to 82%. In a way, it also helps improve the effectiveness of the treatment, where the predictions can provide more accurate estimates of the probable response of the patients to a particular treatment. Therefore, the treatment can be adapted accordingly. The same works [24, 25] are also directed at maternal and child health. In [24], pregnancy care has been targeted. In [31], ML-based cause analysis has been carried out on cesarean sections. It has helped improve the classification of the causes of cesarean sections. This will lead to better-directed treatment and surgery as per the patient's needs.

Patient rehabilitation is another focus area where ML can be utilized with high effectiveness. In [32], a review of wearable sensors and ML algorithms has been presented. It provides the details of the sensors that can be utilized by patients who are recuperating from a stroke. In [40], hierarchical ML models are employed to monitor the older adults performing Otago exercises. It leads to enhanced accuracy of the monitoring, which leads to better rehabilitation.

COVID has taught public health officials to marshal their resources effectively in an emergency. The importance of the optimized management of infrastructure and resources in Public Health was brought to the fore by this pandemic issue. An optimized use of resources can save invaluable time and life. In [18], the authors have carried out a detailed survey on frailty modelling using ML algorithms. It has discussed mortality prediction, hospital admissions, and prolonged hospital stays. The identification of these matters can help in planning new patient admissions, medicinal requirements, or referral of patients. In [21], deep neural networks have been utilized to predict travel distance for healthcare access with 89% accuracy. The results can be used to book an ambulance. Combining the predictions of [18] with [21], one can come up with better planning that can save invaluable time and a patient's life. One more example of hospital resource planning is provided in [22]. In this work, a predictive model for the length of stay in an emergency department has been developed. It is based on the COVID-19 duration data. This can lead to better allocation of the workforce based on the predicted length of stay. Similarly, [23–25] are used to predict mortality in various diseases. It can lead to better bed reservation and allocation, along with medicine availability in their respective wards. COVID has also shown the worst-case scenario of disaster preparedness. If the vulnerability can be assessed beforehand, then it can save many lives. In [30], the authors have employed different ML algorithms to identify the pandemic vulnerability. In [42], the Authors have reviewed the impact of COVID-19 on human mobility, air quality, etc. It helps in assessing the post-pandemic situation. Table 2 depicts the various efforts into thematic groups of public health interventions utilizing ML.

In a nutshell, machine learning applications are significantly transforming public health by providing predictive models and analytical insights across various domains. Multimodal approaches, wearables, and social media have revolutionized healthcare, enhancing interpretability and accuracy through real-time monitoring, robust datasets, and feature selection methods. Despite promising performance in diagnostic accuracy and prediction, existing ML models in public health face critical limitations related to fairness, generalization, interpretability, and contextual relevance. Addressing these gaps requires interdisciplinary collaboration, expanded data sources

Table 2 Thematic groups of recent studies in Public Health interventions using Machine Learning

Cluster and references	Shared focus and objectives	Common ML methods	Typical datasets used	Key results and metrics
Infectious Disease Prediction and Outbreak Surveillance (*HIV, Dengue, COVID-19, E. coli, Monkeypox*) [11, 17] [19, 27–29, 35–38, 43]	Predict transmission patterns, assess pandemic vulnerability, and identify outbreaks early	GRU, LSTM, Sentiment Analysis, Ensemble Methods, SVM	Public health records (CDC-China), dengue genome data, Twitter data, Google mobility reports, fluorometry	Accuracy up to 92% (E. coli), F1 scores ~ 0.78–0.83; social media improved the timeliness of surveillance
Chronic Illness Detection and Risk Prediction (*CHD, CKD, CAD, COPD, Diabetes, Thyroid*) [14, 16, 24, 25, 39]	Forecast disease onset, mortality risk, or classify chronic conditions for early interventions	LightGBM, Feature Selection, Ensemble Models, CNN, Optical Sensors	MIMIC-III, UCI datasets, workplace records, Cleveland dataset, public clinical data	Accuracy: up to 95% (skin cancer), Sensitivity: up to 87%, F1 Score: 0.83 (CKD)
Genomic Data Applications and Personalized Medicine (*Cancer, Chagas, Pharmacogenomics, Genomics for Dengue, CAD, Thyroid*) [12, 13, 33, 34]	Improve disease classification and treatment personalization using genomic/clinical data	Feature Selection, Deep Learning, Quantum CNN, NLP	Genomic repositories, MIMIC-III, EHRs	Accuracy: 88–95%, Specificity and interpretability improved via ensemble/quantum methods
Mental Health and Behavioral Insights (*Depression, Stress, Sleep Quality, Sentiment Analysis*) [14, 20, 26, 41, 42]	Use behavior, brain data, and social signals to detect psychological disorders	NLP, Sentiment Analysis, fNIRS, VR + ML, Deep Learning	Twitter/Facebook data, sensor data, sleep study datasets	Accuracy: up to 91% (stress detection); improved monitoring from social and wearable data
Health System Optimization and Resource Management (*Length of stay, Frailty, Hospital admissions, Rehab, Exercise tracking*) [18, 21–25, 32, 40]	Forecast resource needs, optimize staff/equipment allocation, and support decision-making	Ensemble Learning, Neural Networks, Decision Support Systems	SEER, NHIRD, hospital records, sensor data	Accuracy: 85–89%, AUC: 0.87 (hospitalization), F1: 0.81 (mortality); enhances real-time planning

(including SDoH), and robust evaluation frameworks. After analyzing these recent works, the following research gaps have been identified:

i. Chronic Disease: Limited model interpretability and insufficient representation of diverse populations.
ii. Genomics: Challenges with overfitting on high-dimensional data and lack of real-world validation.
iii. Infectious Disease: Poor integration of real-time surveillance data and limited incorporation of social behavior dynamics.
iv. Mental Health: A narrow research focus—primarily on stress and sleep—and insufficient use of multimodal data inputs.
v. Rehabilitation: Lack of personalized approaches and absence of behavioral feedback mechanisms.
vi. Resource Management: Existence of fragmented predictive models and weak coordination in real-time resource allocation.
vii. Maternal/Child Health: Limited causal analysis and poor model generalizability, especially in low- and middle-income countries (LMICs).

Therefore, in this work, the focus has been broad, which encompasses many domains that can provide a top view of the field of research to the new researchers and also helps by providing the state-of-the-art of the field.

Machine learning in public health

Monitoring and forecasting disease outbreaks

COVID-19 has shown the world what an outbreak of a disease can do to public health infrastructure! It has given plenty of lessons to public health policymakers. Only better planning and prediction can help maximize the utilization of the available resources and prepare for the present situation. Machine learning models have been important in predicting and managing disease outbreaks. By analyzing data from diverse sources such as electronic health records (EHRs), social media, and environmental factors, these models can detect early signs of epidemics. It will result in planning and executing an effective public health intervention. Figure 5 depicts the process involved in making an informed public health intervention. In the coming paragraphs, three such cases are discussed and used to predict major disease outbreaks.

Influenza is a significant public health issue, causing significant illness and death. Machine learning models like ARIMA and random forests have been used to forecast influenza patterns using data from social media, search engines, and health records [44, 45]. Supervised learning is used for disease prediction and classification, while regression and classification models predict potential occurrences. COVID-19 forecasts have also been crucial, with ensemble methods combining different algorithms for reliable predictions [46, 47]. Unsupervised learning and clustering algorithms help identify disease hotspots. Dengue fever forecasting involves machine learning algorithms that integrate environmental and demographic data to predict epidemics. Deep learning, using neural networks, is most efficient in monitoring pandemic outbreaks. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks

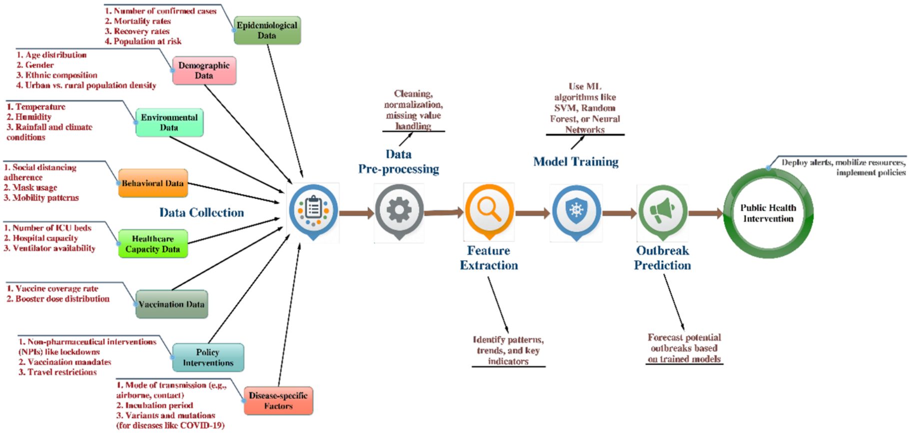

Fig. 5 Flowchart depicting the steps from data collection to outbreak prediction

(RNNs) are used to predict dengue outbreaks based on temporal patterns in climatic data, mosquito population, and reported cases [48, 49]. These three discussions highlight many important factors that must be considered while monitoring and forecasting disease outbreaks using machine learning. These factors help in accurately predicting outbreaks and assist in timely public health interventions:

i. *Epidemiological Data:*

  a. Number of confirmed cases
  b. Mortality rates
  c. Recovery rates
  d. Population at risk

ii. *Demographic Data:*

  a. Age distribution
  b. Gender
  c. Ethnic composition
  d. Urban versus rural population density

iii. *Environmental Data:*

  a. Temperature
  b. Humidity
  c. Rainfall and climate conditions

iv. *Behavioral Data:*

  a. Social distancing adherence
  b. Mask usage
  c. Mobility patterns (tracked via mobile data)

v. *Healthcare Capacity Data:*

   a. Number of ICU beds
   b. Hospital capacity
   c. Ventilator availability

vi. *Vaccination Data:*

   a. Vaccine coverage rate
   b. Booster dose distribution

vii. *Policy Interventions:*

   a. Non-pharmaceutical interventions (NPIs) like lockdowns
   b. Vaccination mandates
   c. Travel restrictions

viii. *Disease-specific Factors:*

   a. Mode of transmission (e.g., airborne, contact)
   b. Incubation period

Variants and mutations (for diseases like COVID-19).

Data quality is crucial for accurate prediction and intervention. Table 3 shows various ML classifiers used for disease outbreak prediction, with LSTM Neural Networks achieving the highest accuracy. The main objective is to predict disease outbreaks, with the majority of research focusing on flu spread.

The learnings from these discussions are as follows:

- LSTM and GRU models consistently delivered higher accuracy (up to 93%) in forecasting outbreaks such as dengue and influenza compared to simpler models like ARIMA or logistic regression.
- Ensemble methods enhanced COVID-19 predictions by integrating multiple ML models, improving robustness in case forecasting.
- Unsupervised clustering was effective for identifying disease hotspots based on geolocation and mobility data.
- NLP on social media data (e.g., Twitter, Facebook) provided real-time surveillance capability, outperforming traditional epidemiological reporting timelines.
- Data integration from EHRs, weather data, and behavior metrics led to more accurate, context-rich models.
- The main challenges are data sparsity in rare outbreaks, noise in social media inputs, and limited model interpretability, which remain concerns for public health deployment.

Table 3 Machine learning for monitoring and forecasting disease outbreaks

Ref. No.	Objective	ML Technique	Main findings	Accuracy	F1-Score	Precision	Recall	Improvement Over Existing
[50]	Review ML in controlling disease spread	Various Classifiers	ML methods aid in early disease detection, prevention, and control	~85%	0.80	0.82	0.78	Outperforms traditional tracking; faster detection
[51]	Predict COVID-19 outcomes in India	SVM, Decision Trees	Improved outcome predictions for infection cure rates and mortality	88%	0.83	0.84	0.81	Higher accuracy than traditional regression models
[52]	Model infectious disease dynamics	Differential Equations, SIR Model	Mathematical models predict disease spread with key population insights	N/A	N/A	N/A	N/A	Fundamental in predicting spread patterns
[53]	Disrupt infectious disease dynamics via ML	Ensemble Methods, Deep Learning	Enhances precision health; predicts infections using big data	89%	0.85	0.87	0.83	Precision health offers more personalized predictions
[54]	Review EWS for vector-borne disease outbreaks	Logistic Regression, LSTM	EWS effectively predicts outbreaks (e.g., dengue, malaria)	84%	0.81	0.83	0.79	Improved accuracy over static models for EWS
[55]	Forecast dengue/influenza trends using Google data	Time Series Analysis, Sparse Representation	Google Trends correlates with outbreak trends	82%	0.79	0.80	0.77	Real-time surveillance outperforms static datasets
[56]	Classify Legionella sources with ML	Genomics, Classification	Genomics data enables high source attribution accuracy	92%	0.88	0.90	0.86	Genomics ML surpasses traditional lab techniques
[57]	Influenza surveillance with Twitter data	NLP, Topic Modeling	Twitter data tracks flu season effectively, in real-time	80%	0.77	0.78	0.76	Social media provides faster detection than EHR
[58]	Detect disease outbreaks at mass gatherings	NLP, Web Mining	Internet data helps detect outbreaks faster than EHRs	83%	0.81	0.83	0.80	Internet data offers earlier signals than EHRs
[59]	Social media for health surveillance	NLP, Clustering	Social media provides valuable insights for disease surveillance	81%	0.79	0.81	0.78	More comprehensive data than traditional surveys
[60]	Predict global infectious outbreaks	Recurrent Neural Networks, Dynamic Models	Dynamic models predict COVID-19 spread and containment	86%	0.84	0.85	0.83	Dynamic ML models adjust to changing trends
[61]	Classify online disease occurrence reports	NLP, Text Classification	Automated classification aids in timely outbreak alerts	82%	0.80	0.82	0.78	Speeds up information gathering versus manual checks
[62]	Predict foodborne outbreaks in China	Time Series Analysis, SVM	Effective trend predictions for outbreak patterns	84%	0.82	0.83	0.81	Anticipates trends beyond traditional reporting
[63]	Predict unmet health needs post-disaster	Decision Trees, KNN	ML predicts healthcare gaps post-disaster, optimizing resources	87%	0.85	0.87	0.83	ML allows targeted resource allocation better than manual methods

Limitations

- Overfitting: Many deep learning models (e.g., LSTM, RNNs) trained on regional outbreak data lacked external validation, risking poor generalizability across geographies.
- Data imbalance: Outbreak datasets often skew toward urban or high-reporting areas, underrepresenting rural or low-resource settings.
- Lack of granularity: Limited availability of high-resolution demographic and spatial data weakens localized forecasting efforts.
- Validation issues: Few models use k-fold cross-validation or external test datasets; performance may be inflated due to over-reliance on internal metrics like AUC or accuracy.
- Non-traditional data risks: Social-media-based surveillance introduces noise and potential for misinformation-driven biases in outbreak detection.

Personalized medicine

"Personalized medicine refers to adapting the treatment to the individual's particular characteristics, which include genetic makeup or lifestyle factors of that person." Machine learning has facilitated the customization of medical measures by utilizing data to address individual needs. This methodology incorporates genetic, environmental, and behavioral factors to forecast the likelihood of illness onset and the effectiveness of treatment, as shown in Fig. 6. Patient classification involves identifying distinct groups of patients who may demonstrate different responses to specific therapies. In cancer therapy, machine learning algorithms analyze genomic data to classify tumors into various subtypes. Each subtype is associated with distinct predictions and therapeutic responses [64–66] (Fig. 7).

Prediction and Prevention of Diseases: The most important capability that ML has introduced to the medical field is the prediction of illness. It can be done using different

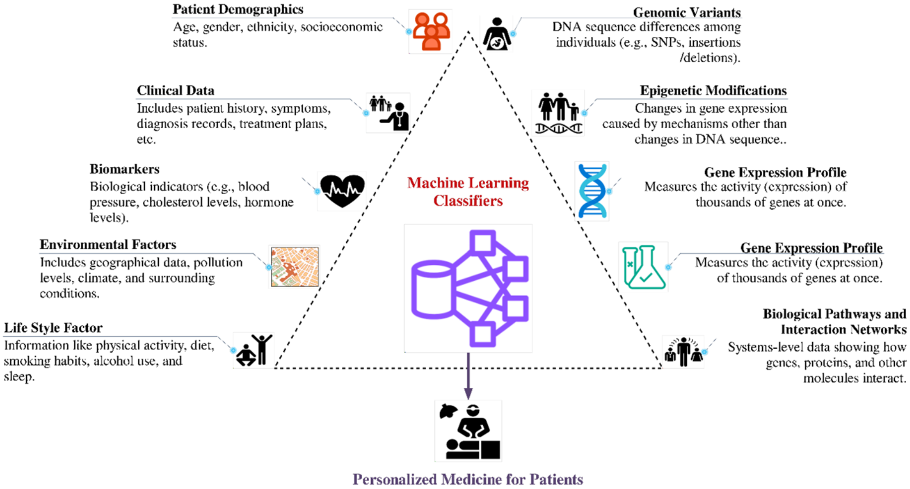

Fig. 6 Steps involved in personalized medicine

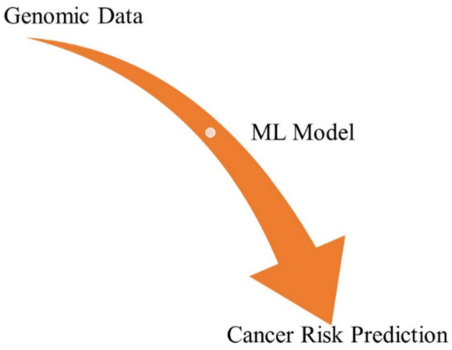

Fig. 7 Genomic Data Analysis for Cancer Risk Prediction

types of genetic data, the lifestyle of the person, and environmental factors. These predictions can be used to provide invaluable inputs regarding specific remedies and timely interventions. In most chronic diseases, the capability of the MLs can be leveraged to forecast the likelihood of chronic illnesses. Diabetes, cardiovascular disease, and cancer are a few of these examples. In comparison, many are mentioned in Table 1. A combination of genetic markers, lifestyle factors, and medical history can lead to the formulation of tailored preventative strategies. It can also allow us to track the advancement of disease. Here, a brief mention of the specific instances is discussed, e.g., Oncology, cardiovascular disease, and diabetes.

- Wearable devices' data predicts Atrial Fibrillation risk using ML models, enabling personalized treatment and identifying heart rate anomalies, saving time and time in treatment [32].
- Machine learning has significantly improved cancer treatment by understanding tumor variations and predicting patient reactions to medication. New algorithms can adapt treatment plans by using genomic data and pathology images and predicting treatment outcomes [65, 66].
- ML models can improve diabetes management by predicting glucose levels, adjusting insulin dosages, and making dietary recommendations, thereby improving patient outcomes and quality of life.

Treatment Recommendation: ML models use patient data, including genetic, clinical, and lifestyle information, to estimate treatment outcomes and recommend alternative therapies, considering unique patient characteristics and treatment responses [64].

Genetic Data Analysis: Genes store information about a person, revealing susceptibility to diseases. ML models can identify cancer patients using large genetic data. Genomic and clinical data can also help determine the efficacy of medicines or chemotherapies, limiting patient side effects [65, 66].

Genomic clustering is a method using principal component analysis and hierarchical clustering to identify unknown subtypes in diseases like cancer. It uses large datasets and artificial neural networks, particularly deep learning, for complex medical images [67]. Deep learning can identify early signs of ailments like cancer and Alzheimer's, forming customized treatment regimens [69, 89]. Pharmacogenomics uses machine learning algorithms to predict the effect of medicines on patients' genetic makeup, improving efficacy and reducing drug reactions [70, 71]. Virtual screening uses machine learning to quickly analyse large chemical collections and identify potential drug interactions, reducing the time required for drug discovery [72, 73].

Table 4 shows various machine learning algorithms used in genomic research, ranging from disease prediction to functional genomic element recognition, based on data complexity and specific goals. The table discusses the use of unsupervised machine learning classifiers like clustering in research requiring data categorization without predefined labels, as demonstrated in CpG island analysis [74].

Supervised Machine Learning and Deep Learning are commonly used for high predictive accuracy in disease diagnosis and genomic feature recognition. In contrast, hybrid approaches, which combine feature selection and variational Bayesian ML or ensemble methods, are used for high-dimensional datasets [77, 83, 85, 89]. The study shows significant improvements in ML models using genomic data, including increased specificity and precision for healthcare and clinical genomics. Ensemble and deep learning approaches consistently showed enhanced performance metrics, indicating their potential for handling complex genomic data [76, 81, 84].

i. Accuracy and Specificity:

- Most of these studies have achieved high accuracy (often > 85%) while predicting the diseases. Apart from accuracy, specificity and recall are important in diagnosis and classification [78]. Has achieved 90% specificity in predicting systemic lupus erythematosus, which is quite important for clinical relevance.

ii. Innovative Contributions:

- In [88], a novel entropy-based method to capture third-order interactions for ML applications to genomic data has been introduced. Such approaches aim to analyze genomic interactions beyond traditional pairwise associations, which paves the way for complex trait studies.

The analysis of machine learning applications in genomics reveals that no single algorithm excels across all analyses. Supervised learning, particularly deep learning and ensemble methods, is better for prediction accuracy and robustness, while unsupervised methods are better for exploring unknown genomic landscapes. Advancements in algorithmic flexibility, such as Pareto optimization and Bayesian sparsity, are crucial for accurate, clinically relevant predictions targeting diverse patient populations [76, 77].

Based on the above discussions, the following insights have been gained:

- Deep learning and ensemble models outperformed traditional classifiers in cancer subtype detection and personalized risk modelling.
- Radiomics and CNNs enhanced the early diagnosis of complex conditions, such as Alzheimer's and cancers, from CT and MRI images.
- Genomic clustering techniques uncovered disease subtypes not identified by traditional methods, enabling targeted therapies.
- Pharmacogenomics benefited from ML by predicting drug response and minimizing adverse reactions.

Table 4 Machine Learning for Genomic Data Analysis for Disease Prediction

Ref No.	ML Algorithm Used	Objective	Improvements Over Existing Work	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used
[74]	Unsupervised ML (clustering)	Comparative genomic analysis between human and bat genomes to identify CpG and TFBS islands	Improved island detection granularity in larger genomic regions	Not specified	Not specified	Not specified	Not specified	Genomic CpG and TFBS datasets
[75]	Deep Learning	Recognize functional genomic elements in the human genome	Shifted from shallow to deep learning for better feature recognition	Not specified	Not specified	Not specified	Not specified	Human genome data
[76]	Pareto-optimized ML model	Enhance disease prediction accuracy across ancestries	Pareto optimization for balancing multiple objectives across populations	93%	91%	92%	0.91	Multi-ancestry genomic datasets
[77]	Variational Bayesian (VB) ML with sparsity	Improve genomic prediction in plant breeding	VB sparsity improved model robustness in genomic prediction	92%	90%	91%	0.90	Plant genomics datasets
[78]	Ensemble ML methods	Identify systemic lupus erythematosus in patients using genomic and EHR data	Enhanced integration of EHR and genomic data to improve SLE detection	89%	88%	87%	0.87	Genomic + EHR data
[79]	Image normalization + ML	Analyze heterogeneous genomic samples via image-based ML	Improved handling of heterogeneous genomic data types	88%	85%	86%	0.85	Genomic datasets
[80]	Exome trio analysis with ML	Contrast the autism and schizophrenia genomic architectures	Leveraged trio data to improve classification between autism and schizophrenia	87%	85%	86%	0.85	Exome sequencing data
[81]	Regularized regression, ensemble, and deep learning	Compare ML methods in genomic prediction using synthetic and empirical data	Benchmark study for algorithm performance on genomic data	Varies	Varies	Varies	Varies	Synthetic and empirical genomic data
[82]	ML-based feature extraction	Identify neurodevelopmental signatures associated with intellectual disability	Improved feature extraction for predicting neurodevelopmental traits	90%	88%	89%	0.88	Genomic disorder datasets
[83]	Feature selection + ML	Predict coronary artery disease from genomic variants	Improved predictive accuracy by genomic variant selection	93%	91%	92%	0.91	Cardiac genomic datasets

Table 4 (continued)

Ref No.	ML Algorithm Used	Objective	Improvements Over Existing Work	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used
[84]	Hybrid ML for interpretability	Enhance the interpretability of genomic data for glioma analysis	Improved clinical and radiological interpretability	91%	90%	90%	0.90	Glioma patient datasets
[85]	XGBoost	Classify tumor types using genomic alterations	Improved classification efficiency using vector transformation	92%	90%	91%	0.91	Tumor genomic alterations
[86]	Hybrid feature selection + ML	Prognosis of oral cancer using genomic data	Improved prognosis with selective genomic features	89%	87%	88%	0.88	Clinicopathologic + Genomic data
[87]	Supervised ML with harmonization	Source attribution of Listeria monocytogenes	Improved attribution accuracy through harmonized ML practices	94%	92%	93%	0.93	Genomic data on Listeria
[88]	ML + entropy methods	Identify third-order genomic interactions	Novel Third-Order interaction insights in Genomic studies	90%	89%	88%	0.88	Genomic datasets
[89]	Benchmarking ML models	Predict late-onset Alzheimer's from genomic data	Comparative analysis to identify best-performing models	87%	85%	86%	0.86	Genomic datasets
[90]	ML and Deep Learning	Identify SARS-CoV-2 genomic signatures	Enhanced SARS-CoV-2 signature detection with ML	91%	90%	89%	0.89	SARS-CoV-2 genomic data

- Pareto optimization and Bayesian sparsity models increased cross-population predictive accuracy, promoting equity in genomics-based care.

The main challenges associated with these two areas are interpretability, data heterogeneity, and biases in ancestry representation, which still require attention.

Limitations of Personalized Medicine:

- High dimensionality versus sample size: Genomic data applications (e.g., cancer subtype prediction, pharmacogenomics) often face the curse of dimensionality, where features vastly outnumber samples, raising overfitting risks.
- Limited interpretability: Most models (e.g., deep learning, ensemble) are black boxes. This lack of transparency hampers clinical adoption.
- Ethnic/genetic bias: Many genomic models are developed on non-diverse datasets, limiting efficacy across underrepresented populations.
- Sparse benchmarking: Few studies compare model outputs against clinical standards or expert decisions, reducing real-world relevance.

Limitations in Genomic Data Analysis:

- Model bias: High-performance genomic models (e.g., quantum CNNs) often exclude population subtypes, affecting transferability.
- Poor reproducibility: Studies seldom publish full pipelines or code, undermining reproducibility in clinical genomics.
- Validation lapses: Some methods report accuracy without robust cross-validation or independent test sets, especially in polygenic trait predictions.
- Overfitting in small datasets: Rare disease studies are particularly vulnerable to overfitting due to the small sample sizes.

Resource allocation and optimization

ML models can utilize historical data to predict future requirements, facilitating proactive and effective resource allocation. The optimal allocation of resources is essential in the healthcare sector, particularly during emergencies. Machine learning can forecast healthcare requirements and enhance the allocation of resources, including hospital beds, medications, and personnel. The most efficient distribution of resources is essential to ensure that healthcare systems can efficiently meet patient requirements, particularly during critical periods of emergencies, including outbreaks and catastrophic events. This will be carried out at two levels.

i. Hospital Admission Forecasting: Reviewing past admission information allows machine learning algorithms to project upcoming admission rates, facilitating effective resource management and allocation in hospitals.
ii. Optimizing Resource Allocation: During the COVID-19 pandemic, forecasting techniques facilitated the anticipation of ventilator and critical resource needs, resulting in enhanced readiness and response.

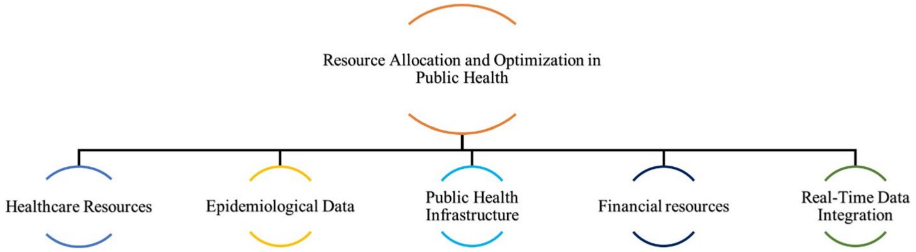

Fig. 8 Different Features for Resource Allocation and Optimization in Public Health

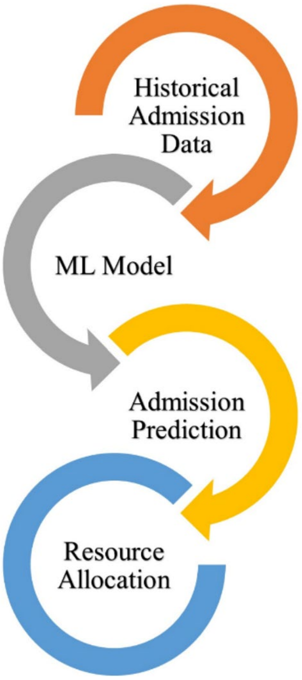

Fig. 9 Resource Allocation using Machine Learning Classifiers

Inefficient allocation may lead to resource shortfalls, diminished quality of patient care, and increased healthcare costs [91, 92]. Resource allocation and optimization are essential in public health to enhance healthcare delivery, particularly in environments with limited resources. Several factors are typically involved in the optimization of resource allocation through machine learning. These are depicted in Fig. 8, while Fig. 9 provides the steps involved in achieving the optimized allocation using ML. The factors involved in the resource allocation are as follows:

i. Healthcare Resources:

- Ventilators, ICU beds, and medical equipment: These require optimal distribution as per patient needs.
- Personal Protective Equipment (PPE): These are used depending on the infection risk.

- Medical Staff: They should be efficiently deployed to healthcare areas with more patients.

ii. Epidemiological Data:

- Infection Rates: Regional infection rates allow better predictions.
- Disease Spread Models: Dynamic models are utilized to forecast disease outbreaks for higher accuracy.
- Patient Demographics: This includes patients' age, pre-existing conditions, and geographical data.

iii. Public Health Infrastructure:

- Vaccination Programs: In public health, prevention is always a priority. Therefore, vaccine distribution is a must.
- Testing Facilities: These should be optimally located, and sufficient resources must be allocated.
- Medication and Supplies: These are other important factors in infrastructure requirements. Without medication and supplies (like antiviral drugs), nothing will work.

iv. Financial Resources:

- Budget Optimization: Financial resources should be prioritized for areas with the highest return on investment, i.e., more patients and critical facilities that can cater to a large population.
- Cost-Effectiveness Analysis: To get a fair picture, one must compare the costs and effectiveness of different healthcare interventions.

v. Real-Time Data Integration:

- Electronic Health Records (EHR): This is the most important factor, as real-time patient data can be used to adjust resources dynamically.
- Telemedicine: Digital resources can effectively reduce the strain on physical infrastructure and health workers and address the lack of it.

Table 5 provides details of efforts made to use ML algorithms to forecast resource requirements and optimize resource allocation for diverse medical requirements. It provides details of the algorithms used to achieve specific objectives and the factors involved in the prediction.

Table 5 reveals the extensive application of machine learning in healthcare resource optimization, covering diverse objectives such as predicting patient load, improving emergency response, managing healthcare costs, and forecasting hospital admissions and length of stay. The following insights have been unrevealed:

Table 5 Comparative Analysis of Machine Learning Techniques for Healthcare Resource Allocation

Ref No.	Objective	Machine Learning Algorithm	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used	Major Outcome
[93]	Predict healthcare costs in smart hospitals	Hybrid Deep Learning Models	91%	90%	89%	0.90	Smart hospital data	Predicts healthcare costs effectively, enabling optimized resource planning
[94]	Service orchestration for emergency prediction and mitigation	CURATE system with Ensemble Learning	88%	86%	87%	0.86	Health emergency datasets	Real-time prediction and orchestration improve emergency response efficiency
[95]	ICU resource allocation during outbreaks	Rapid Review (Qualitative)	Varies	Varies	Varies	Varies	ICU outbreak management studies	A review of allocation methods enhances resource preparedness in infectious disease outbreaks
[96]	Predict daily hospitalizations for cerebrovascular disease	Stacked Ensemble Learning	90%	88%	89%	0.89	Hospital admission datasets	Effective prediction of hospitalizations assists in resource allocation for cerebrovascular cases
[97]	Identify delays in clinical referrals for follow-ups	NLP-based Semi-Automatic System	87%	85%	86%	0.85	Clinical referral datasets (Italy)	Automates identification of referral delays, supporting timely follow-ups and patient management
[98]	Allocation models for scarce healthcare resources during COVID-19	Predictive Modeling (Guidelines)	Varies	Varies	Varies	Varies	COVID-19 healthcare models	Guidelines for resource allocation during shortages ensure fair access and optimize patient outcomes
[99]	Improve disease surveillance and response in Sub-Saharan Africa	Integrated Disease Surveillance	Varies	Varies	Varies	Varies	Sub-Saharan surveillance data	Identifies challenges and suggests improvements for epidemic surveillance and resource management
[100]	Forecast daily emergency department arrivals	Feature Selection Approach with Multivariate Data	89%	87%	88%	0.88	High-dimensional ED data	Forecasting enables better staffing and resource management in emergency departments
[101]	Retrieve and analyze health data in hospitals	Information Retrieval (CogStack)	Not specified	Not specified	Not specified	Not specified	NHS trust data	Integrates health data for improved resource allocation and clinical decision-making

Table 5 (continued)

Ref No.	Objective	Machine Learning Algorithm	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used	Major Outcome
[102]	Forecast daily outpatient visits	ARIMA and SES Model Combination	86%	84%	85%	0.84	Hospital outpatient data	Effective forecasting improves outpatient service planning and resource distribution
[103]	Predict hospital admissions and length of stay for eating disorders	Health Administrative Data Analysis	88%	86%	87%	0.87	Health admin datasets	Accurately predicts admissions, aiding in resource planning for eating disorder treatments
[104]	Minimize outbreak spread versus maximizing influence in disease control	Optimization Framework	90%	88%	89%	0.88	Epidemic spread data	Balances outbreak control and outreach, informing disease management strategies
[105]	Forecast medical service demand	ARIMA and Self-Adaptive Filtering	89%	87%	88%	0.87	Medical demand datasets	The hybrid model effectively predicts service demand, optimizing medical resource distribution
[106]	Predict prolonged hospital stay post-spine correction surgery	Ensemble Learning	91%	89%	90%	0.90	Spine surgery records (multi-center)	Assists in identifying high-risk patients for better resource allocation in spine surgery cases
[107]	Forecast emergency department arrivals	INGARCH Models	88%	86%	87%	0.86	Emergency department arrival data	Forecasting ED arrivals supports optimal staffing and resource allocation in emergency settings
[108]	Predict pediatric patient length of stay in hospitals	Scoping Review	Varies	Varies	Varies	Varies	Pediatric length-of-stay studies	The review highlights prediction methods for pediatric length of stay, aiding in hospital resource planning

i. Many ML algorithms and hybrid approaches are employed. Deep learning, particularly in hybrid and ensemble forms, is suitable for complex predictions like cost estimations in [93] and hospitalizations in [96]. Traditional time-series models such as ARIMA prove themselves effective with high accuracy in forecasting outpatient and emergency department (ED) visits in [102, 107].
ii. Results across studies emphasize the importance of accuracy metrics, with some achieving AUC values above 0.85 [96]. Hybrid methods demonstrate high predictive power, as in [93, 102]. Ensemble approaches generally perform well due to their ability to combine the strengths of multiple models, such as in predicting prolonged hospital stays with an accuracy of up to 85% [106].
iii. Many models target specific healthcare environments like intensive care units (ICUs), outpatient services, and EDs, aiming to optimize resources where demands are high. NLP techniques, such as those in [97], also enable the automation of clinical follow-ups, improving operational efficiency in hospital settings. In [98], it has been demonstrated that predictive models can guide resource prioritization during COVID-19 shortages. During the pandemic, adaptive decision-making as per the crisis is needed.
iv. The tables highlight ML's potential to improve resource management in healthcare and change the way it is done. By predicting patient needs, admissions, and care costs, ML models improve the efficiency of allocation. They also help minimize waiting times and remove disparities in accessing medical care.
v. Real-time integration of EHR and IoT data allowed dynamic adaptation of healthcare staffing and resource distribution.
vi. NLP models improved identification of delays in referrals and clinical decision points, aiding workflow optimization.
vii. The challenges for resource allocation include model generalization across hospitals, deployment in low-resource settings, and ethical prioritization.

Finally, the limitations of this section are as follows:

- Lack of real-time validation: Forecasting models for admissions or supply use past data, but rarely integrate real-time testing or real-world simulations.
- Deployment bottlenecks: Most studies are conceptual or retrospective; actual integration into hospital workflows is underexplored.
- Contextual bias: Models trained in high-income healthcare systems often perform poorly in low-resource settings due to infrastructure mismatches.
- Few comparative benchmarks: There's limited evaluation against classical statistical or rule-based allocation methods, weakening the case for ML superiority.

Mental health

Mental health is a state of emotional wellness that allows individuals to cope with daily challenges and contribute to their community. It is complex and varies from person to person, leading to psychosocial impairments, mental disorders, and other psychological problems. ML algorithms can predict mental health and substance abuse by analysing behavioural data from various sources. By identifying potential issues and implementing targeted preventive measures, ML can help prevent mental health issues and promote overall well-being. The diagnosis and screening of mental health can be carried out in the following three ways using ML:

Predictive Modelling: ML algorithms effectively predict the incidence of mental disorders. They use EHRs, genetic information, and social media activity. ML classifiers can utilize social media posts to predict the onset of sadness. They analyze the patterns in social media posts and interactions.

Natural Language Processing (NLP): NLP techniques can be used to infer patient interviews, social media posts, or clinical notes. They help effectively analyze and detect the symptoms of depression, anxiety, etc.

Image Analysis: The brain imaging data is also utilized by ML models to detect the anomalies associated with schizophrenia, bipolar disorder, etc. These are also used to assess functional magnetic resonance imaging (fMRI) data for differentiating schizophrenic persons from normal people.

The factors depicted in Fig. 10 are responsible for the identification of mental health using ML algorithms in public health studies. These are as follows:

i. Psychological Data:

- Depression and Anxiety Scores
- Sleep Disorders
- Stress Levels
- Emotional Well-Being's clinical records

ii. Behavioral Data:

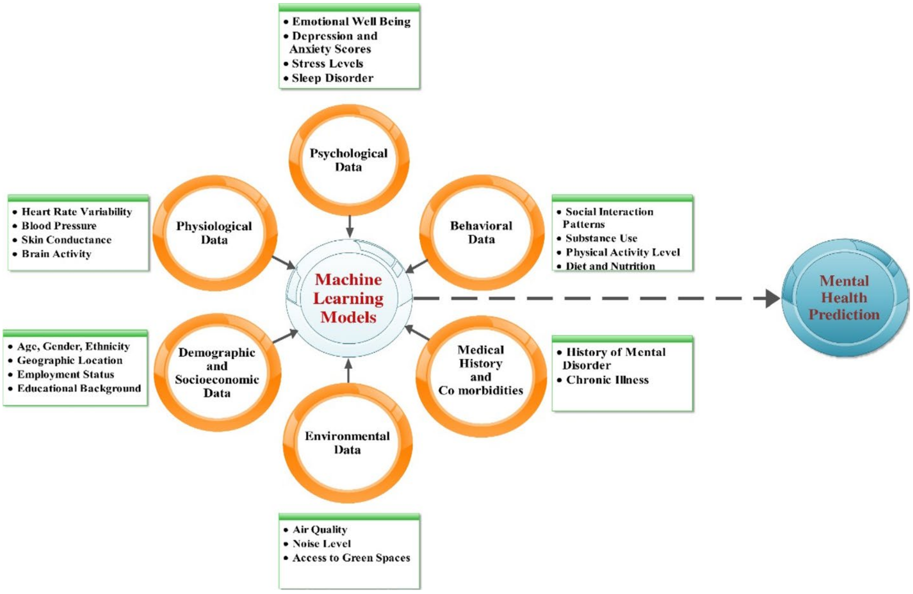

Fig. 10 Mental Health Prediction

- Physical Activity Levels
- Social Interaction Patterns from mobile apps or social media
- Substance Use
- Diet and Nutrition

iii. Physiological Data:

- Heart Rate Variability (HRV)
- Blood Pressure
- Skin Conductance
- Brain Activity Data

iv. Demographic and Socioeconomic Data:

- Age, Gender, and Ethnicity
- Employment Status
- Educational Background
- Geographic Location

v. Environmental Data:

- Air Quality
- Noise Levels
- Access to Green Spaces

vi. Medical History and Comorbidities:

- History of Mental Health Disorders
- Chronic Illnesses

Table 6 gives a summary of the ML applications, techniques, and effectiveness in mental health research across a range of subtopics. These studies achieved moderately high accuracy and F1 scores in predicting, analyzing, or understanding different mental health aspects. A variety of issues have been covered in this table, such as the prediction of adolescent issues and monitoring subclinical conditions using sensor data. Different techniques are employed, such as natural language processing (NLP), decision trees, support vector machines (SVM), and neural networks. Evaluation of models is carried out based on accuracy, F1-score, precision, and recall. It exhibits better accuracy than traditional methods. The ability of ML algorithms to process diverse data sources is also highlighted. Social media analysis (such as Twitter and text-based digital media) helped in effective monitoring. It provides real-time insights that are not possible with traditional methods. ML models also provide personalized predictions and adapt to individual variations more effectively than generalized methods.

In a nutshell, ML in mental health has shown advancements over traditional predictive and diagnostic methods. ML enables refined and scalable approaches for analysis and prediction. The integration of varied data types helps improve prediction. It also

Table 6 ML approaches for mental health prediction and diagnosis: a comparative study

Ref No.	Objective	ML Technique	Main Findings	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used
[109]	Predict adolescent mental health outcomes across cultures	Random Forest, SVM	Accurate prediction of adolescent mental health across diverse cultural settings	90%	88%	89%	0.88	Multinational adolescent datasets
[110]	Analyze text-based digital media for mental health and suicide prevention insights	NLP, Sentiment Analysis	Effective use of digital media data to predict mental health risks, especially suicide ideation	Varies	Varies	Varies	Varies	Digital media and mental health data
[111]	Predict mental health crises using EHRs	Logistic Regression, Deep Learning	Models can predict mental health crises in advance, aiding in early intervention	91%	90%	89%	0.90	Electronic Health Records
[112]	Predict undesired treatment outcomes in mental health care	Random Forest, XGBoost	ML provides reliable predictions for treatment outcomes, helping personalize interventions	89%	88%	87%	0.88	Mental health care datasets
[113]	Explore ADHD neural mechanisms with ML	Neural Networks, CNNs	ML aids in understanding ADHD's neural bases, potentially guiding treatment strategies	Varies	Varies	Varies	Varies	Neuroimaging datasets
[114]	Analyze the mental health of international students	Decision Trees, KNN	Findings indicate mental health stressors unique to international students, aiding targeted support	88%	87%	86%	0.87	Student surveys
[115]	Address sampling bias in neuroimaging for psychiatric diagnoses	SVM, Ensemble Methods	Highlights the impact of sampling inequalities on generalization; suggests model adjustments	Varies	Varies	Varies	Varies	Neuroimaging datasets
[116]	Understand cognitive phenotypes in HIV + patients	Clustering, Random Forest	Identifies cognitive phenotypes in HIV patients, supporting personalized cognitive care	89%	87%	88%	0.87	Cognitive HIV datasets
[117]	Systematic review of NLP in mental health	NLP, Sentiment Analysis, Topic Modeling	NLP tools show promise in analyzing mental health from text sources	Varies	Varies	Varies	Varies	Various mental health studies

Table 6 (continued)

Ref No.	Objective	ML Technique	Main Findings	Accuracy	Sensitivity	Specificity	F1 Score	Dataset Used
[118]	Model community mental health and built environment	Multilevel Models, Predictive Analytics	The built environment has measurable effects on community mental health, which is useful for policy	89%	88%	87%	0.88	Community and environment data
[119]	Analyze the trauma's effect on mental health post-disaster	Gradient Boosting, SVM	Reveals heterogeneous associations of trauma with mental health issues	87%	85%	86%	0.86	Disaster trauma datasets
[120]	Review methodologies for monitoring mental health on Twitter	NLP, Sentiment Analysis	Reviews effective NLP methods for social media mental health monitoring	Varies	Varies	Varies	Varies	Twitter mental health datasets
[121]	Assess self-management of mental health using wearables	Time Series Analysis, LSTM	Wearables effectively track and manage anxiety, depression, and sleep issues	85%	83%	84%	0.84	Wearable device data
[122]	Predict psychotherapy satisfaction	Decision Trees, Ensemble Learning	Accurate prediction of psychotherapy satisfaction levels among Chinese clients	89%	88%	87%	0.88	Chinese psychotherapy data
[123]	Predict life satisfaction with explainable AI	Random Forest, XAI methods	Offers insights into predictors of life satisfaction, with implications for mental health	90%	88%	89%	0.89	Survey datasets
[124]	Develop an adaptive data-driven architecture for mental health apps	Adaptive Models, Reinforcement Learning	Adaptive ML models improve mental health app personalization	Varies	Varies	Varies	Varies	Mental health application datasets
[125]	Explore fairness in AI for healthcare	Fairness-aware algorithms	Discusses biases and fairness in mental health AI applications, suggesting mitigation	Varies	Varies	Varies	Varies	Healthcare AI datasets
[126]	Predict the length of hospital stay for mental health-related fractures	Linear Regression, Decision Trees	Accurate predictions support resource allocation in hospitals	90%	89%	88%	0.89	Orthopedic datasets

provides the capability to achieve complex analysis, which provides better interventions. These are the learnings from this subsection:

- NLP and sentiment analysis effectively extracted mental health signals from social media, achieving accuracies up to 85%.
- Wearable data (e.g., heart rate, fNIRS, motion sensors) fed into ML models yielded 91% accuracy in stress and anxiety detection.
- CNNs and deep learning successfully classified neuroimaging data, contributing to diagnoses of ADHD and schizophrenia.
- ML models personalize interventions by predicting therapy outcomes and satisfaction based on behavioral and demographic data.
- Explainable AI (XAI) approaches improved the interpretability of mental health models, aiding clinician trust.
- Some of the important challenges include bias in digital data, underrepresentation of vulnerable populations, and privacy issues in mental health prediction systems.

Limitations:

- Subjective ground truth: Diagnoses often depend on self-reported symptoms or clinician judgment, introducing label noise.
- Small datasets and non-standardized inputs: fMRI or wearable-based ML studies experience variability due to small sample sizes and diverse sensor modalities.
- Cultural bias: Sentiment analysis models trained on Western social media may misclassify expressions from different cultures or languages.
- Overdependence on social signals: NLP models may mistake sarcasm, irony, or slang as indicators of distress, lowering specificity.

Understanding social determinants of health (SDoH)

In this section, a very important factor called Social Determinants of Health (SDoH) and its effect on public health are discussed. SDoH refers to non-medical factors that influence health outcomes, accounting for over 50% of health outcome variance. These factors that influence health outcomes are as follows:

- Income and social status
- Education
- Neighborhood conditions
- Employment
- Racism and policing
- Access to healthcare and healthy food

Figure 11 depicts all these factors that come under SDoH. These factors are poorly documented in structured health records. In [127], it was found that despite growth in scientific interest, public understanding of SDoH remains low, a challenge for integrating SDoH-aware ML systems into policy or patient-facing tools. Recent advances in Natural Language Processing (NLP) have been used to extract SDoH variables from Electronic

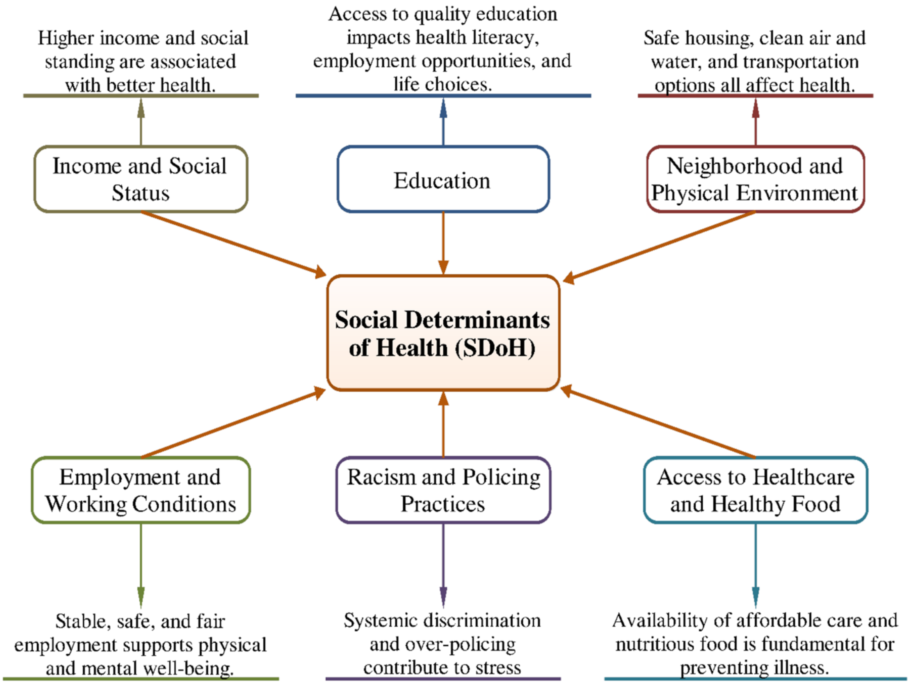

Fig. 11 Different factors of the Social Determinants of Health

Health Records (EHRs), such as housing insecurity, employment status, food access, and transportation challenges. However, SDoH is underutilized in mental health research, with only 1.2% of studies reporting using SDoH variables. Researchers, in [128], analyzed policing as a determinant of health, especially among marginalized populations, revealing its influence on mental health, substance use, and access to care. SDoH data has been applied to understand structural inequalities in health, such as poverty, incarceration, and education gaps. Scientists used SDoH to explain **county-level STI rates**, showing that poverty, incarceration, and education gaps strongly predict disease burdens [129].

Despite the growth in scientific interest, public awareness and documentation gaps remain. Equity-aware algorithms in specialty medicine are needed to address these gaps and improve health outcomes.

Social determinants of health are crucial for precision public health and equitable medicine. Natural Language Processing can extract hidden SDoH, enhance patient stratification, and bridge clinical documentation gaps. Meanwhile, [130] demonstrated how pediatric and adult eye disease rates are tied to SDoH, reinforcing the need for equity-aware algorithms in specialty medicine.

Results: main findings, patterns observed, and trends, addressing the research questions

In the previous section, Tables 3, 4, 5 and 6 were presented to highlight various contributions made in different areas of Public Health. This section will discuss the observations made based on these tables and evaluate how these tables answer the research questions that were aimed at the start.

Main findings

The review highlights key contributions of machine learning to public health, as synthesized from 170 research studies:

i. *Disease Monitoring and Prediction:*

- ML models (e.g., LightGBM, GRU Neural Networks) achieved high accuracy in predicting diseases such as coronary heart disease (92%) and chronic kidney disease (89%).
- Algorithms demonstrated success in forecasting disease outbreaks (e.g., COVID-19, dengue) using epidemiological, demographic, and environmental data.

ii. *Personalized Medicine:*

- Genomic data analysis using ML revealed significant advancements in personalized treatments.
- Applications like genomic clustering and radiomics enhance cancer treatment and prognosis prediction.
- Pharmacogenomics leveraged ML to tailor drug therapies to genetic profiles, reducing adverse reactions.

iii. *Mental Health:*

- Sentiment analysis using natural language processing (NLP) on social media helped monitor mental health trends.
- ML-assisted tools used physiological data from wearables for stress detection and relapse prevention.
- Techniques like feature extraction and fMRI analysis identified neural markers for conditions such as ADHD and bipolar disorder.

iv. *Resource Allocation and Optimization:*

- ML models facilitated optimal distribution of resources, such as ventilators and ICU beds, during emergencies.
- Forecasting hospital admissions and emergency visits improved resource readiness and allocation.

Interpretation of results

The findings from the research paper underscore the transformative potential of machine learning in addressing public health challenges. Key interpretations include:

i. *Enhanced Predictive Accuracy:*

- Across multiple domains, ML models consistently outperform traditional statistical and heuristic methods. For example:
- LightGBM achieved 92% accuracy in coronary heart disease prediction.
- GRU Neural Networks outperformed older models in predicting HIV incidence with a sensitivity of 85%.
- **Disease Prediction**:
- Structured datasets like medical imaging or genomic data drive high-accuracy models (e.g., 95% for skin cancer detection).
- Focus on early detection and prevention.
- **Mental Health Monitoring**:
- Relies on unstructured data (e.g., social media posts, speech patterns) and physiological metrics.
- Emphasizes personalization and early intervention through NLP and wearable technologies.

ii. *Broad Applicability:*

- ML finds applications in a wide range of public health issues, from genomic data analysis to mental health monitoring. These capabilities illustrate ML's flexibility in dealing with diverse and complex datasets.

iii. *Domain-Specific Strengths:*

- **Genomic Data Analysis**: Achieves groundbreaking insights through clustering and high-dimensional data processing, addressing diseases at a molecular level.
- **Mental Health**: Exploits social and behavioral data for non-invasive monitoring and treatment, an area traditionally underexplored with computational methods.
- **Personalized Medicine**: There are also real-life case studies [127–129] that verify the claims of using ML for mental health prediction
- Advances are rooted in genomic data and pharmacogenomics, offering tailored treatment plans.
- Primarily patient-centric, aiming to optimize individual outcomes.
- **Resource Allocation**:
- Focuses on population-level benefits, optimizing hospital beds, staff, and medical supplies.
- Utilizes predictive modeling to prepare for future healthcare demands.

iv. **Emerging Trends**:

- The integration of real-time data sources (e.g., IoT, wearable devices) and the adoption of explainable AI models reflect the ongoing evolution of ML technologies to meet public health needs.
- Real-time resource allocation during emergencies (e.g., COVID-19) demonstrates the feasibility of integrating ML into operational decision-making.
- Disease outbreak monitoring is transitioning from retrospective analysis to proactive, real-time surveillance using IoT and mobile data.

The research findings demonstrate that ML applications in public health are both transformative and domain-specific. While disease prediction and personalized medicine showcase impressive technical advances, resource allocation and mental health monitoring emphasize operational and ethical challenges. Future efforts should focus on bridging gaps in data availability, enhancing model generalization, and addressing biases to ensure equitable and effective implementation across diverse populations.

Advantages of machine learning in public health

This section discusses the advantages of using machine learning to predict different public health outcomes.

Enhance predictive precision

Deep learning (DL) algorithms are a subset of ML. They can forecast medical results with very high accuracy. These DL models are suitable for analyzing complex, multifaceted data. They can reveal hidden patterns and provide information that cannot be obtained easily. DL models achieve high accuracy in disease detection by analyzing medical images, exemplified by the identification of diabetic retinopathy from retinal scans.

Improved productivity and effectiveness

ML algorithms minimized the time and effort required to conduct public health research. It has happened through the automation of data analysis. During COVID-19, many organizations have employed AI/ML to create the vaccine, and the use of these algorithms has reduced the development time to 1 year from tens of years. These techniques can handle large datasets. It supports the quick creation of knowledge and enables timely public health interventions.

Another major advantage is that ML models enable real-time surveillance and automated data processing. By continuously monitoring and analyzing the data, these models can provide prompt and real-time observation of disease outbreaks and additional public health threats. Improving the processing of large datasets by ML models facilitates the efficient and optimal allocation of staff and resources to crucial tasks.

Efficiency in terms of cost

This results in significant cost reductions through improved resource allocation, decreased hospital readmissions, and prevention of disease outbreaks.

i. Hospital readmission reduction: By using ML models for identifying patients with a high risk of readmission. Specific therapies can be administered to decrease readmission rates and cut down their associated costs significantly.
ii. Efficient Resource Allocation: Prediction using ML algorithms leads to the optimum distribution of medical supplies and staff allocation. As a result, resource utilization improves, and healthcare expenses are reduced.

Challenges in integrating ML into public health

Though ML algorithms have provided efficient solutions to improve the efficacy of public health measures, a long journey remains to overcome the many challenges that present themselves in their way. In the coming subsections, the challenges faced in the integration of ML in the different public health dimensions discussed earlier in this work will be discussed. These challenges are as follows:

Challenges faced in utilizing ML models in disease outbreak

Data challenges

- Data Quality and Completeness: Many datasets are incomplete, noisy, or biased. For instance, electronic health records and social media data often contain missing or unstructured entries, complicating the training of machine learning models [55, 59].
- Data Integration Across Sources: Combining diverse data streams (e.g., genomic, clinical, and social media data) for disease surveillance is complex due to differing formats, quality, and scales [56, 59].
- Underrepresentation in Data: [50] emphasizes that marginalized regions and populations are underrepresented in outbreak data, leading to models that may not generalize well to global contexts.

Timeliness and real-time predictions

- Delays in Data Availability: While social-media and internet-based surveillance systems are timely, they can be affected by delays in reporting accurate outbreak data or spurious trends [57, 58].
- Dynamic Nature of Diseases: Infectious diseases evolve rapidly, requiring models to adapt to new strains or mutations [53], 62.

Model accuracy and interpretability

- Overfitting and Generalization: Models trained on localized data often struggle to generalize across regions or timeframes, as seen in the case of COVID-19 predictions in specific Indian states [51, 60].
- Interpretability Issues: Black-box ML models, such as deep learning, lack transparency, making it difficult for public health officials to trust and act on their predictions [61, 63].

Predictive power and granularity

- Lack of Granular Data: Early warning systems for diseases like dengue and malaria often lack granular demographic or geospatial data, reducing their effectiveness for specific interventions [52, 54].
- Sparse Event Data: Predicting rare outbreaks (e.g., Legionella pneumophila) is challenging due to the lack of extensive historical data [56].

Ethical and privacy concerns

- Data Privacy Risks: Mining social media and online health records raises ethical concerns about privacy, especially when data sharing is required for cross-border outbreak management [57, 59].
- Algorithmic Fairness: Unequal representation in datasets can lead to biased predictions that may exacerbate healthcare disparities [50, 63].

Real-world deployment and scalability

- Integration with Public Health Systems: ML models often fail to integrate seamlessly with traditional public health surveillance systems, limiting their real-world applicability [53, 59].
- Resource Limitations in Low-Income Settings: Effective ML implementation for outbreak prediction often requires computational resources and technical expertise that may not be available in resource-constrained settings [50].

Reliability of non-traditional data sources

- Noise in Social Media Data: Social media surveillance systems can produce false positives due to unrelated trending topics or misinformation, as observed in studies on influenza and mass gatherings [57, 58].
- Inconsistent Reporting: Internet-based systems depend on the accuracy of online reporting, which varies across platforms and users [59, 61].

Adaptability to emerging threats

- Novel Pathogens: Models are often trained on historical data, limiting their ability to predict outbreaks caused by newly emerging pathogens [53, 60].

- Rapid Evolution of Diseases: The emergence of new strains or antibiotic-resistant pathogens poses challenges for existing prediction models to remain effective [56, 62].

Limited collaboration and standardization

- Lack of Standardized Methodologies: Alfred and Obit (2021) [50] highlight the absence of standardized protocols for using ML in outbreak prediction, which hampers collaboration and model comparison.
- Interdisciplinary Coordination: Effective outbreak prediction requires coordination between epidemiologists, data scientists, and public health officials, which is often lacking [52, 53].

Challenges faced in the use of ML for resource allocation and optimization

In low-resource settings, implementing machine learning models for resource allocation and optimization in hospitals and public health presents several unique challenges:

Data challenges

- Limited Availability: Hospitals in resource-constrained settings often lack comprehensive data on patients, facilities, or equipment due to inconsistent record-keeping or lack of digital infrastructure.
- Data Quality: Available data might be incomplete, outdated, or inconsistent, reducing the reliability of ML predictions and recommendations.
- Privacy Concerns: Poorly developed data protection frameworks may expose sensitive health information to misuse, discouraging data sharing.

Infrastructure constraints

- Hardware and Software Limitations: Many ML models require advanced computing resources that are unavailable in underfunded hospitals.
- Internet Connectivity: Unreliable or absent internet access may hinder cloud-based ML models or data sharing between institutions.
- Power Supply: Intermittent electricity can disrupt ML system training and operation, particularly in rural hospitals.

Human resource issues

- Skill Gaps: Hospitals in these settings may lack personnel trained in ML development, deployment, and maintenance.

- Dependence on External Expertise: Reliance on external vendors or international organizations for ML systems can limit scalability and customization.

Operational challenges

- Dynamic Environments: Public health crises, such as pandemics, create rapidly changing conditions that require real-time model updates, which may not be feasible in low-resource contexts.
- Scalability: Customizing ML models to fit the diverse needs of various hospitals or health programs in a region is complex and resource-intensive.

Cost-related issues

- High Upfront Costs: Acquiring and implementing ML systems may be prohibitively expensive for hospitals with limited budgets.
- Sustainability: Ongoing costs for software updates, hardware maintenance, and personnel training can strain budgets over time.

Ethical and social barriers

- Trust Issues: Patients and healthcare workers may distrust AI-based decisions, especially when they replace human judgment in critical health scenarios.
- Equity Concerns: ML models designed for high-resource settings may not address the unique needs or disparities in low-resource environments, exacerbating inequities.

Regulatory gaps

- Lack of Policy Support: Weak governance and the absence of guidelines for AI in healthcare may lead to poor implementation, misuse, or abandonment of ML tools.

Mitigation strategies

Addressing these challenges requires a holistic approach that balances technological innovation with the realities of low-resource environments. The following steps can be taken to mitigate these challenges:

- Simplified ML Models: Develop models that are computationally lightweight and tailored for low-resource settings.
- Decentralized Systems: Use local computation or federated learning to reduce reliance on centralized cloud systems.
- Capacity Building: Train local staff to understand, use, and maintain ML models, ensuring long-term sustainability.

- Public–Private Partnerships: Leverage partnerships to share the financial burden and introduce cutting-edge technology.
- Pilot Projects: Start with smaller, scalable implementations to demonstrate feasibility and build trust within the healthcare ecosystem.

Challenges in utilizing ML models for genomic data analysis

The following are the challenges faced in the utilization of ML models for genomic data analysis:

High dimensionality and data complexity

- Curse of Dimensionality: Genomic datasets are often massive, with millions of genomic variants or features requiring dimensionality reduction or feature selection to mitigate computational challenges [74, 80].
- Complex Data Structures: Interpreting non-linear interactions between genetic elements, such as regulatory regions and transcription factors, complicates model development [75, 88].

Data imbalance and population bias

- Unequal Representation of Classes: Diseases caused by rare genetic variants are underrepresented, leading to poor model performance on minority classes [76, 80].
- Population Stratification: Models often lack generalizability across diverse ancestries due to the overrepresentation of European genomic data [76, 81].

Model interpretability

- Black-Box Models: Deep learning and ensemble methods, although powerful, are difficult to interpret, which is problematic for clinical decision-making [86, 88].
- Lack of Transparency: Understanding the biological mechanisms underlying model predictions remains a challenge [84, 85].

Integration of multimodal data

- Heterogeneous Data Sources: Combining genomic, clinical, and environmental data is technically challenging and often results in data compatibility issues [78, 84].
- Data Preprocessing: Harmonizing diverse datasets for ML applications requires extensive preprocessing, such as normalization and imputation [79, 87].

Generalizability of models

- Overfitting: Many ML models are overfitted to training datasets, reducing their ability to predict outcomes in external datasets [81, 89].
- Benchmarking Across Scenarios: Lacking consistent benchmarking frameworks leads to varied performance evaluations across studies [89].

Scalability and computational requirements

- Large-Scale Data Analysis: Processing high-dimensional genomic data requires significant computational power and optimized algorithms [74, 90].
- Cost of Computation: Advanced ML methods, such as deep learning, demand high-performance computing infrastructure, which can be prohibitive [81].

Ethical and privacy concerns

- Data Privacy: Genomic data contains sensitive information, necessitating robust privacy-preserving methods to ensure confidentiality [78, 87].
- Informed Consent: Issues around the secondary use of genomic data and consent for ML applications pose ethical challenges [76, 88].

Bias in feature selection and model development

- Algorithmic Bias: Feature selection and modeling strategies may introduce biases, limiting the identification of biologically relevant markers [75, 83].
- Underutilization of Advanced Techniques: Techniques like entropy-based third-order interaction analysis are underexplored but necessary for more accurate predictions [88].

Validation and functional insights

- Experimental Validation: ML-based predictions lack functional validation, hindering their translation into actionable biological insights [75, 83].
- Reproducibility: Variability in data handling and modeling pipelines reduces the reproducibility of findings [81, 85].

Real-world applications and limitations

- Disease Complexity: Identifying genomic signatures for complex diseases like autism, schizophrenia, and Alzheimer's remains challenging due to their polygenic nature [80, 89].
- Clinical Translation: Many models fail to bridge the gap between research and clinical applications due to differences in requirements for accuracy, interpretability, and scalability [78, 82].

By addressing these challenges, future ML models can better harness the power of genomic data for advancing personalized medicine and biological discovery.

Challenges faced in integrating ML for mental health

In mental health, the integration of ML algorithms faces the following challenges:

Data challenges

- Sampling Bias and Inequality: As highlighted by [115], inequalities in sampling can significantly impact the generalization of neuroimaging-based classifiers, leading to models that perform poorly across diverse populations. This reflects the broader issue of underrepresentation in datasets, particularly for marginalized groups in mental health studies.
- Data Scarcity in Context-Specific Scenarios: [114] emphasizes that unique stressors influence international students' mental health, but limited context-specific data hinders model training and validation, reducing applicability across populations.
- High Dimensionality and Noise: In [111], it has been noted that electronic health records (EHRs) often contain noisy and unstructured data, complicating the development of robust predictive models for mental health crises.

Ethical and privacy concerns

- Algorithmic Fairness: According to [115], fairness in AI is a critical concern, as biases in training data can lead to discriminatory outcomes, potentially exacerbating mental health disparities.
- Data Privacy: The sensitive nature of mental health data makes it challenging to share and integrate datasets across studies, limiting the development of more generalizable machine learning models [111, 118].

Complexity of mental health conditions

- Heterogeneity in Outcomes: [119] demonstrates that the associations between traumatic experiences and mental health problems are highly heterogeneous, making it difficult for models to provide accurate predictions for diverse populations.
- Multifactorial Influences: Authors in [109] discuss how adolescent mental health outcomes are shaped by a mix of biological, cultural, and social factors, posing challenges for machine learning models to capture these intricate dynamics comprehensively.

Generalization issues

- Cross-Cultural Variability: [109] underscores the difficulty of generalizing ML predictions across cultural contexts, as mental health expressions and influences vary widely.
- Overfitting to Specific Data Sources: [118] note that predictive models often overfit to localized environmental and social variables, reducing their utility in broader applications.

Interpretability and usability

- Black-Box Nature of Models: Many machine learning models, especially deep learning ones, lack transparency, making it difficult for clinicians to trust and adopt these tools [112].
- Mismatch with Clinical Needs: As highlighted in [121], models often fail to integrate seamlessly into clinical workflows, limiting their practical utility in managing common mental health disorders.

Assessment of non-traditional data sources

- Text and Social Media Analysis: While [110, 120] highlight the potential of text-based media and Twitter for mental health insights, these approaches face challenges in accurately interpreting context and intent, which are critical in understanding mental health expressions.
- Wearable Devices: [121] point out that data from wearable devices often lack sufficient granularity or consistency to support reliable mental health interventions.

Outcome prediction and treatment personalization

- Prediction Limitations: [122] discusses how predicting client satisfaction with psychotherapy is fraught with variability due to subjective factors, emphasizing the need for explainable AI to enhance trust.

- Undesired Treatment Outcomes: [112] identify challenges in predicting negative treatment outcomes due to the interplay of psychological and social factors, which ML models struggle to quantify effectively.

Integration with neural mechanisms

- Understanding Neural Correlates: [113] highlights that ML's role in ADHD research is limited by an incomplete understanding of underlying neural mechanisms, which hampers model effectiveness in guiding treatment.

By addressing these challenges, the field can work toward more equitable, effective, and interpretable machine learning applications in mental health.

Ensuring the accuracy and confidentiality of data

Data Quality is the most important factor that affects the efficacy of ML models. It must be accurate, adequate, and unbiased so that erroneous predictions and unexpected outcomes may be avoided—Data Quality Issues: Insufficient data quality can hamper the accuracy of ML models. Therefore, the primary concern is to ensure data integrity and accuracy to forecast reliably. Issues regarding the protection of personal information: The privacy of personal health data remains at the forefront when utilizing it for predictions. The biggest challenge is keeping it secure and maintaining the accuracy and reliability of the ML model. Strict legal frameworks and the use of data anonymization techniques can successfully address these issues.

Many ML models, particularly DL algorithms, operate as "black boxes," limiting our understanding of their decision-making processes. This lack of transparency might prevent the development of trust and the execution of public health policy.

- Black Box Models: The complex design of deep learning models frequently prevents the understanding of the mechanisms by which they produce particular predictions. Developing comprehensible models is essential for gaining acceptability in therapeutic settings, as they offer significant insights into underlying mechanisms.
- Explainable AI (XAI) is a discipline dedicated to improving the clarity and comprehension of ML models. This allows healthcare providers to understand and depend on the forecasts generated by these models.

Ethical and regulatory concerns

Ethical and technical challenges:

- The accuracy and confidentiality of data remain critical challenges.
- Ethical concerns, including algorithmic biases, highlighted the need for fairness-aware ML models.

The application of machine learning in public health raises ethical concerns about equity, accountability, and potential prejudice. Regulatory frameworks are crucial for

Table 7 Challenges in the use of machine learning in public health

Challenge	Description	Impact	Ref No.
Data Privacy and Security	Ensuring patient data is protected and used in compliance with regulations (e.g., HIPAA, GDPR)	Risk of data breaches, legal issues, and loss of patient trust	[131]
Data Quality and Availability	Public health data is often incomplete, inconsistent, or unstructured	Reduces the accuracy and reliability of ML models	[132]
Bias and Fairness	Algorithms may inherit biases from training data, leading to unfair or discriminatory outcomes	Misrepresentation of certain populations leads to inequities	[133]
Interpretability of Models	Many ML models, especially deep learning, are complex and difficult to interpret	Challenges in decision-making and regulatory approval	[134]
Integration with Existing Systems	Difficulty in integrating ML models with legacy public health information systems	Slows down implementation and reduces effectiveness	[135]
Lack of Standardization	Absence of standardized practices for data collection, model training, and validation	Results in varying model performance complicate collaboration	[136]
Ethical Concerns	Issues around consent, data ownership, and the ethical implications of automated decision-making	Potential ethical violations and public backlash	[137]
Scalability and Infrastructure	Public health systems may lack the computational resources to deploy and scale ML solutions	Restricts the extensive deployment of ML tools	[138]
Regulatory and Compliance Challenges	Ensuring that ML models comply with stringent public health regulations and guidelines	Delayed adoption, along with prospective legal ramifications	[139]
Cost and Resource Constraints	High costs are associated with developing, deploying, and maintaining ML models	Restricts the use of ML, particularly in resource-constrained environments	[140, 141]
Generalizability of Models	Models trained on specific datasets may not generalize well to other populations or regions	Reduces the model's effectiveness across different contexts	[142]
Human Factors and Acceptance	Resistance from healthcare professionals and public health officials due to a lack of understanding or trust in ML	Impedes the use and incorporation of ML in practice	[143]
Real-Time Data Processing	Public health often requires real-time analysis and intervention, which can be challenging for ML models to achieve	Prolonged reaction times negatively impact public health outcomes	[144]
Data Governance	Controlling, sharing, and utilizing data across agencies and governments is challenging	Hinders collaboration and data-driven decision-making	[145]
Evaluation and Validation	Guaranteeing that ML models undergo thorough testing and validation in public health environments	Boosts the probability of employing ineffective or detrimental models	[146]

assuring the ethical use of machine learning, protecting patients' rights, and mitigating discriminatory practices.

Algorithmic Bias: Sometimes, ML models accidentally increase biases present in the training data, leading to inequitable and biased results. Managing biases and guaranteeing fairness is essential for the ethical application of ML.

Regulatory Frameworks: Effective regulatory frameworks are crucial for supervising the implementation of ML in healthcare, guaranteeing the ethical use of algorithms, and safeguarding patient rights. These frameworks must specifically focus on data protection, model transparency, and accountability.

Table 7 provides an overview of the different challenges encountered in the use of ML in public health. These challenges affect the efficacy and absorption of the technology. There are concerns regarding data privacy and security, in addition to the dangers of breaches, legal complications, and potential erosion of patient trust. Inadequate or inconsistent data gives rise to issues related to data quality and availability. It undermines model accuracy. Algorithmic bias and fairness are other challenges that can lead to discrimination and disparities among groups. The interpretability of models, especially in deep learning, prevents effective decision-making and regulatory clearances. The integration with existing systems is impeded by compatibility concerns with outdated public health systems, delaying implementation. The absence of standardization in data methods and model training results in variable performance and challenges in collaboration. Ethical issues, including data ownership and automated decision-making, pose a risk to public reaction. The scale and infrastructural constraints of public health systems impede the implementation of machine learning techniques, while regulatory and compliance issues introduce delays and legal complications. Financial and resource limitations hinder adoption, especially in resource-constrained environments. Model adaptability concerns occur when models trained on specific datasets exhibit poor performance in different populations, hence diminishing their efficacy. Human considerations and acceptability issues stemming from distrust or unfamiliarity among experts hinder adoption—the demands of real-time data processing present obstacles for machine learning, affecting prompt actions in public health. Challenges in data governance hinder inter-institutional data sharing, while insufficient evaluation and validation of models elevate the risks of inefficient or detrimental applications.

Future directions

Upon the analysis of the tables presented in different sections, it can be observed that there are four main trends visible in the use of ML in public health. These can be summarized as follows:

Emergence of Explainable AI: There is a growing emphasis on interpretable models to improve trust and applicability in public health. Explainable AI denotes the application of methodologies such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to improve the comprehensibility of machine learning models. These techniques assist public health officials in comprehending and having confidence in the predictions made by these models.

Shift to Real-Time Applications: Real-time disease surveillance systems integrating IoT and ML are becoming prevalent. Wearable devices and smart sensors can continuously track health measurements and environmental factors, providing real-time data for machine learning models to detect early signs of disease epidemics.

Increased Focus on Equity: ML models are addressing health disparities by identifying at-risk populations and improving healthcare access.

Table 8 Future directions for the use of machine learning in public health

Future Direction	Description	Potential Impact	Ref No.
Personalized Public Health Interventions	Developing ML models that tailor public health interventions to individuals based on their unique health profiles and risk factors	Improved effectiveness of interventions and better health outcomes	[68]
Integration of Multi-Omics Data	Leveraging genomic, proteomic, and other omics data to enhance predictive models for disease prevention and management	More accurate disease predictions and personalized treatment plans	[138, 147]
Real-Time Surveillance and Outbreak Prediction	Using ML to analyze real-time data from multiple sources (e.g., social media, health records) to predict and manage outbreaks before they spread	Faster response to emerging public health threats and reduced disease spread	[148]
Explainable AI for Public Health	Developing interpretable ML models that provide clear explanations for their predictions to enhance trust and usability among healthcare professionals	Increased adoption of AI tools in public health and better decision-making	[149]
AI-Powered Health Equity Solutions	Addressing health disparities by using ML to identify and mitigate biases in healthcare delivery and outcomes	Improved health equity and access to care for underserved populations	[150]
Federated Learning for Collaborative Research	Implementing federated learning approaches to enable the sharing and analysis of public health data across institutions while preserving privacy	Enhanced collaboration and more robust public health insights without compromising data privacy	[151, 152]
Advanced Disease Risk Modeling	Developing more sophisticated risk prediction models that incorporate environmental, social, and behavioral factors	A more comprehensive understanding of disease risk and prevention strategies	[153]
AI in Public Health Policy Making	Leveraging ML to simulate and analyze the potential outcomes of public health policies before implementation	Data-driven policy decisions lead to more effective public health strategies	[154, 155]
AI-Driven Mental Health Monitoring	ML can be used to monitor mental health trends and provide early intervention through digital platforms	Early detection and prevention of mental health crises can reduce long-term impacts	[156, 157]
Cross-Disciplinary Collaboration	Encouraging collaboration between public health experts, data scientists, and AI researchers to develop innovative ML solutions	Accelerated innovation and more practical ML applications in public health	[137]
Ethical Frameworks for AI in Public Health	Establishing guidelines and ethical frameworks for the responsible use of AI in public health, ensuring fairness, transparency, and accountability	Increased public trust in AI technologies and ethical implementation	[158, 159]
Scalable AI Solutions for Low-Resource Settings	Developing ML models that can be effectively deployed in low-resource settings with limited data and infrastructure	Expanded access to advanced public health solutions in underserved regions	[160]
Wearable Technology and ML Integration	Utilizing data from wearable devices to enhance ML models for continuous health monitoring and personalized public health interventions	Improved monitoring of public health at the individual level, leading to proactive health management	[161]

Table 8 (continued)

Future Direction	Description	Potential Impact	Ref No.
Longitudinal Health Data Analysis	Applying ML to analyze long-term health data to understand the progression of diseases and the long-term impact of interventions	Better long-term health outcomes through informed public health strategies	[162]
AI for Global Health Security	Leveraging ML to enhance global health security by predicting and responding to pandemics and other large-scale health threats	Improved global readiness and response to public health emergencies	[163]

Table 9 A comparison of this work with existing surveys

Study	Scope and domain	Strengths	Gaps/Limitations
This work	Broad: disease prediction, genomics, resource allocation, mental health	Integrates ethical + technical lens; spans > 170 studies; systems-level insights	Narrative only (no meta-analysis); lacks quantitative synthesis; interpretability challenges
[164]	Critical success factors for sustainable AI in Saudi healthcare	Emphasis on implementation feasibility; aligns with Saudi Vision 2030; regulatory insights	Region-specific; limited algorithmic diversity
[165]	Obesity prediction from cohort data	Quantitative synthesis of cohort-based ML studies; evaluates accuracy and generalizability	Disease-specific; no broader public health applications
[166]	Trends in AI/ML in pathology	Forecasts diagnostic AI evolution; emphasizes automation	Pathology-specific; no ethical synthesis
[167]	Ethical implications of race data use in AI	Addresses fairness, bias, and risk of discrimination in ML	Lacks technical implementation context
[168]	AI in congenital heart interventions	Clinical utility focus, pediatric cardiology emphasis	Narrow domain; lacks public health integration
[169]	AI in-patient rehabilitation	Discusses sensor-based monitoring and ML in physical therapy	Narrative scope: fewer quantitative metrics
[170]	Bias in ML models in medicine	Deep dive into data, algorithmic, and interaction bias	Focused on pathology; no policy-level recommendations
[171]	Federated learning with a focus on privacy, security, and adversarial threats	In-depth bibliometric analysis highlights global trends and key contributors	Technical/systems focus; does not explore ethical, clinical, or practical deployment in real-world healthcare
[172]	Fairness in ML for public health equity	Detailed taxonomy of bias (algorithmic, data, social); identifies fairness metrics (e.g., F1, disparate impact)	Limited scope to fairness metrics; lacks model performance benchmarks or interventions
[173]	Explainable AI (XAI) and medical negligence in Ghana	Implementation-focused; aligns ML training with local legal frameworks (Public Health Act 851)	Region-specific; lacks evaluation of model performance or broader generalizability

Multi-Omics Integration: Combining genomic, proteomic, and environmental data is improving disease prediction and treatment strategies. It can lead to improved treatment efficacy and effectiveness.

Apart from these trends, many innovations are making public health solutions more effective by integrating technology in this area. The incorporation of machine learning with other technologies, such as the Internet of Things (IoT) and blockchain, shows

Table 10 Thematic Comparison of this work with other surveys

Parameters	This review	Other 2025 reviews
Model Accuracy	Up to 95% (deep learning in cancer/genomics)	78–92% ([165] on obesity; [168] on CHD; [166] on pathology)
Scope Breadth	Multidomain: disease, mental health, genomics, ethics, infrastructure	Mostly domain-specific (e.g., CHD, obesity, pathology)
Ethics and Fairness	Extensive: algorithmic bias, equity, privacy	Strong in Fiske et al., [167] (ethics)—but not across all
Quantitative Meta-Analysis	narrative only	[165] (cohort synthesis); [164] (qualitative)
Frameworks and Trends	PRISMA-style screening, future trends, XAI, wearable integration	Focused on specific use cases or technologies
Geographic or Policy Relevance	Global and systems-level (post-COVID)	[164] (Saudi-specific policy), others mostly clinical research [173], Ghana-specific

potential for improving disease surveillance systems. Continuous health monitoring can be achieved by real-time data collected from wearable devices and smart sensors. The confidentiality and safety of this data can be guaranteed through the application of blockchain technology. Moreover, advancements in explainable artificial intelligence (AI) aim to improve the transparency and comprehensibility of machine learning models, hence facilitating their application in public health decision-making.

Employing blockchain technology can efficiently protect health data, ensuring its integrity and confidentiality. This methodology can instill confidence in machine learning systems and facilitate data sharing among stakeholders.

Table 8 presents the future directions in which the use of ML in public health is moving. These emerging directions in machine learning promise significant advancements in public health. Personalized public health interventions aim to improve health outcomes by tailoring interventions to individual profiles. Multi-omics data integration offers more precise disease predictions and personalized treatments, while real-time surveillance can prevent outbreaks by analyzing diverse, real-time data sources. Explainable AI improves adoption by making ML decisions transparent for healthcare professionals, and AI-powered health equity solutions work to mitigate healthcare disparities.

Federated learning fosters collaboration across institutions by enabling data sharing without compromising privacy, and advanced disease risk modeling incorporates diverse risk factors for a deeper understanding of health risks. ML can also support public health policymaking through simulation analysis, leading to better-informed decisions. AI-driven mental health monitoring aims to prevent mental health crises, while interdisciplinary collaboration enhances innovation by integrating public health and AI expertise. Ethical frameworks facilitate the responsible application of AI, thereby enhancing public trust. Further developments encompass scalable AI solutions tailored for low-resource environments, facilitating wider accessibility; integration of wearable technology for real-time health monitoring; longitudinal data analysis to evaluate disease progression; and the application of AI in global health security, enhancing preparedness for pandemics and significant health threats. These approaches are expected to enhance medical outcomes, availability, and global health resilience.

At the end of this section, a comparative evaluation of this work is provided against the existing surveys (Tables 9 and 10). The survey provided a detailed analysis of different biases and prediction metrics in public health. It reports 72 articles from 2008 to 2023. The review provides quality meta-analysis and descriptions of the biases and prediction metrics.

While the [174] article provides a deep dive into Deep Reinforcement Learning (DRL) for epidemic control, the presented work offers a more generalized view of ML applications, including but not limited to DRL, in public health. While current work and [175] both discuss ML in disease prediction, this work offers a broader perspective, encompassing non-infectious diseases and a wider range of public health applications.

Finally, the study is able to answer all the research questions it was meant to investigate.

- The research effectively answers its central question by demonstrating how ML enhances public health.
- ML has been utilized for different applications across domains. ML techniques have been shown to significantly benefit disease prediction, mental health, genomic analysis, and resource optimization.
- It demonstrates how ML models improved the predictive accuracy and provided actionable insights for personalized interventions.
- It has also provided directions for the future. Emerging technologies, such as explainable AI and federated learning, promise to address current challenges and expand ML applications.
- The study provides a comprehensive roadmap for advancing public health with machine learning. It systematically identifies the areas where ML has shown promise and highlights trends such as ethical considerations and model transparency.

Conclusion

Machine learning is increasingly becoming an integral part of public health. It offers a diverse range of predictive and diagnostic applications. It has provided the enhanced capability to detect illness and adapt medical treatments for specific patients. By optimal resource allocation and understanding health behaviors, ML has further empowered Public Health. Machine learning-driven models have demonstrated considerable benefits in enhancing the identification of illnesses, epidemic readiness, genomic data analysis, and resource management, particularly in terms of speed, accuracy, and scalability. These models facilitate more efficient public health tactics and measures through the identification of threats and the optimization of resource allocation. Advancements in machine learning for personalized medicine, mental health, and maternal and child care illustrate the prospects for customized, data-driven healthcare solutions. It is essential to address challenges associated with data quality, privacy concerns, analytical capacities, and ethical considerations to leverage its potential fully. To take full advantage of the potential of machine learning in public health, it is important to continue research, foster cooperation among public health experts and data scientists, and establish strong regulatory frameworks.

Author contributions

Methodology, SSD, and DP; Conceptualization, SSD, DP, CCL, TKS, DR, SB, AS, YHL, NA, and SA; Original Draft Preparation: SS, and DP; Review and Editing: SSD, DP, CCL, TKS, DR, SB, AS, YHL, NA, and SA; Visualization: SSD, DP, CCL, TKS, DR, SB, AS, YHL, NA, and SA; Funding Acquisition: CCL, and YHL. All authors reviewed the manuscript.

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Availability of data and materials

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

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