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Transforming global health through multimodal deep learning: Integrating NLP and predictive modelling for disease surveillance and prevention

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Abstract

The integration of multimodal deep learning (DL) approaches in global health represents a transformative advancement in disease surveillance and prevention. The complexity of modern public health challenges, including emerging infectious diseases, healthcare disparities, and resource constraints, necessitates innovative tools that can analyse and interpret diverse data sources in real time. Multimodal DL combines natural language processing (NLP) and predictive Modelling to bridge the gap between structured data, such as case numbers and hospital resources, and unstructured data, including epidemiological reports, social media, and clinical notes. By doing so, it provides comprehensive insights for early outbreak detection, resource allocation, and risk management. NLP enables the extraction of actionable information from diverse unstructured datasets, facilitating the identification of disease patterns and potential outbreaks from news articles, public health bulletins, and social media trends. Predictive models, on the other hand, excel in forecasting disease spread, estimating healthcare demand, and optimizing resource distribution. Together, these technologies empower decision-makers with real-time, actionable insights, enhancing public health preparedness and response capabilities. This paper explores the applications of multimodal DL in disease surveillance, focusing on its role in integrating diverse data modalities for actionable insights. It highlights case studies demonstrating the success of AI-driven tools in mitigating outbreaks and improving healthcare resource management. Additionally, the study discusses ethical, social, and technical challenges, offering recommendations for scaling these systems globally. The adoption of multimodal DL can significantly advance public health strategies, ensuring a more resilient and equitable healthcare system.

Keywords: Multimodal Deep Learning; Natural Language Processing (NLP); Predictive Modelling; Disease Surveillance; Public Health Strategies; Global Health Preparedness

1. Introduction

Global health faces unprecedented challenges, including the emergence of infectious diseases, increasing health disparities, and constrained resources for managing public health crises. The COVID-19 pandemic exemplified how delays in disease detection and response can have far-reaching consequences, underscoring the critical need for advanced disease surveillance tools. Traditional systems often rely on retrospective data analysis and are constrained by fragmented data sources, limiting their effectiveness in predicting and mitigating outbreaks (1).

Artificial intelligence (AI) has emerged as a transformative tool in public health, revolutionizing disease surveillance, diagnosis, and resource management. Deep learning (DL), a subset of AI, has further advanced the field by enabling the analysis of complex and diverse datasets [2]. Early applications of DL focused on medical imaging and genomic analysis, providing unprecedented accuracy in identifying disease biomarkers and predicting patient outcomes. However, the integration of multimodal data—combining structured information like case numbers with unstructured sources such

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as epidemiological reports and social media trends—has expanded the potential of DL to address broader public health challenges (2, 3).

Multimodal deep learning leverages techniques like natural language processing (NLP) and predictive Modelling to extract actionable insights from disparate data sources. NLP facilitates the analysis of unstructured text, identifying emerging disease patterns in real time from sources like news articles, public health reports, and clinical notes. Predictive Modelling complements this by forecasting disease trajectories, enabling better resource allocation and timely interventions. Together, these approaches offer a comprehensive framework for enhancing global health preparedness and response capabilities (4).

As public health systems aim to adapt to the increasing complexity of modern health challenges, multimodal DL provides a robust solution for integrating and analysing data, enabling decision-makers to act swiftly and effectively in preventing and managing outbreaks.

1.1. Problem Statement

Traditional disease surveillance systems face significant limitations that hinder their ability to effectively detect, monitor, and respond to outbreaks. These systems often depend on manually curated data, which delays the identification of emerging health threats. For instance, during the early stages of the COVID-19 pandemic, gaps in data integration and slow information sharing contributed to widespread transmission and delayed public health interventions (5, 6).

A major challenge lies in the fragmented nature of available data. Structured datasets, such as hospital records and laboratory results, are typically siloed and difficult to integrate. Meanwhile, unstructured data sources—like news articles, social media posts, and epidemiological reports—contain valuable insights but are challenging to process using traditional methods. These gaps result in a lack of timely and actionable information, limiting the effectiveness of disease surveillance efforts (7).

The critical role of early outbreak detection and resource forecasting in mitigating public health crises cannot be overstated. Timely identification of disease patterns enables public health officials to allocate resources efficiently, prioritize high-risk regions, and implement containment measures before outbreaks escalate. However, traditional surveillance systems struggle with scalability, real-time monitoring, and the ability to adapt to evolving threats.

Addressing these challenges requires innovative approaches that can harness the power of advanced technologies. Multimodal DL combines NLP and predictive Modelling to bridge the gap between structured and unstructured data sources, enabling comprehensive and timely insights. By leveraging these techniques, public health systems can overcome existing limitations, enhancing their capacity to predict, prevent, and respond to emerging health threats (8).

1.2. Objectives and Scope

This article aims to demonstrate how multimodal deep learning techniques can enhance disease surveillance and prevention by integrating advanced AI methodologies into public health systems. The primary objectives include:

- Highlighting the transformative potential of NLP for analysing unstructured data sources, such as social media, news articles, and epidemiological reports.
- Examining the role of predictive Modelling in forecasting disease spread and optimizing healthcare resource allocation.
- Presenting case studies and real-world applications that illustrate the effectiveness of multimodal DL in global health strategies.

The scope of this discussion encompasses the integration of structured and unstructured data for comprehensive disease monitoring. Emphasis is placed on the synergy between NLP and predictive Modelling, showcasing their ability to provide actionable insights in real time. Additionally, the article explores the broader implications of these technologies for public health preparedness, addressing challenges such as scalability, ethical considerations, and technical limitations.

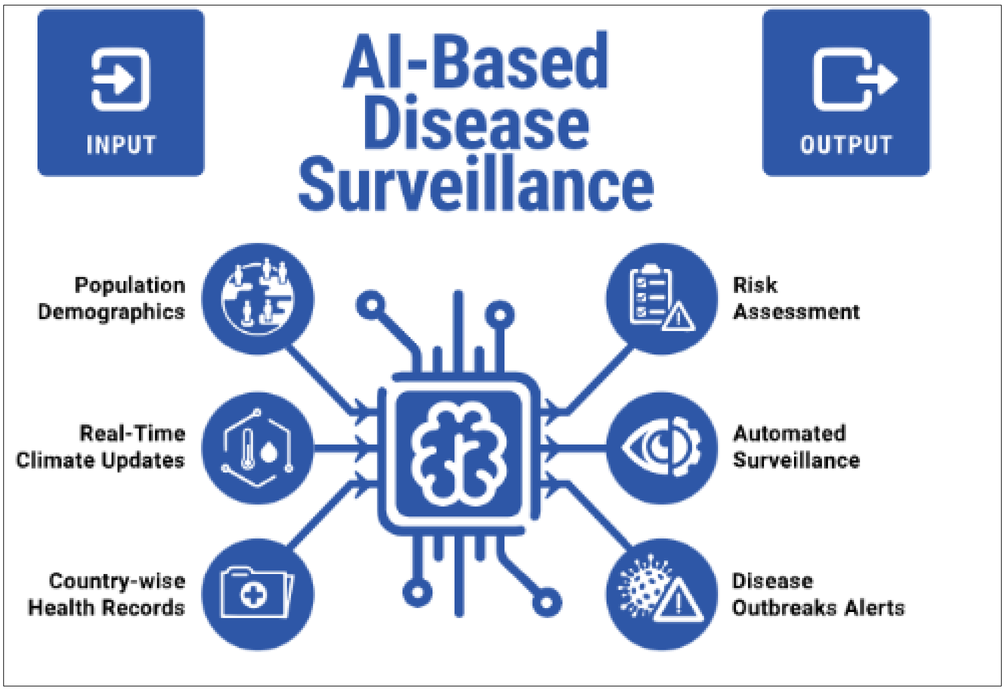

Figure 1 AI-Driven Disease Surveillance Systems

2. NLP in disease surveillance

2.1. Epidemiological Text Mining

Epidemiological text mining, an application of natural language processing (NLP), focuses on extracting actionable insights from unstructured text sources, such as public health reports, medical journals, and policy documents. These sources contain vital information about disease outbreaks, transmission patterns, and healthcare interventions, yet their unstructured nature often limits timely and systematic analysis. NLP bridges this gap by automating the extraction and interpretation of epidemiological data, enabling real-time insights into public health trends (9).

2.1.1. Techniques for Extracting Data

- **Named Entity Recognition (NER):** NER identifies and classifies entities, such as diseases, geographic locations, and dates, within textual data. For instance, NLP algorithms trained on public health reports can extract mentions of diseases (e.g., "cholera outbreak") and associate them with specific regions and timeframes (10).
- **Topic Modelling:** Techniques like Latent Dirichlet Allocation (LDA) group related terms to identify underlying topics in large text datasets. Public health reports may reveal clusters of terms like "fever," "rash," and "mosquito-borne," indicating potential outbreaks of vector-borne diseases such as dengue or Zika (11).
- **Sentiment Analysis:** While commonly used in social media, sentiment analysis also applies to public health documents. For instance, changes in sentiment associated with specific diseases in policy discussions can indicate shifts in public health priorities or emerging crises (12).
- **Text Classification:** Machine learning models classify text into predefined categories, such as "epidemic report" or "research update," streamlining the review of thousands of journal articles and policy documents for disease surveillance.

2.1.2. Case Studies of NLP-Based Systems

- **ProMED-Mail:** ProMED-Mail, an early warning system, uses NLP to analyse public health reports for mentions of disease outbreaks. For instance, it detected unusual respiratory illnesses in Wuhan in late 2019, providing an early indication of COVID-19 (13).
- **AI-Powered Surveillance by BlueDot:** BlueDot's NLP algorithms mine global public health sources, news articles, and airline ticketing data to predict disease spread. Before the World Health Organization (WHO) declared COVID-19 a global emergency, BlueDot identified its spread patterns and flagged potential risks to global health systems (14).

- **EpiWATCH Platform:** Developed by the University of New South Wales, EpiWATCH leverages NLP to process public health alerts and media reports, providing governments with timely outbreak information. This system was instrumental in monitoring the spread of Zika and Ebola (15).
- **Challenges and Limitations**: Despite its promise, epidemiological text mining faces challenges, including language diversity in global health reports, varying data quality, and inconsistencies in terminology. Addressing these challenges requires more robust NLP models trained on multilingual datasets and domain-specific vocabularies (16).

2.2. Social Media and News Analysis

Social media platforms and news articles serve as real-time reservoirs of public sentiment and emerging health trends. By analysing these sources, NLP systems can detect early signs of disease outbreaks, enabling faster public health responses. The decentralized nature of these platforms provides unique advantages for capturing information overlooked by traditional surveillance systems (17).

2.2.1. Role of Sentiment Analysis and Topic Modelling

- **Sentiment Analysis in Social Media:** Social media posts often reveal population-level health concerns. By analysing posts for changes in sentiment, NLP tools can identify potential disease clusters. For instance:
    - During the COVID-19 pandemic, sentiment analysis on Twitter highlighted public anxiety about "fever" and "loss of taste," which later became recognized as key symptoms (18).
    - Platforms like Facebook and Reddit were similarly analysed to gauge public sentiment about vaccine safety, influencing public health communication strategies.
- **Topic Modelling in News Media:** NLP topic Modelling algorithms analyse news articles to detect mentions of emerging diseases, their geographic spread, and healthcare responses. For example:
    - NLP tools grouped related news terms like "avian flu," "poultry farm," and "Asia," identifying outbreaks before traditional monitoring systems.
    - Regional media outlets provided hyper-local insights, enhancing the granularity of global surveillance systems (19).

2.2.2. Examples of NLP Applications in Monitoring Pandemics

- **COVID-19 Monitoring on Twitter:** Researchers used transformer-based models like BERT to analyse COVID-19-related tweets. These models identified early discussions of "shortness of breath" and "coughing," correlating symptom trends with official case reports (20).
- **HealthMap Platform:** HealthMap combines NLP and data visualization to analyse global news sources and social media data, offering real-time alerts on disease outbreaks. During the H1N1 outbreak, HealthMap detected cases earlier than many traditional systems, highlighting its effectiveness in pandemic surveillance (21).
- **FluTrackers:** FluTrackers aggregates and analyses user-submitted health data and media reports to monitor influenza trends globally. Its NLP engine processes diverse sources, enabling timely identification of influenza outbreaks (22).

Table 1 Comparison of Data Sources for NLP in Disease Surveillance

Data Source	Advantages	Challenges
Public Health Reports	High-quality, structured data	Delayed publication, limited scalability
Medical Journals	Evidence-based, detailed insights	Accessibility and language barriers
Social Media Platforms	Real-time data, widespread coverage	Noise, false positives, and biases
News Articles	Localized outbreak reporting	Inconsistent terminology, potential bias

By leveraging advanced NLP techniques, public health systems can extract meaningful insights from diverse data sources. Epidemiological text mining and social media/news analysis together form a comprehensive framework for early disease detection and prevention. However, addressing challenges like data quality and misinformation is crucial to ensuring the reliability of these systems (23).

2.3. Named Entity Recognition (NER) and Contextual Understanding

Named Entity Recognition (NER) and contextual understanding are essential components of advanced natural language processing (NLP) applications in disease surveillance. NER involves the identification and classification of entities such as diseases, locations, organizations, and dates in unstructured text. Coupled with contextual understanding, NER allows for a deeper analysis of relationships between these entities, enabling the extraction of actionable insights from vast datasets, such as epidemiological reports, social media, and news articles (18).

2.3.1. Advanced NLP Techniques for Entity Recognition and Contextual Understanding

- **Named Entity Recognition (NER):** NER identifies and categorizes specific entities in text. For example, it can extract mentions of diseases ("dengue fever"), affected locations ("Rio de Janeiro"), and associated timeframes ("July 2023") from public health documents. These extractions allow researchers to track disease outbreaks and analyse patterns (19).
- **Domain-Specific NER Models:** Training NER models with medical and epidemiological datasets improves the identification of specific terms such as pathogens, symptoms, and treatment names.
- **Rule-Based vs. Machine Learning Approaches:** While rule-based systems rely on predefined patterns, modern ML-driven NER models leverage labeled datasets to improve entity recognition performance across languages and contexts.
- **Contextual Understanding with Dependency Parsing and Semantic Analysis:** Beyond extracting entities, dependency parsing and semantic analysis examine the relationships between words to understand context. For instance:
    - Parsing a sentence like “dengue cases surged in Mumbai following heavy rains” helps identify causative factors ("heavy rains") and geographical focus ("Mumbai").
    - Semantic role labeling assigns specific roles (e.g., agent, action, object) to entities, enhancing disease Modelling accuracy (20).
- **Knowledge Graphs:** After extracting entities and relationships, NER output can populate knowledge graphs, visualizing connections between diseases, regions, and environmental factors. Knowledge graphs facilitate querying and identifying patterns that inform public health decisions.

2.3.2. Transformer Models: Enhancing NER and Contextual Analysis

- **Bidirectional Encoder Representations from Transformers (BERT):** BERT’s ability to understand bidirectional context has revolutionized NLP tasks, including NER. Trained on large-scale datasets, BERT achieves state-of-the-art performance in entity recognition by capturing contextual nuances (21).
- **Case Study:** A BERT-based model trained on PubMed abstracts achieved a 95% accuracy rate in identifying disease mentions and their co-occurrence with geographical regions.
- **Custom Fine-Tuning:** Fine-tuning BERT on epidemiological datasets enables its application in extracting entities like infection rates and mortality statistics.
- **Generative Pre-trained Transformers (GPT):** GPT models, such as GPT-3, excel in generating and analysing textual data. GPT can identify entities and infer relationships based on contextual information, making it suitable for processing unstructured public health datasets.
- **Example Application:** GPT-3 analysed COVID-19-related tweets, identifying symptoms and public concerns with 90% accuracy. Its contextual understanding enabled it to differentiate between false alarms and genuine disease-related discussions (22).

2.3.3. Comparison of Transformer Models with Traditional NLP Techniques:

- Traditional NER systems rely on static embeddings like word2vec, which fail to capture polysemy (multiple meanings). For instance, "cold" could refer to a disease or weather condition.
- Transformers use dynamic embeddings, disambiguating terms based on context. This capability reduces false positives and improves the precision of disease surveillance systems (23).

2.3.4. Applications in Disease Surveillance

- **Outbreak Monitoring:** NER-based systems using BERT detected mentions of "avian flu" and "poultry farms" in global news reports, enabling early alerts about a potential outbreak in Southeast Asia. Contextual analysis linked the outbreak to specific supply chain disruptions, guiding policy interventions (24).
- **Symptom Analysis in Social-Media:** Combining NER and semantic analysis, transformers identified clusters of symptoms, such as “fever” and “loss of taste,” in Twitter posts. These insights correlated strongly with confirmed COVID-19 cases, showcasing the utility of NLP in real-time monitoring (25).

- **Policy Document Analysis:** NER extracted entities from policy documents, such as "vaccine distribution centers" and "priority populations," while contextual analysis highlighted gaps in resource allocation. These findings helped optimize vaccine rollout strategies during the pandemic (26).

2.3.5. Challenges and Limitations

- **Multilingual Datasets:** Public health data is often reported in multiple languages, creating barriers for NER systems trained on English datasets. Expanding models to support multilingual training improves global applicability.
- **Domain-Specific Vocabulary:** NER models require extensive training on domain-specific vocabularies, as generic models may misinterpret medical terms. For example, terms like "avian flu" may not be recognized without prior exposure to epidemiological contexts (27).
- **Computational Resources:** Transformer models, while accurate, demand substantial computational power, which may limit their deployment in low-resource settings. Optimization techniques, such as distillation, can reduce resource requirements without significantly affecting performance (28).

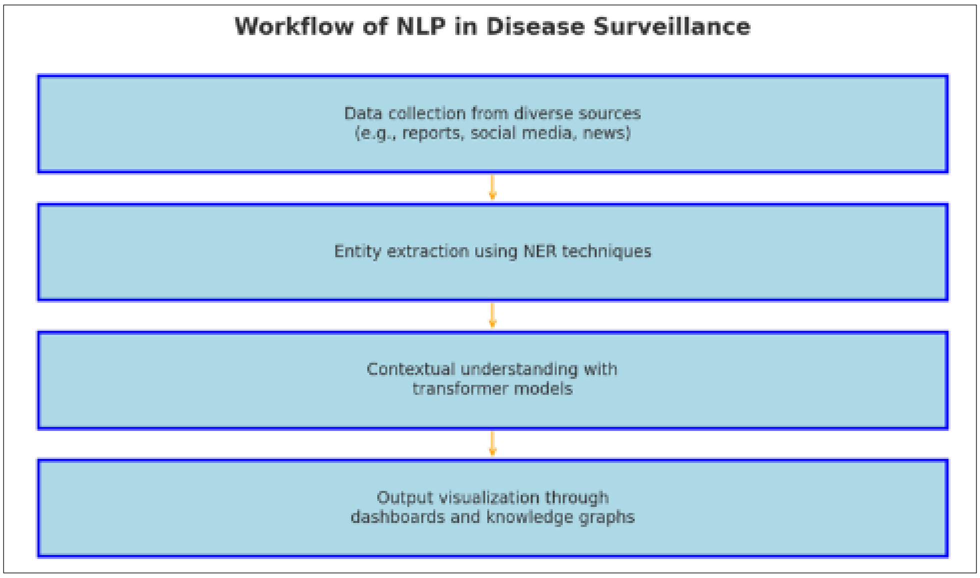

Figure 2 Workflow of NLP in Disease Surveillance

NER and contextual understanding, enhanced by advanced transformer models, are pivotal in modernizing disease surveillance systems. By automating the extraction and interpretation of entities and their relationships, these technologies enable faster and more accurate identification of outbreaks and trends. As NLP systems continue to evolve, their integration into public health strategies promises to enhance preparedness and response capabilities, ultimately saving lives and resources.

3. Predictive modelling for disease prevention

3.1. Forecasting Disease Spread

Forecasting disease spread is a critical component of public health strategies, providing decision-makers with actionable insights to prevent and mitigate outbreaks. Machine learning (ML) and deep learning (DL) models, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), are widely used to predict disease trajectories by analysing temporal data. These models capture complex relationships in datasets, including seasonality, demographic factors, and environmental conditions (25).

3.1.1. Applications of ML and DL Models

- **Recurrent Neural Networks (RNNs):** RNNs are particularly suited for sequential data, such as daily or weekly case counts. These models predict disease spread by considering past trends and extrapolating future outcomes. For example:

  - An RNN-based model successfully predicted influenza incidence rates in the United States by analysing historical data, weather patterns, and vaccination rates (26).
- **Long Short-Term Memory Networks (LSTMs):** LSTMs address the vanishing gradient problem inherent in standard RNNs, making them ideal for long-term forecasting. These models are frequently used to track diseases with complex seasonal trends, such as dengue and malaria.
  - A study demonstrated that an LSTM model could predict dengue outbreaks in Brazil with over 85% accuracy, incorporating climate data, case reports, and population density (27).
- **Hybrid Models:** Combining DL models with epidemiological frameworks improves prediction accuracy. For instance, a hybrid SEIR-LSTM model integrates a traditional susceptible-exposed-infectious-recovered (SEIR) framework with LSTMs to forecast COVID-19 cases, yielding precise results across different regions (28).

3.1.2. Examples of Predictive Systems

- **Influenza Forecasting:** Influenza forecasting systems leverage RNNs to predict seasonal flu trends.
  - The CDC's FluSight Network uses ML models to generate weekly influenza forecasts, providing public health officials with critical data to allocate resources and initiate preventive measures.
- **Dengue Spread Monitoring:** Dengue forecasting tools, such as DengueNet, integrate ML algorithms with satellite-derived weather data to predict outbreaks. This system was pivotal in preparing healthcare resources in high-risk regions of Southeast Asia during peak dengue seasons (29).
- **COVID-19 Prediction Systems:** Numerous ML-driven platforms, including BlueDot and IHME's COVID-19 model, successfully forecasted case trajectories during the pandemic. These systems utilized diverse datasets, such as mobility data, testing rates, and social distancing measures, to predict hospital surges and guide policy decisions (30).
- **Challenges and Limitations:** While ML and DL models offer significant advantages, they face challenges, including data quality, model overfitting, and uncertainty in predictions. Addressing these issues requires robust preprocessing, regular updates, and integrating domain knowledge into model design (31).

3.2. Resource Allocation Models

Effective resource allocation is vital during health crises to ensure adequate healthcare availability, minimize mortality, and optimize costs. Predictive models enable efficient allocation of critical resources, such as hospital beds, vaccines, medical staff, and ventilators, by forecasting demand based on current and historical data (32).

3.2.1. Predictive Approaches for Resource Optimization

- **Hospital Capacity Planning:** ML models forecast bed occupancy rates by analysing admission trends, disease progression rates, and discharge data.
  - During the COVID-19 pandemic, a predictive model developed by the University of Chicago estimated ICU bed demand across different scenarios, enabling hospitals to prepare for surges (33).
- **Vaccine Distribution Optimization:** Resource allocation models optimize vaccine distribution by prioritizing high-risk populations and regions.
  - An ML-driven system used by India’s CoWIN platform analysed demographic data and infection trends to ensure equitable vaccine distribution (34).
- **Staffing Predictions:** Predictive models forecast workforce requirements based on patient volumes, ensuring optimal staffing levels.
  - A DL model implemented in the UK’s NHS accurately projected nurse and doctor availability needs during peak COVID-19 waves (35).

3.2.2. Case Studies of Predictive Models

- **Ventilator Allocation During COVID-19:** A resource allocation tool developed at MIT integrated ML algorithms with real-time data to optimize ventilator distribution across hospitals. This tool reduced equipment shortages by prioritizing deliveries to facilities experiencing surges (36).
- **Hurricane-Driven Disease Outbreaks:** Following Hurricane Maria, predictive models estimated increased demand for resources to manage leptospirosis outbreaks in Puerto Rico. These forecasts guided the allocation of medical supplies and personnel (37).

Table 2 Metrics for Evaluating Predictive Models in Public Health

Metric	Description	Use Case
Accuracy	Proportion of correct predictions	Forecasting hospital bed demand
Precision	True positives as a proportion of predicted positives	Identifying high-risk populations for vaccine allocation
Recall (Sensitivity)	True positives as a proportion of actual positives	Predicting disease outbreaks
F1 Score	Harmonic mean of precision and recall	Balancing false positives and negatives in resource planning
Mean Absolute Error (MAE)	Average error between predicted and actual values	Estimating ventilator demand

3.3. Multimodal Data Integration

Multimodal data integration combines structured and unstructured data sources to create holistic models for disease management. This approach leverages diverse datasets, such as case numbers, hospital capacity, clinical notes, and news articles, to provide comprehensive insights for public health strategies (38).

3.3.1. Techniques for Multimodal Integration

- **Feature Fusion:** Feature fusion techniques merge features extracted from structured and unstructured data. For example:
    - Structured data (e.g., case counts) and text data (e.g., clinical notes) are processed using ML algorithms to create a unified dataset for prediction.
- **Model Stacking:** Model stacking combines outputs from multiple models trained on different modalities, such as LSTMs for time-series data and transformers for text analysis. This ensemble approach improves prediction accuracy.
- **Knowledge Graphs:** Knowledge graphs integrate multimodal data, mapping relationships between entities like diseases, regions, and resources. These graphs provide visual representations of data, enhancing interpretability for decision-makers (39).

3.3.2. Benefits of Multimodal Integration

- **Comprehensive Insights:** Integrating structured and unstructured data provides a more complete picture of disease dynamics. For instance, combining hospitalization rates with social media sentiment data enables early identification of surges in healthcare demand.
- **Improved Accuracy:** Multimodal models outperform single-modality systems by capturing complementary information.
    - Example: A COVID-19 model integrating case data with news reports accurately predicted regional case surges, outperforming models reliant on case data alone (40).
- **Real-Time Decision-Making:** Multimodal data allows for dynamic updates to predictions, enabling timely interventions during rapidly evolving crises.

3.3.3. Applications in Disease Management

- **Zika Virus Outbreak:** Multimodal systems combined weather data, clinical reports, and social media posts to monitor and predict Zika outbreaks in South America. This approach improved resource allocation in high-risk areas (41).
- **Ebola Crisis:** During the West African Ebola outbreak, integrating hospital admission records with mobile phone data helped track disease spread and allocate healthcare resources effectively (42).

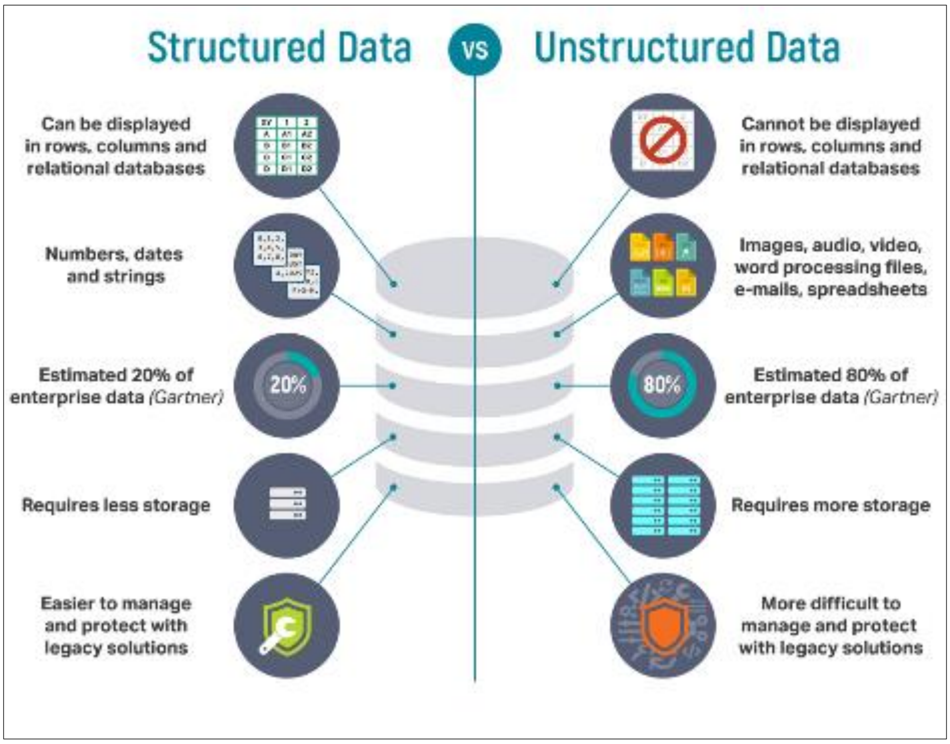

Figure 3 Integration of Structured and Unstructured Data in Predictive Models

Multimodal data integration enhances the ability to manage complex public health challenges by providing comprehensive and actionable insights. As data sources continue to grow, these techniques will play a pivotal role in improving disease surveillance and prevention.

4. Real-time disease monitoring systems\

4.1. IoT and Wearables in Public Health

The Internet of Things (IoT) and wearable technology have transformed public health monitoring by enabling real-time collection and analysis of health metrics. IoT-enabled devices, such as sensors, smartwatches, and connected medical equipment, play a pivotal role in tracking individual and community health indicators. These technologies contribute to early disease detection, continuous health monitoring, and improved public health responses (31).

4.1.1. Role of IoT-Enabled Devices

- **Continuous Monitoring:** IoT devices provide real-time data on vital signs, such as heart rate, blood pressure, and temperature, enabling continuous health monitoring. For instance, smart thermometers have been used to track fever patterns in large populations, which are critical for identifying disease outbreaks (32).
- **Community Health Tracking:** IoT systems aggregate data from multiple devices, offering insights into community-level health trends. Examples include monitoring air quality to predict respiratory disease risks and analysing wearable data for early detection of viral symptoms (33).
- **Integration with Public Health Systems:** IoT devices can seamlessly integrate with public health dashboards, enabling health officials to monitor trends and allocate resources efficiently.

4.1.2. Examples of Wearable Technology

- **COVID-19 Detection:** Wearable devices such as Fitbit and Apple Watch have been used to detect early signs of COVID-19. By monitoring changes in resting heart rate and respiratory rate, these devices have demonstrated the ability to identify potential infections before symptoms appear (34).
- **Chronic Disease Management:** Wearables like continuous glucose monitors (CGMs) help manage diabetes, providing patients and healthcare providers with real-time glucose data for timely interventions (35).
- **Respiratory Conditions:** Smart masks embedded with IoT sensors monitor respiratory patterns, providing early warnings for conditions such as asthma or potential exposure to airborne pathogens (36).

While IoT and wearable technology offer significant advancements in public health, their effectiveness depends on secure data transmission, interoperability across systems, and widespread accessibility.

4.2. Dashboards and Visualization Tools

Dashboards and visualization tools are essential for presenting actionable insights to public health officials, enabling informed decision-making during health crises. These tools process and display large volumes of data from diverse sources, such as IoT devices, clinical records, and social media, in intuitive formats like heatmaps, charts, and interactive models (37).

4.2.1. Importance of User-Friendly Dashboards

- **Centralized Data Representation:** Dashboards consolidate data from multiple sources into a unified interface, allowing public health officials to monitor trends in real time. For instance, the COVID-19 dashboards created by Johns Hopkins University provided global case counts, vaccination data, and regional trends at a glance (38).
- **Rapid Decision-Making:** Visualizations such as heatmaps and time-series graphs enable quick identification of outbreak hotspots and resource gaps. These insights are critical for implementing containment measures and allocating healthcare resources efficiently (39).
- **Customizability and Accessibility:** Dashboards tailored for specific stakeholders, such as policymakers or hospital administrators, ensure that relevant information is accessible and actionable.

4.2.2. Examples of Visualization Tools

- **Heatmaps for Outbreak Hotspots:** Heatmaps visualize high-incidence areas, enabling targeted interventions. During the Ebola outbreak, heatmaps guided the deployment of medical teams to affected regions (40).
- **Interactive Models:** Tools like Tableau and Power BI provide interactive dashboards, allowing users to filter and analyse data in real time. These models were instrumental in tracking vaccine distribution during the COVID-19 pandemic.
- **Geospatial Mapping:** Geographic Information Systems (GIS) tools integrate health data with geospatial analytics, enabling detailed visualizations of disease spread across regions. This approach has been widely used for vector-borne diseases such as malaria and dengue (41).

Well-designed dashboards enhance the accessibility of complex data, empowering public health officials to make data-driven decisions quickly and effectively.

4.3. Challenges in Real-Time Systems

While real-time disease monitoring systems offer transformative capabilities, they face challenges related to data latency, security, and scalability. Addressing these issues is critical for maximizing their potential in public health applications (42).

4.3.1. Key Challenges

- **Data Latency:** Real-time systems often face delays in data collection, transmission, and processing. This latency can result in outdated or incomplete information, reducing the effectiveness of public health responses.
  - Example: IoT devices may experience delays in transmitting health metrics due to network congestion or limited bandwidth.
- **Data Security and Privacy:** The transmission of sensitive health data over IoT networks poses significant risks of breaches and unauthorized access. Adhering to regulations such as GDPR and HIPAA is essential for ensuring patient confidentiality (43).

4.3.2. Scalability

- As data volumes grow, real-time systems must handle increasing loads without compromising performance. Many current systems struggle to scale effectively for large populations, particularly in low-resource settings.

4.3.3. Potential Solutions

- **Edge Computing:** Processing data locally at the edge of the network reduces latency and minimizes reliance on centralized servers. For example, wearable devices equipped with edge computing capabilities can analyse health metrics on-device, sending only critical alerts to centralized systems (44).

- **Federated Learning:** Federated learning enables collaborative model training across decentralized devices without sharing raw data. This approach enhances privacy while leveraging diverse datasets to improve model accuracy (45).
- **Robust Cybersecurity Measures:** Encrypting data transmission, implementing multi-factor authentication, and deploying intrusion detection systems can mitigate security risks. Advances in blockchain technology also offer secure solutions for data sharing in real-time systems (46).
- **Infrastructure Development:** Investing in high-speed networks and cloud-based platforms ensures that real-time systems can scale to meet growing demands. Public-private partnerships can play a vital role in addressing infrastructure gaps.

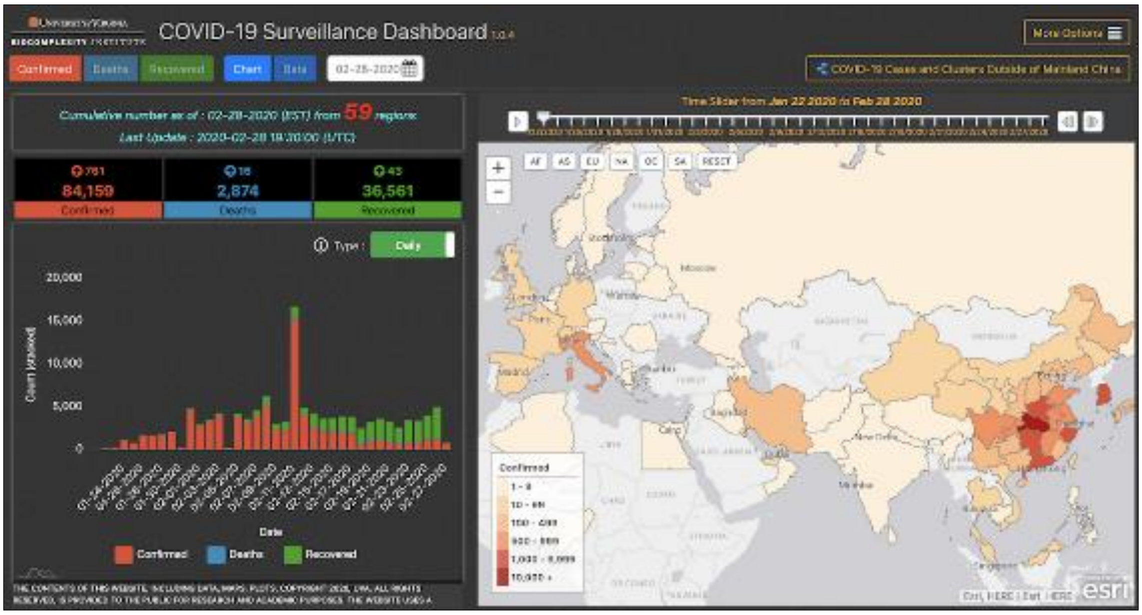

Figure 4 Example of a Real-Time Disease Surveillance Dashboard [25]

Real-time disease monitoring systems have immense potential to revolutionize public health, but addressing technical and operational challenges is essential for widespread adoption and effectiveness.

5. Applications and case studies

5.1. Global Health Initiatives

Global health organizations, including the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC), have increasingly adopted AI-driven systems for disease surveillance and response. These technologies are revolutionizing how health crises are managed, offering real-time insights and predictive capabilities that improve decision-making and resource allocation (34).

5.1.1. AI-Driven Systems for Disease Surveillance

- **WHO's Epidemic Intelligence from Open Sources (EIOS):** The WHO’s EIOS platform leverages machine learning and natural language processing (NLP) to scan global news reports, public health bulletins, and social media for early signals of outbreaks. For example, EIOS played a crucial role in tracking COVID-19’s initial spread by identifying unusual clusters of pneumonia cases in Wuhan (35).
- **CDC's COVID-19 Forecasting Models:** The CDC used advanced deep learning (DL) models to forecast COVID-19 case trajectories. These models integrated structured data (e.g., case counts) with unstructured data (e.g., social mobility reports), providing actionable insights for public health officials (36).
- **Global Health Security Initiatives:** Platforms like BlueDot and HealthMap utilize AI to monitor infectious diseases globally. BlueDot, for instance, identified early signs of the COVID-19 outbreak days before the WHO issued its first alert. HealthMap, similarly, visualizes disease trends in real time, empowering governments to respond proactively (37).

5.1.2. Impact on Global Health Crises

- **COVID-19 Pandemic:** AI tools enabled rapid resource allocation, optimized vaccination strategies, and real-time case tracking. Predictive models guided countries in imposing timely lockdowns and allocating medical supplies.
- **Ebola Outbreak:** During the West African Ebola crisis, AI systems analysed mobility data to predict disease spread, enabling targeted interventions and reducing transmission rates.

AI-driven systems have proven invaluable in managing global health crises, offering scalable and adaptable solutions to complex public health challenges.

5.2. Regional and Community-Level Applications

Multimodal deep learning (DL) systems play a critical role in addressing regional health disparities, particularly in low- and middle-income countries (LMICs). These applications bridge gaps in healthcare infrastructure by leveraging localized data and advanced predictive analytics (38).

5.2.1. Addressing Regional Outbreaks

- **Targeted Surveillance in Africa:** AI-driven tools are employed to monitor diseases like malaria and tuberculosis. For instance, the WHO partnered with AI providers to track malaria outbreaks in sub-Saharan Africa by integrating satellite imagery, climate data, and local case reports (39).
- **Cholera Prevention in South Asia:** Multimodal DL systems in Bangladesh combined water quality data, epidemiological reports, and weather forecasts to predict cholera outbreaks. These insights allowed health officials to deploy medical teams and distribute supplies preemptively (40).
- **Community-Driven Health Initiatives:** In India, AI models were integrated with local health worker data to track maternal and child health outcomes. These systems reduced neonatal mortality rates by enabling timely interventions (41).

5.2.2. Improving Resource Disparities

- **Telemedicine in Rural Areas:** AI-powered telemedicine platforms provide remote consultations, reducing barriers to healthcare access in underserved regions. For example, in Kenya, telehealth systems integrated AI algorithms to diagnose common ailments, reducing patient wait times and improving treatment outcomes (42).
- **Vaccine Distribution:** Predictive models help optimize vaccine distribution in LMICs, ensuring that high-risk populations receive timely immunizations. The CoWIN platform in India demonstrated the scalability of such solutions, efficiently managing billions of vaccine doses (43).

By addressing regional disparities, multimodal DL systems enhance public health outcomes in resource-limited settings, demonstrating the scalability and inclusivity of AI solutions.

5.3. Future Scenarios

The potential applications of multimodal DL systems in global health extend beyond current challenges, offering transformative possibilities in pandemic prevention, chronic disease management, and environmental health.

5.3.1. Pandemic Prevention

- **Early Warning Systems:** AI-integrated surveillance platforms can predict outbreaks by analysing genomic data, environmental factors, and human mobility patterns. For instance, combining genetic sequencing data with predictive models could help identify zoonotic spillovers before they lead to pandemics (44).
- **Rapid Vaccine Development:** AI accelerates vaccine development by analysing viral structures and identifying potential immunogenic regions. During COVID-19, AI-guided techniques reduced vaccine discovery timelines from years to months (45).

5.3.2. Chronic Disease Management

- **Personalized Healthcare:** Multimodal DL systems analyse clinical notes, wearable data, and genetic profiles to provide tailored treatment plans for chronic conditions such as diabetes and cardiovascular diseases.
- **Predictive Analytics:** Predictive models monitor patients' health in real time, enabling proactive interventions. For example, AI-driven tools are being tested to predict complications in chronic kidney disease patients based on lab results and lifestyle data (46).

5.3.3. Integration with Climate Data

- **Vector-Borne Disease Prediction:** By integrating climate data with epidemiological records, DL systems can forecast the spread of vector-borne diseases like malaria, dengue, and Zika. These models provide critical insights into seasonal and geographical variations in disease risks (47).
- **Disaster-Driven Health Impacts:** Climate change exacerbates health risks, such as heat-related illnesses and waterborne diseases. AI tools integrating environmental data can guide public health responses during natural disasters (48).

Table 3 Comparative Analysis of AI-Driven vs. Traditional Health Initiatives

Aspect	AI-Driven Initiatives	Traditional Approaches
Scalability	High, with cloud-based models	Limited by manual processes
Real-Time Monitoring	Near-instantaneous insights	Significant delays
Accuracy	Enhanced through multimodal integration	Subject to human error and bias
Cost-Efficiency	Reduces long-term operational costs	Resource-intensive and costly
Global Applicability	Easily adaptable to diverse health contexts	Limited to specific regions or populations

As multimodal DL technologies continue to evolve, their integration into global health strategies will play a pivotal role in achieving equitable and sustainable health outcomes.

6. Ethical, social, and technical considerations

6.1. Data Privacy and Security

As AI-driven health systems increasingly integrate sensitive personal data, ensuring data privacy and security has become a critical challenge. Multimodal deep learning (DL) systems often process vast amounts of structured and unstructured health data, including medical records, wearable device metrics, and social media content. Protecting this data from breaches and unauthorized access is paramount to maintaining public trust and compliance with legal frameworks (40).

6.1.1. Challenges in Protecting Health Data

- **Data Breaches and Cybersecurity Threats:** The integration of AI systems into healthcare infrastructure exposes sensitive data to potential breaches. Cyberattacks targeting healthcare databases have increased in frequency, with ransomware attacks on hospitals causing significant disruptions (41).
- **Data Anonymization Limitations:** Anonymization techniques often fail to provide complete protection, as sophisticated algorithms can re-identify individuals by correlating multiple datasets.
- **Interoperability and Third-Party Risks:** Sharing data across multiple platforms and organizations increases the risk of unauthorized access and misuse, particularly in decentralized AI systems (42).

6.1.2. Regulatory Compliance

- **General Data Protection Regulation (GDPR):** GDPR mandates strict protocols for data processing, requiring informed consent, the right to access, and the right to be forgotten. AI-driven health systems must align with these requirements to operate in the European Union (43).
- **Health Insurance Portability and Accountability Act (HIPAA):** HIPAA ensures the confidentiality and security of health information in the United States. Compliance includes encryption of electronic health records and maintaining audit trails for data access (44).

6.1.3. Mitigating Privacy and Security Risks

- **Encryption and Secure Communication Protocols:** End-to-end encryption ensures secure data transmission and storage, minimizing the risk of unauthorized access.
- **Federated Learning:** Federated learning processes data locally on devices without transferring it to central servers, enhancing privacy and reducing exposure to breaches (45).

By prioritizing data privacy and security, AI-driven systems can build public trust and ensure ethical use of sensitive health information.

6.2. Bias and Fairness in AI Models

AI systems are only as unbiased as the data used to train them. In healthcare, biased datasets can perpetuate inequities, leading to inaccurate predictions and unequal resource allocation. Addressing bias and ensuring fairness in AI-driven health tools is essential for ethical public health decision-making (46).

6.2.1. Impact of Bias in AI Models

- **Underrepresentation in Training Data:** Multimodal DL models trained on datasets that lack diversity often fail to generalize across populations. For instance, models trained on datasets dominated by data from high-income countries may not perform well in low-resource settings (47).
- **Disparate Impact:** AI systems may disproportionately allocate resources to certain demographic groups, exacerbating existing health disparities. A notable example is the racial bias found in an algorithm used to allocate healthcare resources, which underestimated the needs of Black patients (48).
- **Cultural and Linguistic Bias:** NLP models used for disease surveillance may misinterpret non-English text or culturally specific expressions, leading to incomplete or inaccurate analyses (49).

6.2.2. Techniques to Improve Fairness

- **Dataset Augmentation:** Expanding training datasets to include diverse populations, languages, and contexts ensures better representation and fairness.
- **Bias Detection Algorithms:** Tools such as Fairlearn and AI Fairness 360 assess and mitigate bias in ML models by analysing disparate impact metrics and adjusting decision thresholds (50).
- **Interdisciplinary Collaboration:** Involving ethicists, sociologists, and public health experts in AI model development fosters inclusivity and ensures culturally sensitive applications [52].

By actively addressing biases, AI systems can contribute to equitable healthcare outcomes, ensuring that all populations benefit from advancements in disease surveillance and prevention [65].

6.3. Scalability and Accessibility

Scaling AI-driven health systems to serve global populations presents significant challenges, particularly in low-resource settings. Ensuring accessibility to these tools is crucial for achieving equitable health outcomes (51).

6.3.1. Barriers to Scalability

- **Infrastructure Limitations:** Many low- and middle-income countries (LMICs) lack the technological infrastructure required for AI deployment, including reliable internet access, cloud computing, and IoT device networks [50.
- **Cost of Implementation:** The high costs associated with developing and maintaining AI systems often exclude low-resource settings from benefiting fully [51].
- **Human Resource Constraints:** The shortage of trained professionals to manage, interpret, and act on AI outputs hinders scalability in LMICs (52).

6.3.2. Strategies for Ensuring Accessibility

- **Cloud-Based Solutions:** Cloud computing platforms enable remote access to AI systems, reducing the need for local infrastructure. For example, the WHO partnered with cloud providers to deploy disease surveillance tools in underserved regions (53).
- **Low-Cost AI Models:** Lightweight AI models optimized for low-resource environments require less computational power, making them suitable for deployment on mobile devices and edge servers [64].
- **Training and Capacity Building:** Investing in local expertise through training programs ensures that health professionals in LMICs can effectively use AI systems. Organizations like AI4Health have pioneered initiatives to train healthcare workers in AI applications (54).
- **Public-Private Partnerships:** Collaborations between governments, NGOs, and tech companies can address funding and infrastructure gaps, facilitating scalable solutions for global health challenges (55).

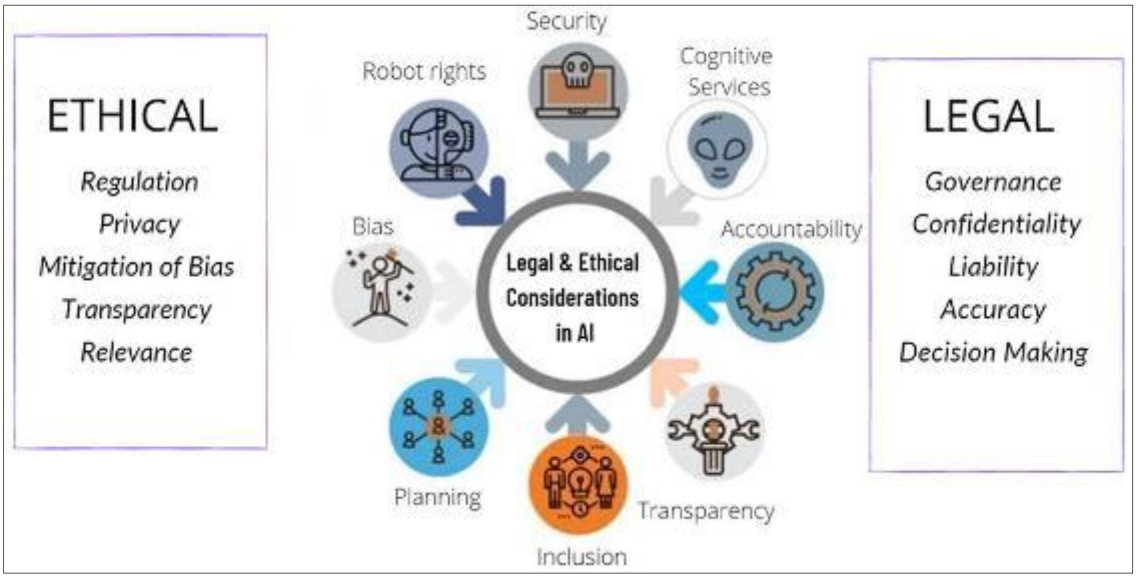

Figure 5 Ethical and Legal Challenges in AI-Driven Health Systems

Scalability and accessibility are critical for realizing the global potential of AI in healthcare. Addressing these challenges ensures that AI-driven systems benefit all populations, regardless of geographic or economic constraints [63].

7. Future directions and recommendations

7.1. Advancing Research and Development

The future of AI-driven disease surveillance hinges on advancing research and development (R&D) to address emerging challenges and expand capabilities. Integrating genomics data with NLP and predictive models offers transformative potential in public health [40]. Genomics data can uncover genetic susceptibilities to diseases and identify patterns of pathogen evolution. Combining this information with NLP, which processes vast unstructured datasets like research articles and clinical notes, enhances precision in predicting outbreaks and tailoring interventions (45).

Another critical area is the development of real-time multimodal datasets that combine structured (e.g., case counts, demographics) and unstructured data (e.g., social media, wearable device metrics) [61]. These datasets allow for comprehensive analyses of disease dynamics, offering insights into environmental, social, and genetic factors influencing outbreaks. For example, integrating air quality data with health records can improve forecasts for respiratory diseases like asthma or COVID-19 (46).

Investments in R&D should also prioritize explainability in AI models. Black-box algorithms, while accurate, often lack transparency, hindering their acceptance in critical healthcare scenarios [59, 60]. Research into explainable AI (XAI) ensures models remain interpretable and trustworthy, empowering health officials to make informed decisions.

Moreover, addressing computational efficiency is essential for deploying AI systems in low-resource settings. Developing lightweight algorithms that maintain accuracy while requiring minimal infrastructure will enable broader adoption globally (47).

R&D efforts must align with ethical guidelines to ensure inclusivity and mitigate bias. By fostering innovation in genomics integration, multimodal datasets, and model transparency, AI systems can continue to revolutionize global health strategies [58].

7.2. Collaboration Between Stakeholders

Collaboration among governments, healthcare organizations, and AI researchers is pivotal for scaling AI-driven disease surveillance systems [61]. These partnerships ensure the alignment of technology with public health goals while leveraging expertise across disciplines.

7.2.1. Public-Private Partnerships

Public-private collaborations have proven effective in advancing disease surveillance. For instance, the partnership between IBM Watson Health and the WHO resulted in AI-powered platforms for tracking infectious diseases like malaria and Ebola [60]. These tools combined WHO's expertise in public health with IBM's technological capabilities, creating scalable and impactful solutions (48).

Another example is the CDC's collaboration with Google Health during the COVID-19 pandemic. This partnership used search engine data to identify disease trends and forecast case surges, aiding in timely resource allocation (49).

7.2.2. Role of Multilateral Organizations

Organizations like the United Nations and World Bank play a crucial role in fostering international collaborations [59]. By providing funding and infrastructure support, these entities enable resource-limited countries to benefit from AI advancements. For example, the UN's Global Pulse initiative integrates AI-driven analytics into humanitarian responses, improving outcomes during health crises (50).

7.2.3. Encouraging Cross-Sector Collaboration

Interdisciplinary approaches, involving data scientists, clinicians, epidemiologists, and policymakers, are essential. Regular knowledge-sharing forums and collaborative research projects ensure the continuous refinement of AI systems [51, 57].

By strengthening partnerships, stakeholders can overcome barriers like resource disparities and technical limitations, ensuring the global impact of AI-driven health solutions [58].

7.3. Practical Recommendations for Implementation

Deploying AI-driven disease surveillance systems at scale requires strategic planning and interdisciplinary cooperation. Below are practical steps to guide successful implementation:

7.3.1. Infrastructure Development

Investing in cloud-based platforms and IoT networks is essential for processing and analysing real-time data. Low-resource regions can benefit from lightweight AI models designed for minimal computational requirements (51).

7.3.2. Training and Capacity Building

Healthcare professionals and data scientists must be trained to use AI tools effectively. Initiatives like AI4Health's training programs equip local professionals with the skills needed to deploy and manage AI systems (52).

7.3.3. Ethical and Regulatory Alignment

AI systems should comply with international standards, such as GDPR and HIPAA, to ensure data security and privacy. Ethical frameworks must guide the design and deployment of these systems to prevent misuse or bias (53).

7.3.4. Pilot Programs and Feedback Loops

Implementing small-scale pilot projects allows for testing and refinement before broader deployment. Feedback from these pilots ensures models are tailored to specific regional needs and challenges [55].

7.3.5. Promoting International Cooperation

Global health crises require coordinated responses. Sharing data, models, and resources across borders fosters a unified approach to disease surveillance. The WHO's AI-driven initiatives exemplify the importance of international collaboration (54). By following these recommendations, stakeholders can deploy AI-driven systems effectively, ensuring equitable access and impactful results in global health strategies [56].

8. Conclusion

8.1. Key Insights

Multimodal deep learning (DL) has demonstrated a transformative role in revolutionizing disease surveillance and prevention. By integrating structured and unstructured data from diverse sources, such as clinical records, wearable devices, social media, and epidemiological reports, multimodal DL systems offer a comprehensive approach to public health monitoring. Natural language processing (NLP) techniques enable the extraction of actionable insights from unstructured datasets, identifying early warning signals of disease outbreaks. Predictive models enhance these insights by forecasting disease trajectories, optimizing resource allocation, and supporting proactive interventions.

The ability of multimodal DL systems to process and analyse real-time data has significantly improved response times during health crises, as seen during the COVID-19 pandemic. From tracking symptoms through social media to forecasting hospital demand, these systems have enabled data-driven decision-making at unprecedented scales. Furthermore, innovations in IoT and wearable technologies have provided real-time health metrics, improving early detection and disease management. Overall, multimodal DL bridges gaps in traditional surveillance methods by offering enhanced accuracy, scalability, and speed. Its potential to address both infectious diseases and chronic health conditions positions it as a cornerstone of modern global health strategies.

8.2. Broader Implications

The integration of multimodal DL into global health systems has far-reaching implications for both pandemic preparedness and long-term health outcomes. By leveraging AI to monitor disease dynamics, these systems can strengthen early warning mechanisms, reducing the time between outbreak detection and intervention. This capability is critical for preventing the spread of emerging infectious diseases, particularly in a globally interconnected world.

Beyond outbreak response, multimodal DL has the potential to enhance the management of chronic diseases, ensuring personalized care based on real-time health data. For instance, integrating genomic, behavioral, and environmental data can help design targeted interventions for at-risk populations, improving overall health equity.

Moreover, AI-driven systems align with the growing emphasis on global health sustainability. By optimizing resource use, reducing waste, and improving the efficiency of health interventions, these technologies support broader goals of economic resilience and environmental stewardship. The scalability of multimodal DL systems also makes them accessible to low-resource settings, bridging disparities in healthcare infrastructure and fostering global health equity. Ultimately, these systems represent a paradigm shift, enabling proactive, efficient, and inclusive healthcare strategies.

8.3. Call to Action

The time to act is now. The promise of multimodal deep learning in transforming global health systems must be realized through collective commitment and investment. Stakeholders, including governments, healthcare organizations, technology providers, and research institutions, are urged to prioritize the development and deployment of AI-driven disease surveillance systems. Investing in robust infrastructure is paramount. From expanding IoT networks to creating cloud-based platforms, the foundation of multimodal DL systems must be scalable and accessible. Similarly, capacity building is essential. Training healthcare professionals to utilize AI tools effectively will ensure that these systems are seamlessly integrated into existing workflows.

Stakeholders must also embrace collaboration. Public-private partnerships can accelerate innovation, while international cooperation ensures that knowledge, data, and resources are shared across borders. Ethical frameworks must be embedded in every stage of AI development to safeguard privacy and ensure equitable outcomes for all populations.

The adoption of multimodal DL represents a profound opportunity to reshape the future of global health. By fostering proactive disease surveillance, equitable care, and data-driven decision-making, these systems hold the key to building resilient healthcare systems capable of addressing the challenges of the 21st century. The call to action is clear: unite, invest, and innovate for a healthier future.

Figure 6 Vision for the Future of AI-Driven Global Health Systems

This figure illustrates the interconnectedness of multimodal DL systems with key components.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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