Artificial Intelligence and Deep Learning in Public Health Surveillance: A Review with Emphasis on Saudi Arabia

Abstract

Background: Effective surveillance and timely detection of infectious diseases are crucial for protecting population health. Artificial intelligence (AI) and deep learning models have emerged as powerful tools to improve disease monitoring, forecasting and decision making. Saudi Arabia, with ambitious Vision 2030 health reforms, provides a unique case study for applying these technologies.

Methods: A narrative review of peer-reviewed articles from 2010–2025 was conducted using databases such as PubMed and Google Scholar. Emphasis was placed on AI and deep learning approaches for disease surveillance, outbreak prediction and public health decision support, with a focus on models evaluated in Saudi Arabia or Gulf Cooperation Council countries. Key findings were extracted and synthesised. We also outline a methodological approach for developing a deep learning model to forecast influenza-like illness in Saudi Arabia using publicly available surveillance data and exogenous variables.

Results: 25 articles were included. Deep learning models such as long short-term memory (LSTM) and convolutional neural networks (CNN) achieved high accuracy (>90 %) in predicting influenza and dengue outbreaks [1],[4]. Hybrid models (e.g., ARIMA-DQN and LSTM-ARIMA) integrated linear and nonlinear dynamics and outperformed individual models [10],[23]. Ensemble and explainable AI techniques improved interpretability and clinician trust [3],[24]. Digital epidemiology approaches leveraged search queries, social media, electronic health records and climate data to detect outbreaks earlier than traditional surveillance [5],[20]. In Saudi Arabia, LSTM models incorporating climate and population mobility data predicted influenza-like illness more accurately than Holt–Winters methods, and deep learning enhanced COVID-19 forecasting [4],[10].

Conclusions: AI and deep learning offer substantial benefits for public health surveillance, particularly when integrated with diverse data sources and explainable frameworks. Saudi Arabia should invest in open data, cross-sector collaborations and ethical AI regulation to realise these benefits. Transparent and locally validated models are essential to gain clinician trust and improve health outcomes.

Introduction

Public health surveillance aims to detect outbreaks early, monitor disease trends and guide interventions. Traditional surveillance relies on clinical case reports and laboratory data, which often result in delays and underascertainment. The COVID-19 pandemic underscored the need for more responsive systems. AI and machine learning can process large, heterogeneous datasets and uncover patterns that humans may miss. Long short-term memory (LSTM) networks and convolutional neural networks (CNNs) have been widely used for time-series forecasting. In the “AI-assisted real-time monitoring” framework, AI and machine learning reduced outbreak response time by approximately 50 % and achieved >90 % prediction accuracy [1]. Integrating Internet of Things (IoT) devices such as wearable monitors and smart thermometers provided rich data for early detection [1]. However, surveillance systems still face underreporting and high false-positive rates [1].

Saudi Arabia has invested heavily in digital health through its *Vision 2030* programme. Hospitals are deploying AI to improve diagnostic accuracy, patient management and operational efficiency [2]. Machine learning optimises telehealth and workflow management, while deep learning combined with IoT devices helps monitor heart failure and reduce readmissions [2]. Nonetheless, data privacy, algorithmic bias and regulatory challenges remain [2]. Understanding how AI can improve national surveillance is therefore timely.

Methods

Literature search and selection

A search of PubMed, Scopus, Google Scholar and IEEE Xplore was conducted in January 2025 using keywords: “artificial intelligence,”“deep learning,”“infectious disease surveillance,”“public health,”“Saudi Arabia,”“time series forecasting” and “digital epidemiology.” Inclusion criteria were peer-reviewed articles from 2010–2025 describing AI or deep learning approaches for infectious disease surveillance, outbreak prediction or hospital infection control. We included studies evaluating models in Saudi Arabia or the Gulf region and global studies providing transferable insights. Exclusion criteria were non-English articles, editorials and studies without technical descriptions.

Extraction and synthesis

Information extracted included study design, region, data sources, AI/ML methods and key findings. We synthesised findings thematically across model categories (deep learning, hybrid/ensemble, explainable AI, digital epidemiology). To illustrate methodological relevance to Saudi Arabia, we outline a deep learning model using LSTM to predict influenza-like illness (ILI). This demonstration uses publicly available ILI case counts (2016–2023) from the Saudi Ministry of Health and exogenous variables such as weather, mobility and Google search trends.

The model pre-processes time series, standardises features and trains an LSTM network with dropout to prevent overfitting. A hold-out test set evaluates root mean square error and mean absolute error, and performance is compared with a Holt–Winters baseline. Although we did not implement the model due to lack of raw data, the methodological blueprint aligns with prior ILI forecasting studies [3].

Deep learning model framework

1. **Data collection:** Weekly ILI counts from national influenza surveillance; climate data (temperature, humidity), population mobility from mobile network data; and Google search volumes for influenza symptoms [4, 5].
2. **Pre-processing:** Missing values imputed using multivariate imputation; series standardised.
3. **Model architecture:** LSTM network with one to two hidden layers and dropout; input sequences of 8–12 weeks; output is a one-week-ahead forecast.
4. **Training and evaluation:** Train on 2016–2022 data; evaluate on 2023 data; compare with Holt–Winters and ARIMA models.
5. **Explainability:** Use SHapley Additive exPlanations (SHAP) to interpret contributions of exogenous variables [6].

Results

Overview of AI and deep learning models

Five principal categories of models emerged from the literature (Table 1). LSTM models were the most common because they model long-term temporal dependencies. CNNs captured local patterns and were applied to dengue forecasting [7]. Hybrid models such as ARIMA-DQN and LSTM-ARIMA combined statistical and deep learning approaches, handling both linear and nonlinear dynamics [8][9]. Gradient boosting models (e.g., XGBoost, LightGBM) enhanced with explainable AI (XAI) techniques, such as SHAP and LIME, improved transparency and predictive performance [10]. Ensemble models blended statistical and machine-learning methods to mitigate non-stationarity and improve accuracy [9].

Table 1. Summary of deep learning models used for infectious disease forecasting

Model	Application	Data sources	Key findings
LSTM (Long Short-Term Memory)	Forecasting influenza-like illness and seasonal influenza	Electronic health records and exogenous variables such as climate and population mobility	LSTM models achieve >90 % accuracy in outbreak prediction and outperform Holt–Winters models.
CNN (Convolutional Neural Network)	Predicting dengue case counts and time-series patterns	Historical disease incidence and meteorological variables	CNNs detect complex temporal patterns but may struggle with short-term peaks; they often require large training datasets.
Hybrid ARIMA–DQN	Predicting COVID-19 case counts in Saudi Arabia	COVID-19 case time series across multiple countries, including Saudi Arabia	Hybrid ARIMA-DQN models capture both linear and nonlinear dynamics and perform better than standalone models.
XGBoost&LightGBM with XAI	Dengue outbreak prediction using explainable AI	Population density, precipitation, temperature and land-use data	XGBoost and LightGBM with SHAP/LIME achieve AUC ≈ 0.89; key predictors include population density and precipitation.
Ensemble Models (LSTM + ARIMA)	Combining statistical and ML models to improve forecasting	Clinical and climatic data from tropical regions	Ensembling ARIMA and LSTM improves accuracy and addresses non-stationarity in dengue forecasts.

Diverse data sources and digital epidemiology

AI-driven surveillance leverages multiple data streams. Electronic health records, wearable sensors and mobile apps capture clinical and physiological data. Digital epidemiology uses search queries, social media posts and web scraping to identify early signals of outbreaks [4]. Climate and mobility data improve forecasting models by accounting for environmental drivers of transmission [5]. A systematic review of early warning systems found that news reports, social media and search engine queries act as early indicators of outbreaks and reduce reporting delays [11]. Studies integrating search trends and climate data improved influenza predictions and detected outbreaks earlier than official surveillance [5]. The Google Flu Trends project, which correlated search query frequency with influenza physician visits, achieved near real-time detection [4]. Machine-learned models like FINDER used aggregated search and location data to identify foodborne-illness restaurants; flagged establishments were 3.1 times more likely to be unsafe [12]. These approaches expand surveillance beyond clinical reports but raise privacy concerns and data quality issues [13].

Performance of deep learning models

Many studies report high accuracy for deep learning models. An AI-assisted framework for urban surveillance achieved >90 % accuracy in predicting outbreaks [1]. In a Saudi ILI study, an LSTM model incorporating exogenous variables outperformed Holt–Winters models in terms of root mean square error and R^2 [4]. However, negative binomial regression (NBR) outperformed LSTM for dengue forecasting in Vietnam when short-term peaks dominated the signal [6]. An integrative review of hospital infection prevention found that deep learning offered slight advantages over other machine-learning approaches but noted limitations due to small datasets and data quality [12]. A hybrid ARIMA-DQN model applied to COVID-19 data in Saudi Arabia and other countries produced more accurate forecasts by combining linear and non-linear components [10].

Explainable AI is gaining prominence. A global dengue prediction study using XGBoost and LightGBM combined with SHAP and LIME achieved an AUC of 0.89 and identified precipitation, temperature and population density as key predictors [10]. Ensemble learning improved accuracy and reliability in early warning systems [2]. A systematic review of explainable AI in healthcare emphasised methods such as SHAP and LIME and highlighted gaps in data diversity and model complexity [6].

Challenges and limitations

Despite promising results, AI-driven surveillance faces challenges. Surveillance data are often incomplete; more than 40 % of cases may go unreported, leading to high false-positive rates [1]. Data quality, standardisation and interoperability across health systems remain obstacles [14]. Implementation of Integrated Disease Surveillance and Response programmes in West Africa revealed inadequate training, weak laboratory capacity and reliance on donor funding [15]. In Saudi Arabia, adoption of AI technologies is constrained by data privacy concerns, algorithmic bias and lack of regulatory frameworks [16].

Ethical considerations include ensuring transparency, fairness and accountability. Clinicians emphasise the need for explainable AI and external validation to build trust [3]. Social media and search-engine data may compromise user privacy; robust anonymisation and consent mechanisms are essential [15]. Cross-sector collaboration is crucial for models that integrate environmental, meteorological and public health data, such as cholera and water-borne disease forecasts [17].

AI applications in Saudi Arabia

Saudi Arabia has rapidly adopted digital health technologies. Hospitals using AI report improvements in diagnostic accuracy and workflow efficiency [18]. Deep learning models predicted hospital readmissions and heart failure progression when combined with IoT devices [19]. A hybrid ARIMA-DQN model applied to COVID-19 data from Saudi Arabia and other countries captured linear and nonlinear patterns and provided more precise forecasts than standalone models [10]. A study forecasting ILI using weekly influenza counts and exogenous variables found that the LSTM model achieved superior accuracy compared with Holt–Winters models [4]. These studies demonstrate the feasibility of implementing deep learning models in the Saudi context.

Discussion

This review synthesises evidence showing that AI and deep learning can substantially improve infectious disease surveillance and control. LSTM and CNN models achieve high predictive accuracy, especially when integrated with diverse data sources. Hybrid models combine the strengths of statistical and machine-learning approaches, handling both linear and non-linear dynamics. Explainable AI methods enhance transparency and foster clinician trust. Saudi Arabia's health system stands to benefit from these technologies, aligning with *Vision 2030* to modernise healthcare and increase efficiency [19]. By leveraging climate data, search trends and mobility patterns, Saudi surveillance systems could detect outbreaks earlier and allocate resources more effectively [20][5].

However, significant challenges remain. Data quality and privacy must be safeguarded. Many models are trained on small, biased datasets; cross-validation and external validation using multi-cohort data are vital [3]. Ethical frameworks and regulations are necessary to address algorithmic bias and ensure fairness [19]. Investment in workforce training and infrastructure, particularly in low-resource settings, is essential [16]. Future research should explore integrated mechanistic-AI models to incorporate realistic disease dynamics and decision-making processes [11].

Conclusions

AI and deep learning offer powerful tools to enhance public health surveillance, especially when combined with digital epidemiology and explainable frameworks. Saudi Arabia's digital health initiatives provide a favourable environment for implementing these technologies, but success depends on high-quality data, ethical oversight and clinician engagement. Future work should focus on integrated models, open data sharing and capacity building to harness AI's potential for timely outbreak detection and better health outcomes.

Data availability

This study did not generate new data. All information was obtained from previously published literature.

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