Public Health Security Systems Empowered by Artificial Intelligence for Early Monitoring and Prevention of Epidemics

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KEYWORDS

Public health, security systems, artificial intelligence, early monitoring, epidemics, CNN, BP-NN

ABSTRACT

Artificial intelligence (AI) methods have been extensively used for detecting and predicting Infectious Disease (ID) outbreaks as time series and modeling and evaluating Public Health responses. The significant tasks of PH monitoring and intervention present distinct technical difficulties, including limited data availability, absence of sufficient positive training examples, challenges in establishing benchmarks, measuring the effectiveness of management policies, complex relationships between spatial and time series elements, and more detailed risk assessments involving interaction and social networks. Conventional PH monitoring mainly depends on statistical methods. In recent years, there has been a significant expansion of approaches that AI enables. This research presents an AI method called Early Monitoring and Prevention of Epidemics (AI-EMPE) for enhancing PH security systems. The suggested approach converts a substantial amount of collected PH security incidents into separate incident characteristics and utilizes a Deep Learning (DL)--based detection technique to enhance EMPE. AI-EMPE incorporates sophisticated AI methods, including integrated Convolutional Neural Networks (CNN) and Backpropagation Neural Networks (BP-NN). These findings indicate that the integrated method is the most efficient in improving PH security systems.

1. Introduction

Over the last decade, AI technology has seen rapid progress and widespread use, mostly driven by significant advancements in big data and computer capacity. The methodologies derived from conventional AI research domains such as computer vision, voice recognition, processing of natural language, and robotics have been successfully used in several practical contexts, including medicine [1]. Recent progress in AI and Machine Learning (ML) algorithms has led to the creation of advanced epidemic monitoring systems. These systems may identify early indications of epidemics by analyzing publicly available data, such as news headlines and social networking information.

Epidemics exhibit exponential growth and may disseminate before health officials become mindful of their existence [3]. While announcements based on receipts from testing facilities and medical facilities are reliable, early detection can be accelerated and improved by utilizing open-source information, including press releases, social networking sites, geographic information, and time-based, ecological, and meteorological satellite information as early epidemic indicators. Timeliness is crucial in an outbreak. For instance, the outbreak of COVID-19 in Wuhan, China, may have originated from a solitary case that quickly escalated to many patients within a short duration [4]. Before the virus extended outside China, propagation might have been effectively controlled by case solitude, surveillance of contacts, and quarantine measures, therefore averting the worldwide pandemic. ID epidemics have non-linear complicated patterns not well represented by standard statistical methods [6].

Utilizing AI technology to analyze available information and conducting official outbreak investigations allows for the quick identification and prevention of severe epidemics. Open-source systems produce vast amounts of unprocessed data with ambiguous significance, which can potentially overpower individuals or result in deceptive interpretations. AI may organize, sort, and interpret this data to offer more reliable warning indicators for PH security [2]. AI technology can forecast the development of a pandemic in a detailed manner, which may help guide data-based local actions in the early phases of the outbreak. This can be crucial for effective management of the situation [8]. Complex, flexible AI-based representing systems, like multi-agent designs, can be used to simulate the emergence of epidemics in a time-wise and geospatially accurate manner. This is particularly useful due to the non-linear and undetermined nature of initial epidemic development, as it allows for directed and efficient PH security [5]. Furthermore, these structures may be used to ascertain the most efficacious therapies and their significance in mitigating the spread. AI technology has the potential to address the difficulties posed by inadequate PH systems, as well as problems like insufficient monitoring and the suppression of epidemic reporting [10].

The adoption of AI technology in PH has been sluggish, resulting in limited use of AI capabilities for the timely and early identification of epidemic indications [12]. AI can also tackle the problem of data censoring and the difficulties encountered by under-resourced healthcare institutions in low-income nations with inadequate staffing for PH monitoring. The Program for Monitoring Emerging Diseases (ProMED-mail) is the predominant outbreak warning system doctors use to report atypical occurrences using an indirect reporting mechanism [14]. This approach depends on health experts informing moderators about atypical outbreaks [11]. Although the system has enhanced the efficiency of conventional health system monitoring and has successfully identified several significant outbreaks, it still heavily relies on human accounting and fails to fully use the potential of freely available data and artificial intelligence [15]. An optimal system should effectively use and analyze various unorganized data, presenting it in a well-organized, refined, and structured manner that may facilitate prompt PH interventions and security [9, 13].

2. Methodology

This section presents an AI method called AI-EMPE for enhancing PH security systems [7]. The suggested approach converts a substantial amount of collected PH security incidents into separate incident characteristics and utilizes a DL-based detection technique to enhance EMPE.

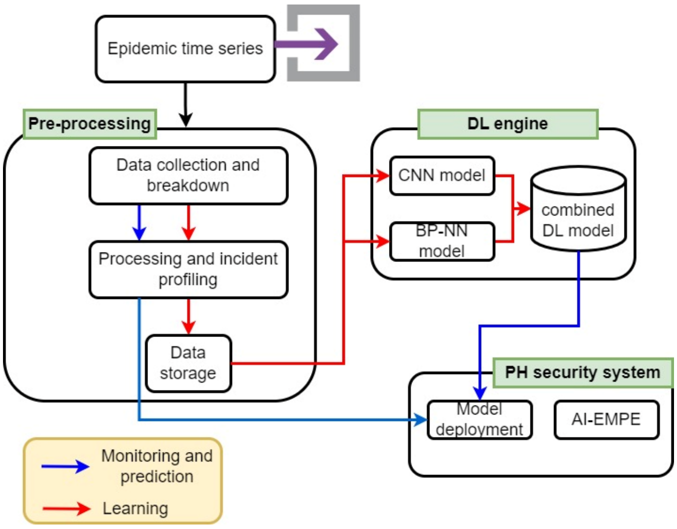

Figure 1 Architecture of AI-EMPE for enhancing PH security systems

Epidemic time series data has been given to the pre-processing phase. The initial pre-processing stage in the system, known as incident profiling, seeks to generate succinct inputs for different DL networks by converting unprocessed data. The AI-EMPE system performs data collection, data standardization, and incident profiling concurrently during the data pre-processing phase. These outputs are then used in the subsequent stages, as illustrated in Fig. 1. This phase occurs before both the data learning phase and the transformation of unprocessed PH security incidents into input data for the DL engine. The second AI-based learning engine utilizes two DLs (CNN and BP-NN) for modeling. During the data learning phase, the pre-processed data is inputted into two ANNs, and each ANN undergoes learning to determine the most precise model for monitoring and preventing epidemics.

DL model

A BP-NN is an example of an ANN that only receives inputs from the previous layer and exclusively transmits outputs to the succeeding layer. This research utilizes a BP-NN, a commonly used tool for PH security settings.

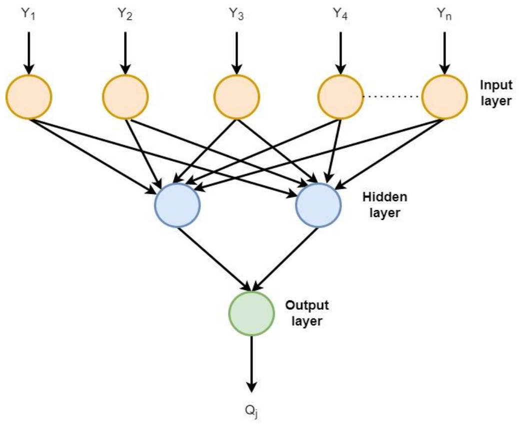

Figure 4 Framework of BP-NN

Fig. 4 displays the framework of BP-NN. Before using the NN for predicting, it must be trained. Assuming there are n neuronal inputs, m neurons that are hidden, and one output neuron, the two steps of a training procedure are as follows:

Hidden layer: The neuronal outputs in the hidden layer are computed as:

$$nt_j = \sum_{i=0}^{n} w_{ij} Y_i, \ j = 1,2 \ldots\ldots m \quad (1)$$

$$Q_j = sigma(nt_j), \ j = 1,2, \ldots\ldots m \quad (2)$$

Where nt_j is the value of activation for the j^{th} node, Y_i is the input to the hidden BP layer, Q_j is the output of the hidden layer, $sigma$ is the activation function (sigmoid function), and w_{ij} is the relative weight of the BP neural network.

Output layer: The neuronal output values are computed as follows:

$$Output_j = actf0 \sum_{j=0}^{m} w_{jk} Q_j, \ k = 1,2 \ldots\ldots n \quad (3)$$

$actf0$ is the linear activation function, w_{jk} is the relative weight of the output of the BP network, Q_j is the output of the hidden layer. Each weight is first given an arbitrary value, which is adjusted by the delta principle following the learning instances.

The DL model used the BP-NN to recognize the long-term association in the Weighted Infectious Diseases (WID) curves. Additionally, CNNs were employed to combine curves from different phases. To mitigate the issue of overfitting, this framework included residual linkages and a dropout function. The combined DL model outperformed autoregressive approaches and Gaussian process regression. The architecture comprises clustering/embedding, coder, and receiver modules for acquiring significant insertions of recurrence curves in an ongoing feature set. It also forecasts the highest intensity, peak duration, starting day, and subsequent occurrences of WID. The acquired embedded data expose the analogies between neighboring items, the correlations with time, variations in magnitude, and other patterns seen in various ID seasons.

3. Results and discussion

The "FluSight" project organized by the ADCP, which promotes the prediction of flu seasons at the national and regional level utilizing the WID information, has been used as an input dataset.

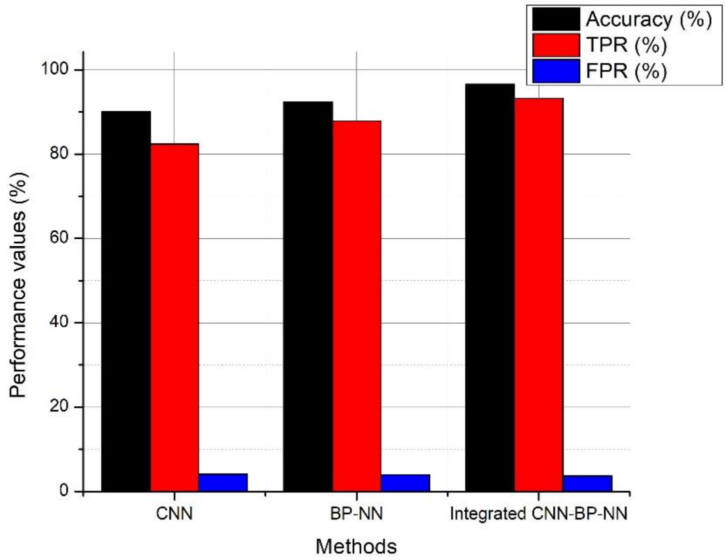

Figure 3 Accuracy, TPR, and FPR (in %) of various DL techniques in AI-EMPE for enhancing PH security systems

Fig. 3 illustrates the Accuracy, True Positive Rate (TPR), and False Positive Rate (FPR) (in %) of various DL techniques in AI-EMPE for enhancing PH security systems. The CNN model attains a precision of 90.1%, a sensitivity (TPR) of 82.4%, and a specificity (FPR) of 4.1%. The BP-NN model achieves a higher level of performance, with an accuracy rate of 92.4%, a TPR of 87.9%, and an FPR of 3.9%. The combined CNN-BP-NN model demonstrates superior performance compared to the separate models, achieving an accuracy of 96.6%, a TPR of 93.2%, and an FPR of 3.7%. These findings indicate that the integrated method is the most efficient in improving PH security systems. It provides more accuracy and higher rates of correctly identifying positive cases while having a lower rate of incorrectly identifying cases as positive compared to using individual models separately.

4. Conclusion and future scope

This study introduces an artificial intelligence technique known as Early Monitoring and Prevention of Epidemics (AI-EMPE) to improve the security systems of PH. The proposed method transforms many gathered PH security occurrences into distinct incident attributes and employs a DL-based detection method to improve EMPE. AI-EMPE utilizes advanced AI techniques, such as integrated CNN and BP-NN. The combined CNN-BP-NN model demonstrates superior performance compared to the separate models, achieving an accuracy of 96.6%, a TPR of 93.2%, and an FPR of 3.7%. These findings indicate that the integrated method is the most efficient in improving PH security systems.

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