Using a Convolutional Neural Network for Early Infectious Disease Detection During Public Health Emergencies

Dr. Abhijeet Madhukar Haval[1], Sharyu Bhushan Ikhar[2]
[1]Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.
[2]Research Scholar, Department of CS & IT, Kalinga University, Raipur, India

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ABSTRACT
Proactively detecting infectious illnesses aids in delivering superior therapy and improves preventing and managing such diseases. This work proposed a Convolutional Neural Network for early Infectious Disease Detection during Public Health Emergencies (CNN-IDD-PHE). The objective is to mitigate the significant damages that Public Health Emergencies (PHE) inflicted on individuals' well-being, everyday routines, and the whole national economy. Statistics on Tuberculosis (TB) cases in a city were gathered from July 2020 to 2022. The Structural Equation Model (SEM) is designed to ascertain the correlation between latent and observed variables by identifying the appropriate indicators and estimating the parameters. A prediction model using Convolutional Neural Network (CNN) has been developed. The strategy's efficacy is validated by assessing the loss value and accuracy of the detection model during both the training and testing phases. Hence, using CNN in Deep Learning (DL) for early warning systems performs better in predicting and alerting Public Health (PH) situations. This advancement is of great importance in enhancing the capabilities of early warning systems.

1. Introduction

Infectious Diseases (ID) have been present throughout human existence and continue to pose a significant hazard to PH in the present day. Despite medical progress, ID remains the primary cause of mortality, morbidity, impairment, and socio-economic upheaval on a global scale [1]. Timely and accurate diagnosis and the appropriate selection of therapy may significantly impact the prognosis of any illness. China enforces a system of categorizing and controlling infectious illnesses. The existing legally notified IDs are categorized into A, B, and C. In 2020, COVID-19 emerged as a new ID, adding to the existing pool of about 40 different types of IDs. The National Health Commission has decided to categorize certain infectious illnesses as Category B and Category C IDs for management purposes. Additional infectious disorders needing PHE surveillance will also be classified under category A administration [3]. Various management strategies are used for distinct categories of infectious illnesses. Category A illnesses must be promptly notified to the National Center for Prevention and Control of IDs within two hours of assessment. Category B and C should be notified within 24 hours of diagnosis [5]. When confronted with many illnesses, it is crucial to identify presumed IDs to effectively prevent and manage them accurately.

Developing a common benchmark for these thresholds continues to be a persistent difficulty. However, by adopting innovative technologies and approaches, we may work towards creating more precise and flexible early detection systems for influenza. Prior research has shown that influenza outbreaks differ across regions in China, with areas in Northern China often seeing a consistent peak throughout the winter. Conversely, several regions in Southern China, including Shanghai, see both seasons with distinct spikes [7]. DL is a field within artificial Intelligence (AI) and computer engineering [2]. DL has been used in ID research to evaluate monitoring information and detect patterns to predict future trends, therefore facilitating both the avoidance and management of infectious illnesses [9, 4].

DL is a suitable way for implementing an integrated influenza epidemic warning version in regions like China, where epidemic attributes differ significantly between the two sides of the country. Unlike the four influenza limit formulation approaches, DL does not require particular information circulation and category. The main goal of this research was to create a new and innovative DL model called the Self-Excitation Attention Residual Network (SEAR), specifically designed for analyzing influenza data with various pandemic features [11]. The framework used coronavirus monitoring information to forecast and provide early alerts for epidemic patterns inside China and later assess its effectiveness. SEAR results from combining ResNet with the Squeeze and Excitation Attention (SE attention) algorithm [13].

Guo et al., (2020) developed a predictive model using ANNs to determine the optimal period for avoiding illness and providing treatment. Through a detailed analysis of highly localized infectious illnesses in China, the severity of the epidemic and the necessity of issuing warning signals were identified. The experimental findings further confirmed the method's efficacy in identifying epidemic conditions [14]. Most previous research identifies and forecasts public crises based on the existing data conditions and objectives. Data gathering and analysis play a crucial role in some PH situations. The present level of PHE management effectiveness is suboptimal. CNN creates a robust early warning system using DL to analyze intelligence data and alert individuals about PH issues with substantial impacts.

Convolutional Neural Network for Early Infectious Disease Detection during Public Health Emergencies (CNN-IDD-PHE)

CNN

The CNN model consists of five deep convolutional layers and fully connected layers to build the classification pathway. Specifically, the suggested approach utilizes a hierarchical framework [6]. This guarantees that as the framework becomes more complex, max-pooling accumulates each level's impact and enlarges the channel of feature maps. A non-overlapping 2x2 max-pooling layer is applied to each convolutional layer to decrease performance measures and introduce transfer invariance [8]. The Rectifier Linear Units (ReLUs) are chosen to activate after the convolutional and fully connected layers because they are less likely to get saturated and can be calculated more quickly than the sigmoid parameter [10]. This research aims to reduce the substantial harm PHE caused to people's welfare, daily activities, and the whole national economy. CNN develops a robust early warning system using DL to evaluate intelligence data and notify individuals about PHE that has significant consequences.

For the pth convolutional layer, input is denoted as I^{p-1} with C_{p-1} channels. For some ith feature map, encoding representation (e) is given by

$$e_i^p = \sum_{j=1}^{C_{p-1}} I_j^{p-1} * R_{ji}^p + S_i^p, i = 1,2,.....,C_p \tag{1}$$

$$H_i^p = F\left(e_i^p\right) \tag{2}$$

where R_{ji}^p denotes ith kernel, S_i^p denotes bias of pth layer, * is the two-dimensional convolution operation, F is the rectified linear units given as

$$F(I) = \max(0, I) \tag{3}$$

Zero padding is used to uphold the size of feature plots after convolution. Zero padding is given by $\left(\frac{r-1}{2}\right)$ where r denotes the size of the kernel. During max-pooling, locations are set with pooling values, and other locations are padded with zeroes. Max-pooling and un-pooling are represented as,

$$downH^p = D\left(H^p\right) \tag{4}$$

$$upH^p = U\left(downH^p\right) \tag{5}$$

Now, reconstruction X^{p-1} is given by

$$X_j^{p-1} = F\left(\sum_{i=1}^{C_p} upH_i^p * K\left(Q_{ij}^{p-1}\right) + c_j^{p-1}\right), j = 1,2,......,C_{p-1} \tag{6}$$

Q denotes kernels in de convolutional layers, $K(.)$ is the kernel Q flipped in two dimensions [12]. To measure reconstruction loss, the loss function is denoted in terms of Mean Square Error (MSE) as

$$L(R, S, Q, c) = MSE^p \tag{7}$$

$$MSE^p = \sum_{j=1}^{C_{p-1}} \frac{1}{2n} \left\| I_j^{p-1} - X_j^{p-1} \right\|^2 \tag{8}$$

n is the size of the feature corresponding to $(p-1)^{th}$ layer.

SEM and IDD

The SEM is a statistical method integrating factor evaluation and route analysis to analyze multivariate data. It compensates for the limitations of classic statistical approaches and becomes a crucial tool for analyzing multiple variables. SEM comprises two main components: the measurement and the architectural component. The architectural component refers to the inner structure primarily representing latent variables, namely the causal link between undetectable factors. The measurement component provides the external framework, depicting the obvious factors and their connection with the measurable and concealed variables. Ellipses in the architectural component symbolize latent variables. The causal link between concealed variables is established by the arrow that points from the reason to the consequence. The term "cause" may also be considered an internally concealed variable, whereas "effect" is an independent variable. The architectural component may have numerous dependent factors. A dependent factor may be associated with many latent variables. To develop SEM, the following procedures must be undertaken.

Step 1: The relevant context of the occurrence is examined- The correlation between apparent characteristics is examined based on the relevant context of the occurrence. The explicit variable associated with each concealed variable is established via logical deduction and presuppositions. Next, the model's predictive structure for the variable is acquired.

Step 2: The concealed and apparent variables are established- The link between them may be described as follows: the concealed variable serves as a comprehensive overview of the apparent variable, while the apparent variable acts as an illustration that indicates the presence of the concealed variable.

Step 3: SEM's route diagram- The model architecture is designed to represent the link between variables using visuals graphically.

Step 4: Estimating parameters- The Partial Least Squares (PLS) approach is used to calculate the variables of the SEM. This strategy is assumption-free for making predictions regarding occurrences. It exhibits rapid convergence and has substantial computational capabilities.

Building a model to forecast for IDD based on the SEM using CNN involves two stages: training and recognition. During training, CNN uses supervised learning to train on the acquired sample information. The activation value of the input neuron is sent to the output layer via the concealed layer, and the neurons in the output layer react to the input sequence of the network. When the magnitude of the forecasting error is significant, the training process is iterated until its final requirement is satisfied, ensuring that the final result value at this point is precise.

2. Results and discussion

This project utilizes the Scrapy crawler platform to extract pertinent data about TB. Statistics on TB cases in a city were gathered from July 2020 to 2022. Additionally, divide the text into individual words and remove any unnecessary elements. The Lenovo Intel(R) Core(TM) i5-7400CPU, with 8GB of RAM, is evaluated on a Windows 10 OS. The collected data consists of 425 samples divided into 340 training specimens, 35 validation specimens, and 50 test specimens.

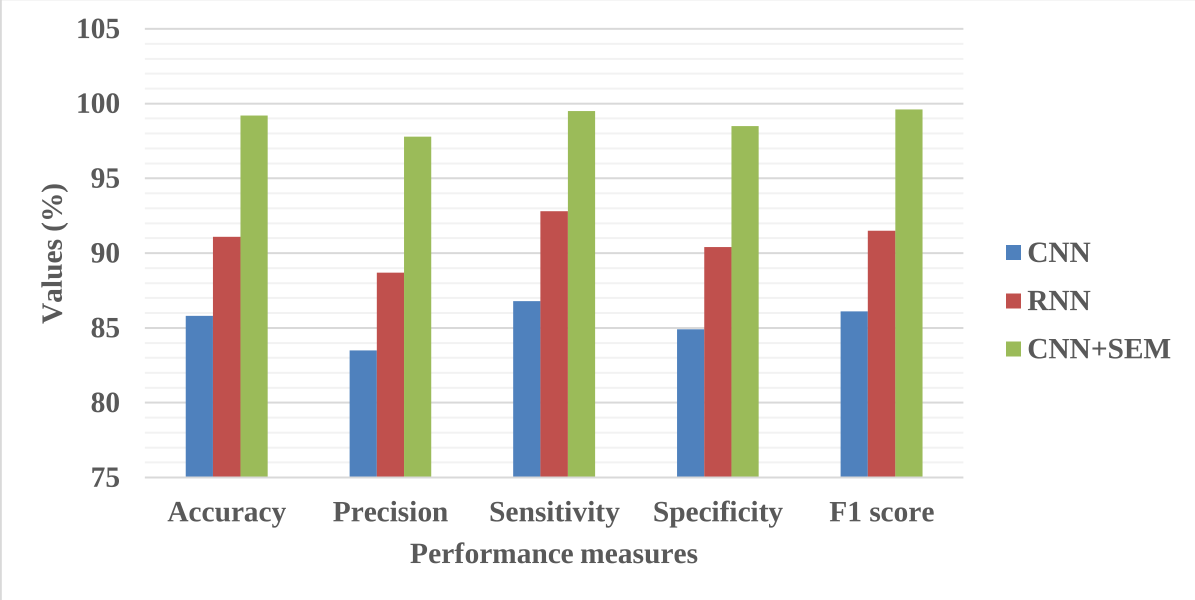

Figure. 1 Performance analysis (%) of various DL models for early IDD during PHE**.**

Fig. 1 depicts the performance analysis (%) of various DL models for early IDD during PHE. The CNN model has an accuracy rate of 85.8% and a precision rate of 83.5%, suggesting that it is quite dependable but not the most optimal. The RNN model surpasses this, with an accuracy of 91.1% and a precision of 88.7%, indicating superior capability in identifying early IDDs. The CNN+SEM model surpasses both models, achieving an amazing accuracy of 99.2% and precision of 97.8%. This model has exceptional sensitivity (99.5%), specificity (98.5%), and F1 score (99.6%), showcasing its outstanding performance and resilience in promptly detecting IDs during PHE.

3. Conclusion and future scope

The study introduces a CNN-IDD-PHE to detect infectious diseases early during public health emergencies. The goal is to reduce the substantial harm caused by PHE to people's welfare, daily activities, and the whole national economy. Data on Tuberculosis (TB) cases in a city were collected from July 2020 to 2022. The Structural Equation Model (SEM) is a statistical technique used to determine the relationship between latent and observable variables by choosing suitable indicators and estimating the parameters. A CNN prediction model has been created. The technique's effectiveness is confirmed by evaluating the detection model's accuracy, precision, sensitivity, specificity, and F1 score. The CNN+SEM model surpasses both CNN and RNN models, achieving an amazing accuracy of 99.2% and a precision of 97.8%. This model has exceptional sensitivity (99.5%), specificity (98.5%), and F1 score (99.6%), showcasing its outstanding performance and resilience in promptly detecting IDs during PHE.

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