An Integrated Climate and Spatio-temporal Determinant for Influenza Forecasting based on Convolution Neural Network

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ABSTRACT

We have proposed convolution neural network (CNN) for influenza forecasting. Our experiment model provided time series datasets consisted of climate variables and the spatio-temporal forms. The climatic variables have included precipitation, snowfall, maximum temperature, and minimum temperature. The spatio-temporal procedure has had two features, a flu feature is the influenza patient count in different time of focus region node. The second feature is the influenza patient count from influenza carrier in adjacent region. We assumed that asymptomatic patients which is a carrier of influenza. They will be able to travel anywhere whenever needed on pedestrians, vehicles or planes in their positions. We have provided two effect flu factors in climatic and human into deep machine learning for accurate predictions of influenza outbreaks results. The integrated variables influenced effectively influenza node predictions. The research compared models on recurrent neural network (RNN), long short-term memory neural network (LSTM) and convolution neural network (CNN). The term of Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Root Mean Square Percentage Error (RMSPE) captured for evaluate model. The performance denoted following resulted the convolution neural network (CNN) combined with Integrated climate and spatio-temporal determinant. CNN approved significant influenza forecasting more effectively than recurrent neural network (RNN) and long short-term memory neural network (LSTM).

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning approaches**;

KEYWORDS

Time series, Forecasting, Influenza, Convolution neural network, Climate data, Spatio-temporal

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1 INTRODUCTION

Influenza (flu) is a contagious respiratory disease caused by influenza viruses. Symptoms of flu can cause mild to severe. This species has a variety of species. Flu can be global spread many people in the world. In addition to causing influenza in people, in animals, such as pigs, birds and horses. The Centers for Disease Control and Prevention, National Center for Immunization and Respiratory Diseases (NCIRD) [1] reported 402 million patients of flu in United States, during 1997 - 2016. The peak flu in 2014 was 38 million illness. Some flu patient might not be in system reports. In some weakness patient might be death. The flu outbreak which swept the globe in 2009 and 2010, sickened 60.8 million Americans. Follow 2012, 2013 hospitalized 710,000 and killed 56,000, according to CDC data. Deaths from the current outbreak will likely far outstrip those of the 2009-2010 season. If the relevant health authorities early know the influenza outbreak will inhibit the spread of the disease effectively. The best way to prevent seasonal flu is to get highest covered vaccinated every year and warning people to careful infected flu from nearly contact disease people.

In order to accurate the resulted of influenza prediction. There are three approaches of influenza forecasting. At first stage, the researchers used the compartment model for influenza forecasting, model compartmental are intuitive in terms of capturing the status of infected populations. Susceptible-Infected-Recovered (SIR) [2, 3], Susceptible-Infected-Recovered-Susceptible (SIRS) [4, 5], and Susceptible-Exposed-Infected-Recovered (SEIR) [6, 7] are Compartmental model that are deterministic and inflexible while calibrated in terms of dynamic capture the influenza epidemic. The second stage, statistical methods and time series such as Box-Jenkins, some automated regression integration (ARIMA) [8], and Generalized Autoregressive Moving Average (GARMA) [9] resulted high accuracy forecasting the spread of influenza.

In the present stage, deep learning models have been widely instrumented in disease prediction over the years. Stacked Linear Regression [10], Support Vector Regression [11] Binomial [12] and Classification and Regression Trees [13]. Machine learning methods are a more flexible method of sorting data in terms of influencing external variables. It is expensive compared to statistical models because it requires retraining when new datasets arrive.

A novel data-driven model for real-time influenza forecasting [14] proposed long short-term memory (LSTM) comparison with ARIMA model for influenza prediction. LSTM processed the deep-learning model was able to effectively capture the temporal dynamics of flu spread in different geographical regions. The extension of deep-learning model captures the influence of external variables that include the geographical proximity and climatic variables. The climate factor consists of humidity, temperature, precipitation and sun exposure in future stages. The model consistently performs well for both the city scale and the regional scale on the Google Flu Trends (GFT) and Center for Disease Control (CDC) flu count. The results offer a promising direction in terms of both data driven forecasting methods and capturing the influence of spatio-temporal and environmental factors for influenza forecasting methods. The mention study had provided two variables, the climatic variable and flu count data of neighborhood region. Our research had increased flu count data from focus region into proposed CNN model which integrated with climate variable and flu count history from node and adjacent region. The flu count feature approved from node and spatio-temporal data in geographical location for effectively prediction.

Convolutional Neural Networks for Text Hashing [15] offers a new text hash framework with convolutional neural networks. More specifically, the first procedure model has embedded the keyword features into compact binary code. The keyword attribute with the area that maintains the constraint, meanwhile, the great model technique consisted word property and position property are introduced together in the network. Besides word embeddings, each word to the two ends also encodes the relative distances of one text into vectors in experiment of CNN. The explicit properties to suit previously trained binary code combined from convolutional resistant to implicit properties. An external tags / labels did not require for a successes basic approach. The model was tested with a single short message dataset and one normal text dataset via multi-state hash method. The word feature convolution with word position feature approach over several state-of-the-art hashing. We proposed CNN model processed flu count feature with flu count in node and adjacent region integrated with climate variable. Those combined features effected a significant high accuracy influenza forecasting.

The first feature is a flu count on the focus node. The reciprocal feature is a flu feature occurred from history flu count in adjacent region around focus region. The contacts of influenza disease in human who can travel to everywhere and every time. In addition, flu has the potential to spread in places where people have a lot gathering such as school, university, football stadium, bus station, airport, shopping center, hotel, hostel etc. In comparison, our model confided influenza forecasting via RNN, LSTM and CNN with two factors from territory region of United Stated. This study proposed an integrated climate variable and two features of spatio-temporal. The convolution neural network improved an accuracy of influenza forecasting on increased an adjustment spatio-temporal factor with region node and adjacent neighborhood regions. Influenza influenced from people in an adjacent region on geographical area, the encounter of people in United Stated provided this factor for significant in flu spread forecasting.

2 PRELIMINARIES

In this proposed convolution neural network model have defined two influencing factors for influenza forecasting: (1) climate factor acquired on snowfall, precipitation, maximum temperature and minimum temperature; and (2) a spatio-temporal factor significance from flu count in region node and adjacent regions around focus region on geographical area.

2.1 Climate multivariate data

The climatic data was downloaded from Climate Data Online (CDO) [16] include precipitation (PRCP) in tenths of mm unit, snowfall (SNOW) in tenths of mm unit, maximum temperature (TMAX) in tenths of degrees C, and minimum temperature (TMIN) in tenths of degrees C. Those climate datasets of United States were itemized from Global Historical Climatology Network (GHCN). Daily online data has been transformed from 284,778,495 daily datasets into weekly data, computed with flu count weekly data [17]. The climatic data accumulate by quarters of years between 2009-2016. We transformed dataset into scaled values to denote the time-series data of climate variables and flu count which are nun-linear line chart. Our study used two determinants for computed flu count forecasting with each feature variable in each node(region).

2.2 Spatio-temporal data

In our experiment model, 10 regions flu count of United States dataset between 1997-2016 from the Centers for Disease Control and Prevention (CDC), National Center for Immunization and Respiratory Diseases (NCIRD). Climate United States dataset from National Oceanic and Atmospheric Administration (NOAA). The geographical region of USA is presented in Figure 1. This study referenced historical flu count data in geographical location followed in Table 1 which is represented region node and adjacent regions. The focus node has around with adjacent regions. We divided five groups of node regions with the adjacent regions: single adjacent region is region 1, two adjacent region is region 2 and region 10, three adjacent regions is region 3 and region 9, four adjacent region is region 4, region 5, region 6 and region 7, the highest number of adjacent regions is region 8. We trained each dataset with 331 samples and 85 samples for validation. Dataset consisted flu count of 10 regions of United States. Each region has single model and implemented 10 submodules(regions) in each RNN, LSTM and CNN model.

2.3 Convolutional Neural Network (CNN)

The traditional multilayer perceptron (MLP) evolved the CNNs architecture. This is to guarantee a certainly degree of shift and distortion invariance [18]. The invent idea have merged three assistant involved local receptive fields, common weights, and spatial and temporal subsampling. CNNs have miscellaneous trainable multilayer levels [19]. Each input and output in each level is the sets of feature maps [20]. For the colored image input, a two-dimensional array that holds a color channel of the inputted image map to feature map, for videos CNNs computed a three-dimensional array and a one-dimensional array for audio input. The output represents from every location in the input, features will be exported and presented as output level. Generally, every level of CNNs have three

Figure 1: The region maps of USA(Regional Office Map, 2018).

Table 1: Node and adjacent regions.

Node	Adjacent regions
Region 1	Region 2
Region 2	Region 1, Region 3
Region 3	Region 2, Region 4, Region 5
Region 4	Region 3, Region 5, Region 6, Region 7
Region 5	Region 3, Region 4, Region 7, Region 8
Region 6	Region 4, Region 7, Region 8, Region 9
Region 7	Region 4, Region 5, Region 6, Region 8
Region 8	Region 5, Region 6, Region 7, Region 9, Region 10
Region 9	Region 6, Region 8, Region 10
Region 10	Region 8, Region 9

layers, the first layer is a non-linearity layer. The second layer is a filter bank layer and finally layer is a feature pooling layer. Finally, several convolution and pooling layers can be single or multiple which is fully connected layers will be present.

2.4 Proposed Influenza forecasting model

This study offered an integrated climate determinants includes precipitation (PRCP), snowfall (SNOW), maximum temperature (TMAX), and minimum temperature (TMIN) into each 1D convolution neural network channel combined with two spatio-temporal features; feature one is the volume of flu count data at the focus region node and extra feature derived from flu count from adjacent regions of the focus region inputed into attached to 2D convolution model. Integrated climatic and spatio-temporal determinant have flattened and concatenated final flu count prediction. The influenza forecasting model based on convolution neural network which improved an accuracy of influenza forecasting by increased the spatio-temporal factor with adjacent neighborhood regions. Influenza epidemic influenced from people in an adjacent region on geographical area. The encountered of people in United Stated provided this significant factor in flu spread. The model procedure present in Figure 2

The CNN influenza forecasting proposed CNN computed, comparison experiment based on RNN, LSTM, and CNN computed multivariate time-series flu dataset consisted with four climate variables and neighbors flu count datasets applied to forecast flu count in difference time steps and difference Dense neural architecture. We provided a deep learning model with multi basic neural network layers. The advantage is integrated climate variable and a volume of flu count in difference a volume of adjacent regions effected whole spread of influenza. Big data approved deep learning to extracted and learned effectively pattern for prediction.

The CNN model had five channels. We defined input X into 1D convolution on each four channels. 1D convolution resulted from one of climate variable C consisted of precipitation (PRCP), snowfall (SNOW), maximum temperature (TMAX), and minimum temperature (TMIN) in previous weekly lags time. The input data processed into each channel with 1D convolution four channels approaches followed to Eq. 1).

$$C^{n} = \left\{ C^{n}_{j1},\ C^{n}_{j2},\ C^{n}_{j3},\ \ldots,\ C^{n}_{jT} \right\} \quad (1)$$

Where C^{n} = climatic variable
n = focus region node | $n \in \{1, 2, 3, \ldots, 10\}$ j = four climatic variable time series j | $j \in$ {PRCP, SNOW, TMAX, TMIN }
T = time series at time *1* to *T*

$$C^{3} = \left\{ \begin{bmatrix} C_{prcp1} \\ C_{snow1} \\ C_{tmax1} \\ C_{tmin1} \end{bmatrix}, \begin{bmatrix} C_{prcp2} \\ C_{snow2} \\ C_{tmax2} \\ C_{tmin2} \end{bmatrix}, \begin{bmatrix} C_{prcp3} \\ C_{snow3} \\ C_{tmax3} \\ C_{tmin3} \end{bmatrix}, \begin{bmatrix} C_{prcp4} \\ C_{snow4} \\ C_{tmax4} \\ C_{tmin4} \end{bmatrix} \right\} \quad (2)$$

The climatic data of region 3 over 4 time steps followed in Eq. 2) and Figure 2

For example, given a climate data of region 3; PRCP = {6,8,2,2,. . .}, SNOW= {5,4,2,7,. . .}, TMAX = {6,2,8,5,. . .} and TMIN = {1,3,5,7,. . .}. The climatic input follows Eq. 3).

$$C^{3} = \left\{ \begin{bmatrix} 6 \\ 5 \\ 6 \\ 1 \end{bmatrix}, \begin{bmatrix} 8 \\ 4 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 2 \\ 2 \\ 8 \\ 5 \end{bmatrix}, \begin{bmatrix} 2 \\ 7 \\ 5 \\ 7 \end{bmatrix} \right\} \quad (3)$$

On a fifth channel of flu prediction model have defined spatio-temporal *A* from two feature; first feature constructed from actual flu count history of focus node and the second feature is a flu count data a from node and all neighbor k of node *A* from previous week *t*. Both directed into 2D convolution neural network approaches followed in Eq. 4).

$$A^{n}_{k} = \left\{ a^{n}_{i1,k} \right\} \quad (4)$$

Where A^{n}_{k} = spatio-temporal flu variable
n = focus region node | $n \in \{1, 2, 3, \ldots, 10\}$ *i1* = first time data
a = actual flu count of adjacent region area
k = adjacent of focus node | $k \in \{1, 2, 3, \ldots, 10\}$

The dataset training formed as $\{x_i,\ y_i\}$ at time *i1* to *it* | $i \in \{1, 2, 3, \ldots, N\}$ from N examples. The sequence of training is $(x_i,\ y_i)$, where $x_i = A^{n}_{k} = \{a^{n}_{i1,k}, a^{n}_{i2,k}, a^{n}_{i3,k}, \ldots, a^{n}_{it,k}\}$ and $y_i = \{a^{n}_{i1+w}, a^{n}_{i2+w}, a^{n}_{i3+w}, \ldots, a^{n}_{it+w}\}$, w = sliding window size. For example, given a flu count of region_3 node = [1, 1–3, 3, 3, 6,. . .] and flu count of three adjacent region consisted of Region_2 = [3, 3–5, 5, 7, 8,. . .], Region_4 = [3, 4, 6, 7, 7, 9, 9,. . .], Region_5 = [1–4, 4, 6, 8,. . .] and sliding window size = 4. The spatio-temporal input x follows Eq. 5).

$$A^{3}_{1,(2,3,4,5)} = \left\{ \begin{bmatrix} 4 & 2 & 7 & 3 \\ 5 & 1 & 3 & 2 \\ 3 & 3 & 9 & 4 \\ 8 & 1 & 6 & 8 \end{bmatrix} \right\} \quad (5)$$

3 RESULTS

Comparison of special neural network model; recurrent neural network(RNN), long short term memory neural network(LSTM) and convolution neural network(CNN) is implemented on Python and Tensorflow library. The flu count data and climate data were selected and computed on five experiments from 1997-2016. The results extracted from each ten regions model. The training data

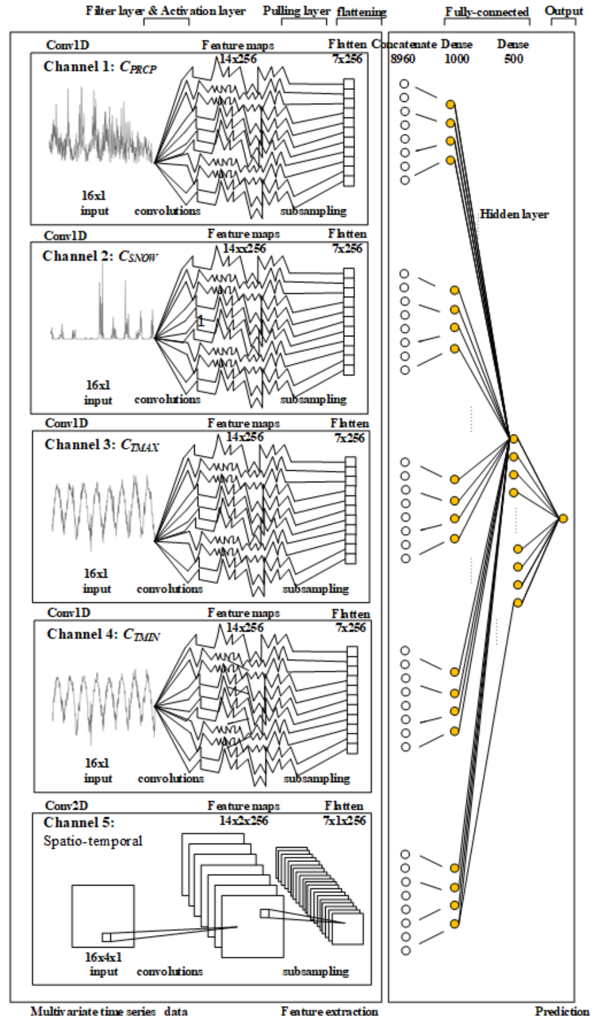

Figure 2: The region 3 dataset pattern of proposed CNN for influenza forecasting.

was trained with four, eight, twelve and sixteen timesteps and differential two hidden DENSE neural architecture.

3.1 Evaluation metrics

Each model is compared and evaluated with three metrics consisted of Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Root Mean Squared Percentage Error (RMSPE). These were used in [21, 22]. According to the Indicator of performance forecasting We defined A is the actual flu count value, F is the resulted forecast flu value, and N is the number of observations, and the vertical bars stand for absolute values. The term of metrics which used for evaluated models following:

The mean absolute percentage error (MAPE): MAPE is a measure of prediction accuracy of a forecasting method in statistics, usually

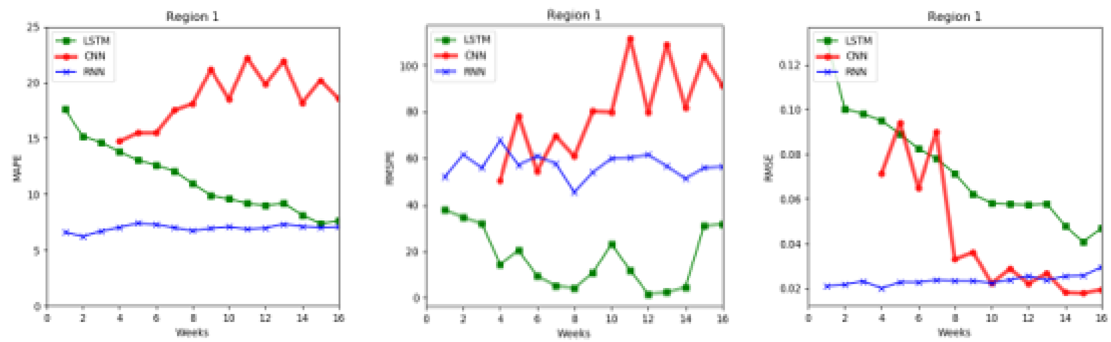

Figure 3: MAPE, RMSPE and RMSE error chart of the RNN, LSTM and CNN influenza prediction model of region1 over 16 weeks.

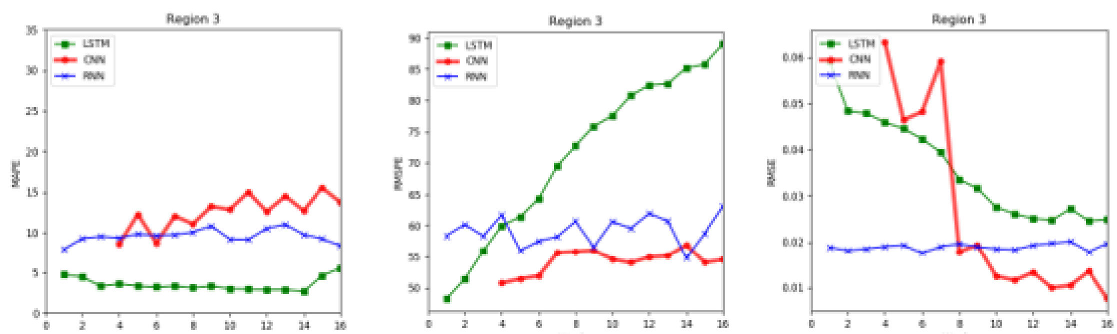

Figure 4: MAPE, RMSPE and RMSE error chart of the RNN, LSTM and CNN influenza prediction model of region3 over 16 weeks.

expresses accuracy as a percentage, and defined by Eq. 6).

$$MAPE = \frac{\sum \frac{|A-F|}{|A|} \times 100}{N} \tag{6}$$

The root mean squared error (RMSE): RMSE is a quadratic scoring rule that also measures the average magnitude of the error. Reprensent the square root of the average of squared differences between prediction and actual observation, and is defined in Eq. 7).

$$RMSE = \sqrt{\frac{1}{N}\sum (A-F)^2} \tag{7}$$

The root mean square percentage error (RMSPE): RMSPE is compute the root mean squared percentage error regression loss, and is defined in Eq. 8).

$$RMSPE = \sqrt{\frac{\sum \left(\frac{A-F}{A}\right)^2 \times 100}{N}} \tag{8}$$

3.2 Resulted of experiments

The results of predictive values compared in difference timesteps, difference DENSE and difference neural network. The CNN model was attuned a filter size vary on an amount of adjacent neighbor region. The convolution neural network (CNN) indicated that flu count on node and flu count in the adjacent neighbor affect to flu epidemic. The CNN model of region area with higher timesteps and higher DENSE architecture have more effectively predictive flu value than recurrent neural network (RNN) and long short-term memory neural network (LSTM). A decreased effectively predictive affected by lower steps of adjacent integrated determinant and lower DENSE architecture. The average performance of MAPE, RMSE, and RMSPE computed on 1600 experiments of ten regions (each region, each model was provided 5 experiments) via RNN, LSTM and CNN in difference timesteps and DENSE architecture. The results are shown in Table 2

Figure 3 exposed the results of a prediction for influenza in the United States with RNN, LSTM and CNN models.

An errors values processed in the term of MAPE, RMSPE and RMSE. Comparison of predictive values from these models through a volume of actual flu CDC datasets. The proposed CNN model outstanding influenza prediction signal presented over eight weeks was improved and more efficient than RNN and LSTM. Significantly considering the overall United Stated, two influencing factors are climate and flu count in region node and adjacent regions. We expose the chart of indicator performance error by the regions with the least number of adjacent regions: region 1 (Figure 3), region with the moderate number of adjacent regions: region 3 (Figure 4), and region with the highest number of adjacent regions. The most is the region 8 (Figure 5). A climate variable and the three size of adjacent

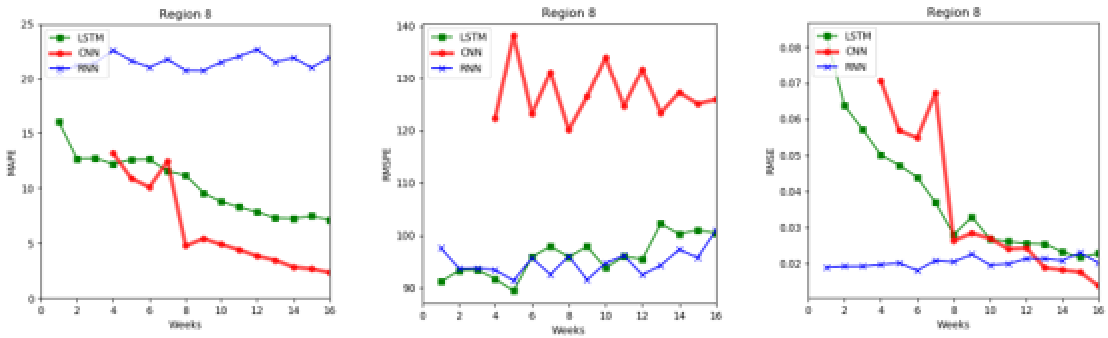

Figure 5: MAPE, RMSPE and RMSE error chart of the RNN, LSTM and CNN influenza prediction model of region8 over 16 weeks.

Table 2: Results of RNN, LSTM and CNN of Flu predicted over 8, 12 and 16 weeks.

MODEL	Architectures		Timesteps								
	Dense(1)	Dense(2)	8			12			16		
			MAPE	RMSPE	RMSE	MAPE	RMSPE	RMSE	MAPE	RMSPE	RMSE
	64	32	28.120	74.065	0.073	29.773	69.978	0.074	31.792	69.291	0.077
RNN	500	250	28.422	74.325	0.048	28.485	76.278	0.051	32.218	75.543	0.052
	1000	**500**	**29.048**	**76.353**	**0.045**	**30.125**	**75.374**	**0.048**	**30.125**	**73.911**	**0.048**
	64	32	9.854	24.346	0.047	10.751	24.355	0.048	10.830	25.688	0.047
LSTM	500	250	7.854	15.914	0.029	8.751	15.386	0.031	9.812	16.261	0.031
	1000	**500**	**7.641**	**14.427**	**0.024**	**8.384**	**14.838**	**0.027**	**9.577**	**15.386**	**0.029**
	64	32	30.119	83.376	0.055	29.043	76.191	0.046	28.782	79.231	0.039
CNN	500	250	26.811	72.213	0.018	26.811	72.345	0.018	18.195	78.801	0.033
	1000	**500**	**26.298**	**79.108**	**0.016**	**26.496**	**76.654**	**0.011**	**26.590**	**80.929**	**0.008**

regions approved the weather variables and contact flu person impacted effectively influenza forecasting based on convolution neural network.

Table 2 shows the performance of influenza forecasting in term of MAPE, RMSE, and RMSPE in the associate of RNN, LSTM and CNN. The performance of CNN resulted effective prediction which computed with timesteps = 8 weeks and DENSE(1), DENSE(2) =1000,500 resulted RMSE of CNN = 0.016 while RMSE of LSTM = 0.024 and RMSE of RNN = 0.045. According experiment decrease timesteps this model continued effective performance denotes RMSE of CNN= 0.011 while RMSE of LSTM = 0.027 and RMSE of RNN = 0.048 over 12 weeks. The result of experiments significant that the CNN has been inferior to extracted and learned the influenza spread pattern from a little time series data at four time steps. At over eight timesteps of CNN significant continued better RMSE error. The finest of RMSE effective performance is on RMSE of CNN= 0.008 while RMSE of LSTM =0.029 and RMSE of RNN = 0.048 over timestep = 16 weeks and DENSE(1), DENSE(2) = 1000,500.

4 CONCLUSION

In this model, we demonstrated the prediction model of influenza in the United States computed via RNN, LSTM and CNN. The dataset contained two determinants; first is a climate data constructed on snowfall, precipitation, minimum temperature, and maximum temperature. The second is a flu count consisted of flu count on region node and a volume of influenza cases from adjacent regions, as we assumed that the patients in adjacent regions have been met and became a factor of higher influenza epidemic. We defined the dataset of an experiment set default timestep was over four, eight, twelve, and sixteen weeks. The greatest effective model was CNN on sixteen timestep weeks, which was statistically significant. This experiment demonstrated that machine learning learned from time-series data with four-month time-series data resulted the prediction of influenza less erroneous. In this paper we used 10 regions data input in United State because both climatic and spatio-temporal source data were completed data from trust organization. For widely benefit, we are looking for more adjacent node source data to implement influenza forecasting in our model. We expect our CNN model could be used to forecasting other clinical outbreak and other infectious diseases.

In the future, we may conduct a disease transmission studies using location data which comprises large numbers of people as a cofactor of spatio-temporal data. The coordinates of place dataset based on location data from google map, which denote the flu prognosis more precise.

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