Global geographical climate impacts on the spread and death of COVID-19 in Asia and America

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Received: 25-October-2020; Revised: 21-January-2021; Accepted: 26-January-2021
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Abstract
A viral infection which is named as Coronavirus disease 2019 (COVID-19) is triggered by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). To date, almost two million cases and over 100,000 deaths from the disease caused by this virus were reported worldwide. The environmental and meteorological factors are claimed to stimulate the spread of the virus in which the transmissibility in terms of climatic fluctuations increases exponentially with high humidity and low temperature. In an attempt to understand this epidemic, there is a need to investigate the factors that could impact the spread and death of COVID-19. We, therefore, proposed to investigate global geographical climate impacts on the COVID-19 spread and death in Asia and America. The Artificial Neural Network (ANN) is a network that seeks to replicate neuronal functionality in the human brain. It is the preferred instrument for several predictive applications of data mining, due to its strength, versatility, and simplicity. A dataset of COVID-19 cases and deaths revealed from 49 states in America and 41 countries in Asia during April 2020 were tested. Nine covariates were used in the networks which are Cases, Death, High Temperature, Low Temperature, Average Temperature, Population, and Percentage of Cases over Population, Percentage of Death over Population, and Total Cases. Based on the analysis conducted, the global geographic climate is observed to have the least impacts on the COVID-19 spread and death in Asia and America particularly. However, different results could be reflected by different datasets used in the future.

Keywords
Geographical climate, Covid-19, Asia, America, Artificial neural network.

1. Introduction
A viral infection which is named as Coronavirus disease 2019 (COVID-19) is triggered by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) [1]. Presently, there are reportedly almost two million infections and more than 100,000 worldwide deaths from the disease caused by this virus [2]. The medical and research groups are working together to reduce the serious effects of the outbreak. With more than 327,000 cases registered, the United States of America reported the highest rise since the beginning of August 2020, in newly reported cases. Meanwhile, the progressive decline in the occurrence of cases and deaths in the area of South East Asia were reported [3].

It is therefore important to generate awareness of mechanisms that contribute to the COVID-19 spread and death, its effect on host immunity, and to have a better understanding on how to strengthen our preparedness for any potential transmission of this pandemic outbreak.

Numerous studies have been conducted to examine causes that may influence the spread of COVID-19 [4] in an effort to explain these epidemics. The transmission agent, host, and surroundings are the three factors that affect the communicable diseases epidemiology [5]. Generally, SARS events have been partially related to environmental factors [6]. The air temperature was another environmental factor. In colder environments, the respirational system infections are more frequent and lesser at higher climatic temperatures since they might not be able to endure climate change [7]. In terms of climatic
variability, the transmissibility of COVID-19 is close to the influenza virus, where it increases exponentially with high humidity and low temperature [8], signifying that climatic variables may have a major effect on viral transmission. The meteorological conditions also tend to affect the spread of the virus [9].

In another note, the Artificial Neural Network (ANN) is a network that seeks to replicate neuronal functionality in the human brain. A neuron can be recognized as a transmitter which interrelates with a specific output when stimulated by a particular input or input array [10]. It is the preferred instrument for several predictive applications of data mining, due to its strength, versatility and simplicity. The predictive neural networks are principally helpful for applications with complex underlying mechanisms, such as wind speed prediction model [11], forecasting of student’s success [12], predicting surface settlement [13], global solar radiation prediction [14], and many more. ANN is widely used in predictive applications [15], for instance, the radial basis function (RBF) and multilayer perceptron (MLP) networks, are controlled in a way that the known target variable values is compared to the model-predicted results.

Thus, on the basis that COVID-1919 plays an important role in various climatic conditions, there is a need to separate the relations between environmental variables, such as global geographical climate (average, minimum, and maximum temperature), population, and COVID-19 cases and death in humans. We, therefore, proposed to investigate the following:

- global geographical climate impacts on the COVID-19 spread and death in Asia
- global geographical climate impacts on the COVID-19 spread and death in America
- most important factors leading to COVID-19 spread and death in Asia and America

The employment of ANN is expected to contribute in understanding the impacts of global geographical climate towards COVID-19 spread and death. The arrangement of the remainder of this paper is as follows: the data background is explained in Section 2. The methods, including a description of the methodology and ANN structures, are covered in Section 3. In Section 4, our results and discussions are described. Finally, we present our conclusion in Section 5.

### 1.1 Data background

The easiest way to format your manuscript is to A COVID-19 dataset for Asia and America that includes the number of cases and deaths from the European Centre for Disease Prevention and Control (ECDPC), global regional climate data from the Weather Forecast, and demographic data from the Current World Population America during April 2020 were compiled.

Forty one countries in Asia and 49 states in America were covered by the dataset. However, three countries, Palestine, Tajikistan and Yemen, were removed from Asia as a result of incomplete data distribution. The data from descriptive statistics for Asia and America can be referred in Table 1 and Table 2 distinctly.

| Table 1 | Descriptive statistics of Asia |
|---------|--------------------------------|
| N       | Valid cases | Deaths | High Temp (°F) | Low Temp (°F) | Average Temp (°F) | Population | Total Cases | Total Death | Percent Cases/ Population | Percent Death/ Population |
|        | 38          | 38      | 38             | 38             | 38                | 38         | 38          | 38          | .0000         | .0000            |
|        | 3           | 3       | 3              | 3              | 3                 | 3          | 3           | 3           | .0000         | .0000            |
| Mean   | 303.853     | 8.5366  | 81.7756        | 63.9220        | 72.8756           | 111331860.0| 11519.7     | 363.8293    | .0094         | .0002            |
|        | 7           |         |                |                |                   | 722        | 805         |             |               |                  |
| Median | 32.0000     | .0000   | 88.7000        | 69.1000        | 79.3000           | 23816775.00| 6991.00     | 165.0000    | .0000         | .0000            |
|        | 3           | 3       | 3              | 3              | 3                 | 3          | 3           | 3           | .0000         | .0000            |
| Mode   | .00         | .00     | 66.20°         | 77.00          | 83.60°            | 437479.00 | 4651.00     | 129.00°     | .0000         | .0000            |
|        | 3           | 3       | 3              | 3              | 3                 | 3          | 3           | 3           | .0000         | .0000            |
| Std. Deviation | 579.743 | 21.18620 | 13.83014 | 14.11557 | 13.39953 | 303784756.3 | 30617.9 | 1238.190 | .05739 | .00151 |
|        | 93          | 4       | 7              | 7              |                   | 0899       | 0898        | 98          |               |                  |
| Variance | 336103.028 | 448.855 | 191.273       | 199.249        | 179.547           | 9228517816 | 937456    | 1533116.895 | .003 | .000 |
|        | 089      | 5714976.00 | 350.326 | 350.326 | 380.326 | 5714976.00 | 5714976.00 | 5714976.00 | 5714976.00 | 5714976.00 |
| Skewness | 3.010 | 2.989 | .785 | .836 | .751 | 4.090 | 6.376 | 6.388 | 6.376 | 6.366 |
Table 2 Descriptive statistics of America

| Std. Error of Skewness | Cases | Deaths | Average Temp (°F) | Population | Total Cases | Total Death | Percent Cases/ Population | Percent Death/ Population |
|------------------------|-------|--------|------------------|------------|-------------|-------------|---------------------------|--------------------------|
| .369                   | .369  | .369   | .369             | .369       | 10.7500     | .683138     | .0484                     | .0000                    |
| 10.588                 | 8.308 | .341   | .134             | -.433      | 40.762      | 40.869      | 40.757                    | 40.666                   |
| .724                   | .724  | .724   | .724             | .724       | .724        | .724        | .724                      | .724                     |
| Minimum                | 0.00  | 0.00   | 49.00            | 24.30      | 16.218      | 0.340       | 16.066                    | .037                     |
| Maximum                | 2936.00 | 89.00 | 52.70            | 56.10      | 52.00       | 67896463.50 | 0.00                      | 187.0000                 |
| Sum                    | 12458.00 | 350.00 | 3352.80          | 2620.80    | 2987.90     | 472311.00   | 14917.00                 | .0100                   |
| Percentiles 25         | 1.0000 | .0000  | 72.1500          | 51.1000    | 60.6500     | 5478484.00  | 0.00                      | 0.0000                  |
| Percentiles 50         | 0.0000 | 88.7000 | 69.1000          | 79.3000    | 23816775.00 | 6991.00     | 165.0000                 | .0000                   |
| Percentiles 75         | 280.000 | 4.5000 | 92.8500          | 76.0000    | 84.1000     | 76896463.50 | 0.00                      | 187.0000                 |

International Journal of Advanced Technology and Engineering Exploration, Vol 8(74)
2. Research methods

The Artificial Neural Network of Multilayer Perceptron (ANN-MLP) model was chosen in this analysis. ANN was carried out using SPSS 23. In [16–19], a similar approach can be seen. With the hyperbolic tangent transfer function in the first layer and the purelin transfer function in the second layer, the two-layer neural network is adapted. The training function used in this research is Trainscg, with a mean square error (MSE) equivalent to 0.0 as the criterion function. The theoretical structure consists of two variables, as seen in Table 3, which are independent and dependent variables. Meanwhile, Figure 1 indicates the theoretical structure of this study.

The neural network model with nine predictor variables for Asia and America are represented in Equation (1) and Equation (2).

![Independent Variables](Image)

![Dependent Variable](Image)

**Table 3 Descriptive type of variables**

| Variable          | Description                      | Notation                  | Type      |
|-------------------|----------------------------------|---------------------------|-----------|
| Dependent         | Total Death                      | TOTAL DEATH               | Continuous|
|                   | Daily Cases                      | cases                     | Continuous|
|                   | Daily Death                      | death                     | Continuous|
|                   | High Temperature                 | HIGH TEMPERATURE          | Continuous|
|                   | Low Temperature                  | LOW TEMPERATURE           | Continuous|
|                   | Population                       | population                | Continuous|
|                   | % Cases over Population          | PERCENT CASES POPULATION  | Continuous|
|                   | % Death over Population          | PERCENT DEATH POPULATION  | Continuous|
| Independent       | Average Temperature              | AVERAGE TEMPERATURE       | Continuous|
|                   | Total Cases                      | TOTALCASES                | Continuous|

\[
Y = \text{purelin} \left( \text{tanh} \left( x \right) \right)
\]

\[
Y = \text{purelin} \left( \text{tanh} \left( \sum_{i=1}^{9} \left( \sum_{j=1}^{1} (IW_{ij}) \cdot X_{j} \right) \right) \right)
\]

Figure 1 Theoretical structures

Equation (1)
The Cases, Death, High Temperature, Low Temperature, Population, Percentage of Cases over Population, Percentage of Death over Population, Average Temperature, and Total Cases were the covariates of the network. These nine covariates were the input nodes of the network’s input layer. These networks consist of one hidden layer with a single node for both Asia and America. The hyperbolic tangent was an activation function from the input layer to the hidden layer. The target of the network is COVID-19 spread and death, where the activation function from hidden layer to output layer was identity (purelin). The default error function in back propagation neural network was based on Sum of Square Error (SSE). The configurations of these networks were 9-1-1, to simplify. Figure 2 and Figure 3 display the architecture of the networks. Next, the overall network information for Asia and America are tabulated in Table 4.

**Table 4 Network information – Asia and America**

| Input Layer | 1 | Cases |
|-------------|---|-------|
| 2 | Death |
| 3 | High Temperature |
| 4 | Low Temperature |
| 5 | Population |
| 6 | % Cases over Population |
| 7 | % Death over Population |
| 8 | Average Temperature |
| 9 | Total Cases |

| Covariates | Number of Units* |
|------------|-----------------|
| 1 | 9 |

| Rescaling Method for Covariates | Standardized |
|--------------------------------|--------------|
| Hidden Layer(s) | Number of Hidden Layers |
|                  | 1             |

9,1
9
8,1
8
7,1
7
6,1
6
5,1
5
4,1
4
3,1
3
2,1
2
1,1
1
1,2

\[
\text{LW}^{2,1} \tanh \{ (I_W)_{1}^{1} \times \text{cases} + (I_W)_{1}^{2} \times \text{death} + \} \text{HIGH TEMPERATURE} + \ (I_W)_{1}^{3} \times \text{LOW TEMPERATURE} + \ (I_W)_{1}^{4} \times \text{PERCENT POPULATION} + \ (I_W)_{1}^{5} \times \text{PERCENT DEATH} + \ (I_W)_{1}^{6} \times \text{AVERAGE TEMPERATURE} + \ (I_W)_{1}^{7} \times \text{TOTAL CASES} \} \]

\[
\text{AsiaAmericaTotalDeath} = \text{purelin} \quad \text{IW}^{9,1} - \text{E}^{19}
\]
Input Layer

|   |     |
|---|-----|
| 1 | Cases |
| 2 | Death |
| 3 | High Temperature |
| 4 | Low Temperature |
| 5 | Population |
| 6 | % Cases over Population |
| 7 | % Death over Population |
| 8 | Average Temperature |
| 9 | Total Cases |

Covariates

|   |     |
|---|-----|
| Number of Units | 9 |
| Rescaling Method for Covariates | Standardized |
| Number of Units in Hidden Layer 1 | 1 |
| Activation Function | Hyperbolic tangent |

Output Layer

|   |     |
|---|-----|
| Dependent Variables | 1 |
| Total Death |
| Number of Units | 1 |
| Rescaling Method for Scale Dependents | Standardized |
| Activation Function | Identity |
| Error Function | Sum of Squares |

Figure 2 Network architecture – Asia
3. Results

Table 5 and Table 6 show the case processing summary for Asia and America. Based on the tables, the data was split into two parts in the preprocessing section; training and testing. The training set consists of 73.17% (30/41) of the total data, while the test set consists of 19.5% (8/41) of the total data, N=41. Three excluded data were recorded. The training set consists of 77.6% (38/49) of the overall data for America, while the test sets consist of 22.4% (11/49) of the overall data, N= 49. No excluded data has been registered.

Table 7 and Table 8 depict the model summary for Asia and America accordingly. For Asia, the SSE for training set was 0.045, with Relative Error (RE) equals to 0.003. On the other hand, the SSE for testing sets was 0.036, with RE equals to 9.527.

Table 5 Case processing summary – Asia

|          | N   | Percent |
|----------|-----|---------|
| Sample   |     |         |
| Training | 30  | 73.17%  |
| Testing  | 8   | 19.51%  |
| Valid    | 38  | 92.68%  |
| Excluded | 3   |         |
| Total    | 41  |         |

Table 6 Case processing summary – America

|          | N   | Percent |
|----------|-----|---------|
| Sample   |     |         |
| Training | 38  | 77.6%   |
| Testing  | 11  | 22.4%   |
| Valid    | 49  | 100.0%  |
| Excluded | 0   |         |
| Total    | 49  |         |
Table 7 Model summary - Asia

| Model Summary | Training | | Testing | |
|---------------|----------|----------------------|----------------------|
| Sum of Squares Error | .045 | Sum of Squares Error | .036 |
| Relative Error | .003 | Relative Error | 9.527 |
| Stopping Rule Used | 1 consecutive step(s) with no decrease in error
| Dependent Variable: TOTALDEATH |

Alternatively, for the training sets, America is observed to record 0.026 of SSE and 0.02 of RE. In testing, 0.012 of SE and 0.472 of RE were returned. It can be said that in any network, testing set should be the reference. The RE was 9.527 and 0.757 for both Asia and America, which were quite low. The efficiency of the network is therefore assumed to be in a decent structure.

Table 8 Model summary--America

| Model Summary | Training | | Testing | |
|---------------|----------|----------------------|----------------------|
| Sum of Squares Error | .026 | Sum of Squares Error | .012 |
| Relative Error | .002 | Relative Error | .757 |
| Stopping Rule Used | 1 consecutive step(s) with no decrease in error
| Dependent Variable: TOTALDEATH |

Table 9 Independent variable importance - Asia

| Variable | Importance | Normalized importance |
|----------|------------|-----------------------|
| Cases   | 0.006      | 1.0%                  |
| Deaths  | 0.021      | 3.8%                  |
| High Temperature | 0.039 | 7.0%          |
| Low Temperature    | 0.056 | 10.1%          |
| Population | 0.090 | 16.1%          |
| % Cases over Population | 0.019 | 3.5%          |
| % Death over Population | 0.157 | 28.2%          |
| Average Temperature | 0.054 | 9.8%          |
| Total Cases | 0.558 | 100.0%         |

Table 10 Independent variable importance-Amercia

| Variable | Importance | Normalized importance |
|----------|------------|-----------------------|
| Cases   | .307       | 85.2%                 |
| Death   | .155       | 43.0%                 |
| High Temperature | .011 | 2.9%          |
| Low Temperature    | .010 | 2.9%          |
| Average Temperature | .006 | 1.6%          |
| Population | .133 | 37.0%          |
| Total Cases | .360 | 100.0%         |
| % Cases over Population | .009 | 2.5%          |
| % Death over Population | .010 | 2.7%          |
4. Discussions
Referring to the percentages of normalized importance in Table 9 and Table 10, the Total Cases (100%), Percentage of Death over Population (28.2%) and Population (16.1%) are the three most important factors leading to COVID-19 spread and death in Asia. Contrastively, the three most important variables that lead to COVID-19 spread and death in America are Total Cases (100%), Cases (85.2%) and Death (43%). The global geographical climate defined by High Temperature, Low Temperature, and Average Temperature appear to have a minimum impact on the COVID-19 spread and death in Asia and America as it returned low percentages of normalized importance in both Asia and America in the range of 1.6%-10.1% only. Figure 4 and Figure 5 display the corresponding figures.

![Normalized importance – Asia](image)

**Figure 4** Normalized importance – Asia

![Normalized importance – America](image)

**Figure 5** Normalized importance – America
In view of the minimum impacts of geographical global climate on the COVID-19 spread and death in Asia and America, the correlation graphs of Average Temperature and Total Cases, and Average Temperature and Total Deaths are then constructed in Figure 6 and Figure 7.

Based on the correlation analysis in Figure 6 and Figure 7, it is monitored that the COVID-19 cases and death has negative association with climate as the total number of cases and death are unpredictably distributed along the Average Temperature. Small number of cases and death could be monitored in the high temperature countries, as well as the low temperature countries. The findings of the study are summarized as below:

- The three most important factors leading to COVID-19 spread and death in Asia are: total cases, percentage of death over population, and population.
- The three most important factors leading to COVID-19 spread and death in America are: total cases, cases, and death.
- Global geographical climate which represented by High Temperature, Low Temperature, and Average Temperature appear to have a minimum impact on the COVID-19 spread and death in both Asia and America.

It can therefore be inferred that the global geographic climate has the least impacts on the COVID-19 spread and death in Asia and America. Nevertheless, an investigation on the global geographical climate impacts on the COVID-19 spread and death at different continents could summarize the findings in future.

5. Conclusion and future work
This paper presents a study on the impacts of global geographic climate towards the COVID-19 spread and death in Asia and America. The objective of this paper has been successfully achieved. The Artificial Neural Network of Multilayer Perceptron (ANN-MLP) model was implemented. The configuration of the networks adapted were 9-1-1 for both Asia and America, with hyperbolic tangent and purelin activation functions in hidden layer and output layer respectively. Nine covariates were set for each Asia and America. The Total Cases, Cases, Death, Percentage of Death over Population, and Population were observed to contribute to the major effects of
COVID-19 spread and death in Asia and America. On the other hand, temperatures appear to give small impacts on the spread and death. Thus, it can be concluded that the global geographic climate has the least impacts on the COVID-19 spread and death in Asia and America particularly. A lot of studies on COVID-19 spread and death at different world continental could be done in which the impacts of the global geographical climate could be seen comprehensively in future. An implementation and incorporation of the current prediction and analysis techniques are also suggested.

Acknowledgment

None

Conflicts of interest

The authors have no conflicts of interest to declare.

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