Implementation of Deep Learning Using Matlab-Based Convolutional Neural Network for Covid-19 Forecasting and Classification

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***Abstract*— The outbreak of the Corona Virus Disease or better known as the Korona virus or Covid-19 was first detected to appear in China precisely in China's Wuhan city at the end of 2019, suddenly becoming a terrible terror for the world community, especially after taking the lives of hundreds of people in a relatively short time. Almost approximately 200 countries in the world infected with Corona viruses including Indonesia, the number of virus infection status known as Garry-19 is increasing there are cases that are easy to do forecasting and some are difficult to predict, forecasting process and classification depends on the following that is related to the related factors, mathematical model to be used and the existence of the data owned. In this study can be produced percentage accuracy of the training data for classification with CNN method of 89.79% and for predictions of 90.47% for the type of positive cases Garry with the output data of emergency status with 3 status i.e. transition, standby and responsiveness.**

Keywords*— *classification, covid-19, CNN, prediction

I. Introduction

Coronaviruses are a large family of viruses that cause mild to severe pneumonia, such as the common cold or the common cold, and serious illnesses such as MERS and SARS. Transmission from animals to humans (zoonosis) and transmission from humans to humans is minimal for 2019-nCoV. It is still unclear how it is transmitted. It is suspected from animals to humans because the cases that emerged in Wuhan all had a history of contact with the Huanan animal market [1] [2]. The swift spread of the virus is continuing until now due to lack of awareness from the public to carry out physical distancing and implement health protocols. For this reason, the public needs to receive education about patterns of cleanness[3] with the aim of preventing and controlling COVID-19.

In the animal market, several cases of illness with this mystery pneumonia have been discovered. Until transmission, the Coronavirus, or COVID-19, is considered to be carried by bats and other animals ingested by humans. Coronavirus is not uncommon in animal health, but only a few varieties can cause inflammatory lung illness in humans. Infected persons can infect others with the virus while displaying no symptoms for 14 days from infection to beginning of symptoms, according to reports on the outbreak. These qualities also make managing the outbreak more challenging. The CNN method was used to perform this investigation, which was followed by a detailed presentation and discussion of the findings.

II. Research Methodologies

A. Method Convolutional Neural Network

Data categorization techniques utilizing the Convolutional Neural Network (CNN) approach were used to conduct research based on the epidemic that happened [4][5]. The Convolutional Neural Network (CNN) is a derivative of the Multilayer Perceptron (MLP) that is used to handle two-dimensional input. Because of its large network depth, CNN is included in Deep Neural Network [6] [7] [8][9] [10].

The input, feature extraction, classification, and output processes make up the CNN structure. The convolution layer, activation fun CNN works in a hierarchical fashion, with the output of the first convolution layer feeding into the next [11] [12] [13]. An input layer (input layer), a convolutional layer (convolutional layer), a pooling layer, and a fully connected layer make up the classification process [14][15]. Action (ReLU), and pooling are three hidden layers in CNN's extraction process [16]. CNN works in a hierarchical fashion, with the output of the first convolution layer feeding into the next [17][18]. An input layer (input layer), a convolutional layer (convolutional layer), a pooling layer, and a fully connected layer make up the classification process [7][19].

B. Convolutional Neural Network Architecture

There are several layers in a Convolutional Neural Network. There are four primary types of layers on a CNN, according to the LeNet5 architecture [20][21][22]:

1) Input Layer
Reshape the feature map into a vector so that we can use it as an input to the fully linked layer.
2) Layer of Convolution
On the output of the previous layer, the convolution layer conducts a convolution process. The primary process that underpins a CNN is this layer. Convolution is a mathematical term that refers to the process of repeatedly applying a function on the outcome of another part.
3) The Layer Is Completely Connected
This layer is typically used in MLP applications to alter data dimensions so that they can be categorised linearly.

Before entering a fully connected layer, each neuron in the convolution layer must be turned into one-dimensional data. The fully connected layer can only be implemented at the network end since it causes the data to lose its spatial information and is not reversible.

4) Pooling Layer

A down-sampling operation is used to minimize the input spatially (and hence the number of parameters).

III. Result and Discussion

The first stage in determining which data will be categorised using the Convolutional Neural Network (CNN) approach is to classify the data collected on April 29, 2020. In terms of the training data, Table I shows the number of COVID-19 cases, recoveries, and deaths that were used.

A. *Classification*

The following is the classification process for COVID-19: The number of Covid positive cases, the number of recovered patients, and the number of patients who died are the input data. The emergency status data produced has three statuses: transition state, standby status, and response status. The training data for the classification method is described in Table I below.

TABLE I. Training Data

Data	Coronavirus Case	Cured Case	Death Case
Data-1	2	0	0
Data-2	0	0	0
Data-3	0	0	0
Data-4	0	0	0
Data-5	2	0	0
Data-6	0	0	0
Data-7	2	0	0
Data-8	13	0	0
Data-9	8	0	0
Data-10	7	2	1
Data-11	0	1	0
Data-12	35	2	3
Data-13	27	3	1
Data-14	21	0	0
Data-15	17	0	0
Data-16	38	1	2
Data-17	55	2	12
Data-18	82	4	6
Data-19	60	2	7
Data-20	81	3	6
Data-21	64	9	10
Data-22	65	1	1
Data-23	107	0	6
Data-24	104	1	3
Data-25	103	4	20
Data-26	153	11	9
Data-27	109	13	15
Data-28	130	5	12
Data-29	129	11	8
Data-30	114	6	14
Data-31	149	22	21
Data-32	113	9	13
Data-33	196	22	11
Data-34	106	16	10
Data-35	181	14	7
Data-36	218	28	11
Data-37	247	12	12
Data-38	218	18	19
Data-39	337	30	40
Data-40	219	30	26
Data-41	330	4	21
Data-42	399	73	46
Data-43	316	21	26
Data-44	282	46	60
Data-45	297	20	10
Data-46	380	102	27
Data-47	407	59	24
Data-48	325	24	15
Data-49	327	55	47
Data-50	185	61	8
Data-51	375	95	26
Data-52	283	71	19
Data-53	357	47	12
Data-54	436	42	42
Data-55	396	40	31
Data-56	275	65	23

The existing training data method is shown in Table I. Table II is connected to training data, and there are 56 data for the classification process.

TABLE II. Training Data

Data	CoronavirusCase	Cured Case	Death Case
Data-1	2	0	0
Data-2	0	0	0
Data-3	0	0	0
Data-4	0	0	0
Data-5	2	0	0
Data-6	0	0	0
Data-7	2	0	0
Data-8	13	0	0
Data-9	8	0	0
Data-10	7	2	1
Data-11	0	1	0
Data-12	35	2	3
Data-13	27	3	1
Data-14	21	0	0
Data-15	17	0	0
Data-16	38	1	2
Data-17	55	2	12
Data-18	82	4	6
Data-19	60	2	7
Data-20	81	3	6
Data-21	64	9	10
Data-22	65	1	1
Data-23	107	0	6
Data-24	104	1	3
Data-25	103	4	20
Data-26	153	11	9
Data-27	109	13	15
Data-28	130	5	12
Data-29	129	11	8
Data-30	114	6	14
Data-31	149	22	21
Data-32	113	9	13
Data-33	196	22	11
Data-34	106	16	10
Data-35	181	14	7
Data-36	218	28	11
Data-37	247	12	12
Data-38	218	18	19
Data-39	337	30	40
Data-40	219	30	26
Data-41	330	4	21
Data-42	399	73	46
Data-43	316	21	26
Data-44	282	46	60
Data-45	297	20	10
Data-46	380	102	27
Data-47	407	59	24
Data-48	325	24	15
Data-49	327	55	47

Tables I and II pertain to training data and training data, respectively, before creating a target table to correspond to the classification in Table III, which includes transition, alert, and responsive target state.

TABLE III. TARGET DATA

Target	State
1	'Transition'
2	'Transition'
3	'Transition'
4	'Transition'
5	'Transition'
6	'Transition'
7	'Transition'
8	'Transition'
9	'Transition'
10	'Transition'
11	'Transition'
12	'Transition'
13	'Transition'
14	'Transition'
15	'Transition'
16	'Transition'
17	'Ready'
18	'Ready'
19	'Ready'
20	'Ready'
21	'Ready'
22	'Ready'
23	'Ready'
24	'Ready'
25	'Ready'
26	'Ready'
27	'Ready'
28	'Ready'
29	'Ready'
30	'Ready'
31	'Ready'
32	'Ready'
33	'Ready'
34	'Ready'
35	'Ready'
36	'Response'
37	'Response'
38	'Response'
39	'Response'
40	'Response'
41	'Response'
42	'Response'
43	'Response'
44	'Response'
45	'Response'
46	'Response'
47	'Response'
48	'Response'
49	'Response'

Fig. 1 shows the presentation of the training process using the CNN method after reading the data and selecting the target.

Fig. 1. Process View

Table IV shows the network output after processing the data to be displayed.

TABLE IV. NETWORK OUTPUT DATA

Target	State
1	'Transition'
2	'Transition'
3	'Transition'
4	'Transition'
5	'Transition'
6	'Transition'
7	'Transition'
8	'Transition'
9	'Transition'
10	'Transition'
11	'Transition'
12	'Transition'
13	'Transition'
14	'Transition'
15	'Transition'
16	'Transition'
17	'Transition'
18	'Ready'
19	'Transition'
20	'Ready'
21	'Transition'
22	'Transition'
23	'Ready'
24	'Ready'
25	'Ready'
26	'Ready'
27	'Ready'
28	'Ready'
29	'Ready'
30	'Ready'
31	'Ready'
32	'Ready'
33	'Response'
34	'Ready'
35	'Ready'
36	'Response'
37	'Response'
38	'Response'
39	'Response'
40	'Response'
41	'Response'
42	'Response'
43	'Response'
44	'Response'
45	'Response'
46	'Response'
47	'Response'
48	'Response'
49	'Response'

The training accuracy for the classification procedure is 89.79 percent when the training data is calculated using the CNN method. The data will be examined using the CNN method after the next training. The test data is shown in Table V.

TABLE V. TEST DATA

Data	Cases	Recovery	Dead
50th data	185	61	8
51st data	375	95	26
52nd data	283	71	19
53rd data	357	47	12
54th data	436	42	42
55th data	396	40	31
56th data	275	65	23

After obtaining the test data, create Table VI as the target data.

TABLE VI. TEST TARGET DATA

Target	State
50	'Ready'
51	'Response'
52	'Response'
53	'Response'
54	'Response'
55	'Response'
56	'Response'

The output data acquired using the CNN method after conducting the test target is displayed in Table VII.

TABLE VII. TEST NETWORK OUTPUT DATA.

Target	State
50	'Response'
51	'Response'
52	'Response'
53	'Response'
54	'Response'
55	'Response'
56	'Response'

The CNN method calculated using the test data yielded a test accuracy of 85.7143 %.

From training classification data to testing, implementation on the GUI display.

Fig. 2. GUI before data is entered

Fig. 2 shows the screen before data is entered. There is a textbox for data input, and then there are process and reset buttons in the sub-classification, as well as an emergency status that will explain the state of the Covid-19 case.

Fig. 3. Transition status display

Fig. 3 shows that the current status was transition after inputting case data with a value of 7 cases, 2 of which were recovered and 1 of which died while processed.

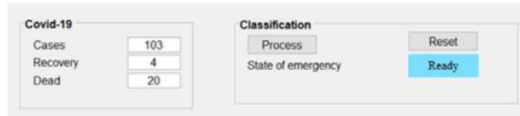

Fig. 4. Ready status display

The emergency status shifts to standby in Fig. 4 when a case is entered with a total of 103 cases, 4 recoveries, and 20 deaths.

Fig. 5. Responsive status display

The emergency status switches to a response state in Fig. 5 when a case is entered with a total of 327 cases, 55 recovering, and 47 dying.

B. *Prediction*

The number of positive COVID cases for the previous seven days is used as input data in the prediction method. The emergency state on the eighth day, including transition, standby, and reaction status, is the output data. Furthermore, using training and testing data, provide predictions for Covid-19 instances following classification. Table 8 shows the training data from the covid-19 cases.

TABLE VIII. TRAINING DATA FOR COVID-19 CASES

Data	Number of Covid-19 cases
Data-1	2
Data-2	0
Data-3	0
Data-4	0
Data-5	2
Data-6	0
Data-7	2
Data-8	13
Data-9	8
Data-10	7
Data-11	0
Data-12	35
Data-13	27
Data-14	21
Data-15	17
Data-16	38
Data-17	55
Data-18	82
Data-19	60
Data-20	81
Data-21	64
Data-22	65
Data-23	107
Data-24	104

Data-25	103
Data-26	153
Data-27	109
Data-28	130
Data-29	129
Data-30	114
Data-31	149
Data-32	113
Data-33	196
Data-34	106
Data-35	181
Data-36	218
Data-37	247
Data-38	218
Data-39	337
Data-40	219
Data-41	330
Data-42	399
Data-43	316
Data-44	282
Data-45	297
Data-46	380
Data-47	407
Data-48	325
Data-49	327
Data-50	185
Data-51	375
Data-52	283
Data-53	357
Data-53	436
Data-54	396
Data-55	275

Table IX displays the time series data after reading the next training data.

TABLE IX. DATA TIME SERIES.

Pattern	Data-1	Data-2	Data-3	Data-4	Data-5	Data-6	Data-7
1	2	0	0	0	2	0	2
2	0	0	0	2	0	2	13
3	0	0	2	0	2	13	8
4	0	2	0	2	13	8	7
5	2	0	2	13	8	7	0
6	0	2	13	8	7	0	35
7	2	13	8	7	0	35	27
8	13	8	7	0	35	27	21
9	8	7	0	35	27	21	17
10	7	0	35	27	21	17	38
11	0	35	27	21	17	38	55
12	35	27	21	17	38	55	82
13	27	21	17	38	55	82	60
14	21	17	38	55	82	60	81
15	17	38	55	82	60	81	64
16	38	55	82	60	81	64	65
17	55	82	60	81	64	65	107
18	82	60	81	64	65	107	104
19	60	81	64	65	107	104	103
20	81	64	65	107	104	103	153
21	64	65	107	104	103	153	109
22	65	107	104	103	153	109	130
23	107	104	103	153	109	130	129
24	104	103	153	109	130	129	114
25	103	153	109	130	129	114	149
26	153	109	130	129	114	149	113
27	109	130	129	114	149	113	196
28	130	129	114	149	113	196	106
29	129	114	149	113	196	106	181
30	114	149	113	196	106	181	218
31	149	113	196	106	181	218	247
32	113	196	106	181	218	247	218
33	196	106	181	218	247	218	337
34	106	181	218	247	218	337	219
35	181	218	247	218	337	219	330
36	218	247	218	337	219	330	399
37	247	218	337	219	330	399	316
38	218	337	219	330	399	316	282
39	337	219	330	399	316	282	297
40	219	330	399	316	282	297	380
41	330	399	316	282	297	380	407
42	399	316	282	297	380	407	325

Then, as indicated in Table X, establish target data to determine the targets, which are transition status, alert, and responsive.

TABLE X. TARGET DATA

Target	State
1	'Transition'
2	'Transition'
3	'Transition'
4	'Transition'
5	'Transition'
6	'Transition'
7	'Transition'
8	'Transition'
9	'Transition'
10	'Ready'
11	'Ready'
12	'Ready'
13	'Ready'
14	'Ready'
15	'Ready'
16	'Ready'
17	'Ready'
18	'Ready'
19	'Ready'
20	'Ready'
21	'Ready'
22	'Ready'
23	'Ready'
24	'Ready'
25	'Ready'
26	'Ready'
27	'Ready'
28	'Ready'
29	'Response'
30	'Response'
31	'Response'
32	'Response'
33	'Response'
34	'Response'
35	'Response'
36	'Response'
37	'Response'
38	'Response'
39	'Response'

40	'Response'
41	'Response'
42	'Response'

Fig. 6 shows the presentation of the training process using the CNN method after reading the data and selecting the target.

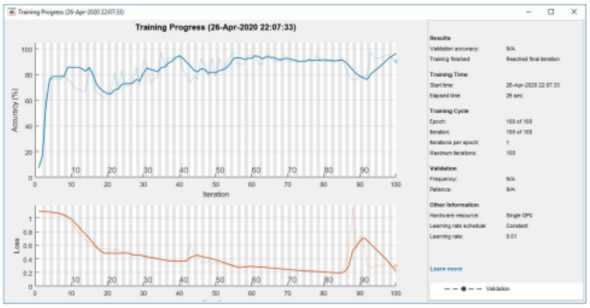

Fig. 6. View of the training procedure

After determining the target and carrying out the process, the network output data is obtained as Table XI.

TABLE XI. NETWORK OUTPUT DATA

Target	State
1	'Transition'
2	'Transition'
3	'Transition'
4	'Transition'
5	'Transition'
6	'Transition'
7	'Transition'
8	'Transition'
9	'Transition'
10	'Ready'
11	'Ready'
12	'Ready'
13	'Ready'
14	'Ready'
15	'Ready'
16	'Ready'
17	'Ready'
18	'Ready'
19	'Ready'
20	'Ready'
21	'Ready'
22	'Ready'
23	'Ready'
24	'Ready'
26	'Ready'
27	'Ready'
28	'Ready'
29	'Ready'
30	'Response'
31	'Response'
31	'Response'
32	'Response'
33	'Response'
34	'Response'
35	'Response'
36	'Response'
37	'Response'
38	'Response'
39	'Response'
40	'Response'
41	'Response'
42	'Response'

The training accuracy is 90.4762 % when utilizing the CNN method to calculate the training data.

The data will be examined using the CNN method after the next training. Table XII is a graph of time series data.

TABLE XII. DATA TIME SERIES.

Pattern	Data-1	Data-2	Data-3	Data-4	Data-5	Data-6	Data-7
43	316	282	297	380	407	325	327
44	282	297	380	407	325	327	185
45	297	380	407	325	327	185	375
46	380	407	325	327	185	375	283
47	407	325	327	185	375	283	357
48	325	327	185	375	283	357	436
49	327	185	375	283	357	436	396

Then, using the data in Table XIII, establish the target.

TABLE XIII. TEST TARGET DATA

Target	State
43	'Ready'
44	'Response'
45	'Response'
46	'Response'
47	'Response'
48	'Response'
49	'Response'

Table XIV shows the network output data after determining the goal data.

TABLE XIV. NETWORK OUTPUT DATA

Target	State
43	'Response'
44	'Response'
45	'Response'
46	'Response'
47	'Response'
48	'Response'
49	'Response'

The test accuracy is 85.71 % when the test data is calculated using the CNN method.

After calculating with the CNN approach, the result is displayed on the GUI.

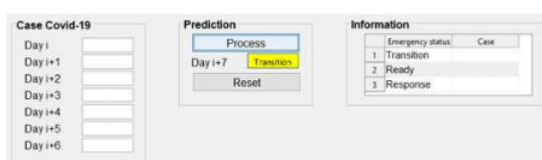

Fig. 7. GUI display

Fig. 7 shows a graphical user interface (GUI) that shows the number of cases, predictions, and descriptions.

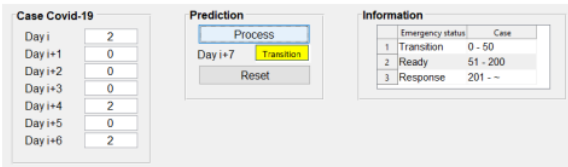

Fig. 8. Display with a prediction transition

Fig. 8 shows that after entering data in the scenario with day I 2, i+1 is 0, i+2 is 0, i+3 is 0, i+4 is 2, i+5 is 0, and i+6 is 2, the forecast for day i+7 is the number of transition instances with cases 0-50.

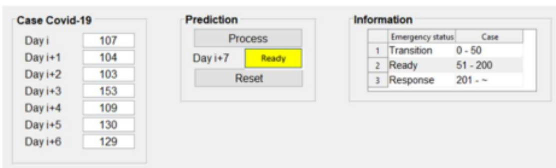

Fig. 9. Display with a prediction ready

After entering data in the case with the I day of 107, i+1 of 104, i+2 of 103, i+3 of 153, i+4 of 109, i+5 of 130, i+6 of 129, the forecast for day i+7 is the number of standby cases with 51-200 cases, as shown in Fig. 9.

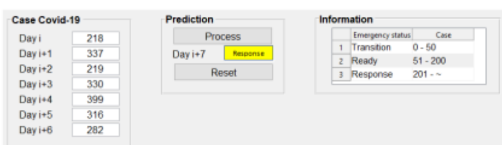

Fig. 10. Display with a prediction response

After entering data in the case with day I of 218 and i+1 of 337, i+2 of 219, i+3 of 330, i+4 of 399, i+5 of 316, and i+6 of 282, the forecast for day i+7 is the number of response cases, with the number of cases being 201 -~.

IV. CONCLUSION

Based on the findings of the investigation, it can be concluded that utilizing the CNN approach to classify the emergency state of covid -19 has relevant outcomes in trials for the sort of data utilized in this study and may be used as a reference for those who are familiar with the status classification. It's an emergency with Covid-19. The accuracy of training data for classification using the CNN approach was 89.79 percent, and predictions were 90.47 percent for positive covid instances with emergency status output data with three statuses, including transition, standby, and response, in this study.

V. SUGGESTION

Several ideas can be included in this research to help further develop and improve the CNN algorithm: Because the CNN method is the more training data used, the more appropriate the results delivered, the volume of data utilized is expected to be increased.

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