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Deep Learning Approach For Modelling The Spread of Covid-19

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***Abstract*— In March 2020, the Covid-19 outbreak in Indonesia, where the symptoms of the corona virus made the Indonesian people worry and experience depression. It has been almost two years that Covid-19 has not known what causes it, let alone a person's body condition is not good which can result in being attacked by the virus. Covid-19 first appeared in the city of Wuhan, part of China, where it spread very quickly and was deadly. Its spread through direct physical contact with humans is transmitted through the mouth, nose and eyes, therefore a model is needed for the spread of the corona virus. The spread of COVID-19 affects the pattern of interaction between susceptible (susceptible) and infected (infectious) individuals, where human social contact is very heterogeneous and in groups. To influence the impact of the spread of COVID-19 using deep learning approach that is modeled on the spread of COVID-19, individuals are exposed, infected, recover and die. The purpose of this research is to produce good predictions with a deep learning approach for modeling the spread of COVID-19. The results of the deep learning approach for the COVID-19 spread model carried out the 400 time iteration with an MSE achievement of 0.021112.**

***Keywords*— Epidemic, COVID-19, Heterogen, Deep Learning**

I. INTRODUCTION

In March 2020, virus corona or Covid-19 broke out in Indonesia, where symptoms of being exposed to the virus appeared which made the Indonesian people worry and experience depression [1]. It has been almost a year that the corona virus or Covid-19 is not yet known what causes it, let alone a person's body condition is not good which can result in being attacked by the virus. The corona virus or Covid-19 first appeared in one of the cities of Wuhan [2] part of China where it spread very quickly and was deadly. Its spread through direct physical contact with humans is transmitted through the mouth, nose and eyes [2] and [3]. Efforts to break the chain of the spread of Covid-19 are carried out by the government and religious institutions by issuing several regulations to be obeyed by the community [4]. One of the approaches used is the deep learning (DL) method, where deep learning is an artificial neural network algorithm that uses data as input and processes using a number of hidden layers [5]. Deep learning technology is one of the most popular technologies for recognizing an activity or object that has a higher level of accuracy than other machine methods [6] . The prediction of active cases of Covid-19 was solved using the deep learning method, using a dataset of 260 data with 10 parameters [7]. According to [8] research using Google Trends, Linear Regression and LSTM models in deep learning to predict the prediction of the number of positive cases of Covid-19 patients in Iran. Based on the problems mentioned above, the researcher wants to develop a deep learning approach to model the spread of COVID-19 city Medan. According to research results from [9] using a deep learning approach on CNN for Covid-19 cases through a GSA-DenseNet121-Covid-19 chest X-ray. In this study [7] predicted active cases of Covid-19 which were solved by deep learning. The dataset used is 260 data with 10 parameters. Applying the Optimize Selection feature optimization algorithm to the deep learning algorithm. The results showed a significant increase in accuracy with the value of classification accuracy on forest plant population types generated from the deep learning algorithm [10]. Research [11] as the detection of Covid-19 virus infection by using deep learning as a model with CT images as input.

II. METHOD

Research from [12] describes the network of contacts that are increasingly recognized as the center of the dynamics of infectious diseases and other transmission phenomena. As a consequence of the structure of the contact network, the heterogeneous population size assumed for mass action does not apply to the description of the spread of the epidemic. Research results from [13] state that the deterministic and derivative equations known as the 'mean field' or 'mass action' models which characterize homogeneous mixing, are that each individual is in the same contact with the others in the population. However, a large population gives connected individuals with weak contacts, clusters, subpopulations and correlations resulting from transmission in structured networks that are not accounted for by the mean field model [14]. Research from [15] explains how the weakness of homogeneous mixtures, where contributions are made from theory as assumptions. The simplicity of the equations performed provides a model that is easy to solve analytically. The developed theory provides for heterogeneous mixing in the population by considering various source subgroups and transmission matrices to determine who is infected and from whom [16].

The method used in this study is a deep learning method, namely the Convolutional Neural Network (CNN) using data from the Covid-19 task force of the Medan city government. This study aims to produce a deep learning approach to model the spread of COVID-19. The dataset is in the form of a time series, where the data is taken from December 1, 2021 to December 31, 2021, from the field city covid task force. The data analyzed to obtain the accuracy of the model for the spread of COVID-19 in the city of Medan is shown in Fig 1 and Table 1.

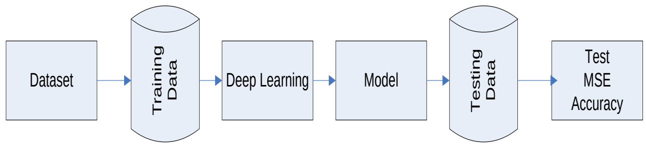

Fig 1. Data Analysis

Table 1. Data Set Covid-19

Date	Covid (+) Healed	Covid (+) Treated	Covid (+) Died
1	3,397	1,867	237
2	3,465	1,854	242
3	3,508	1,835	244
4	3,565	1,874	245
5	3,679	1,966	247
6	3,772	1,976	248
7	3,813	1,950	252
8	3,813	1,950	252
9	3,938	1,900	260
10	3,946	1,944	261
11	3,984	1,927	264
12	4,032	1,892	269
13	4,099	1,845	270
14	4,276	1,702	272
15	4,356	1,638	276
16	4,394	1,635	278
17	4,397	1,654	278
18	4,446	1,634	278
19	4,544	1,569	283
20	4,594	1,559	283
21	4,642	1,552	286
22	4,698	1,527	290
23	4,768	1,484	291
24	4,708	1,484	291
25	4,862	1,452	291
26	4,902	1,426	293
27	4,952	1,420	295
28	4,975	1,454	295
29	5,025	1,441	297
30	5,076	1,416	298
31	5,115	1,401	299

Deep learning has existed since the 1980s with four evolutions of artificial neural networks, including: more neurons than the previous network, more complex ways of connecting layers, the amount of computing power available for training and automatic feature extraction [17]. Deep learning is a branch of machine learning to solve problems with large datasets that utilize artificial neural networks. Deep learning is a branch of supervised learning. The deep learning model can be seen in Fig 2 [18].

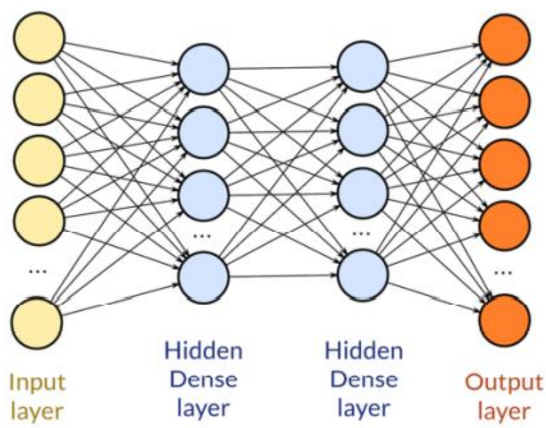

Fig 2. Model Deep Learning

Research from [19] used deep learning on LSTM to predict the trend of the Covid-19 epidemic in case studies of Russia, Peru and Iran. According to research results from [9] using a deep learning approach on CNN for Covid-19 cases through a GSA-DenseNet121-Covid-19 chest X-ray. Research [7] predicts active cases of Covid-19 which are solved by deep learning. The dataset used is 260 data with 10 parameters. Applying the Optimize Selection feature optimization algorithm to the deep learning algorithm. The results showed a significant increase in accuracy with the value of classification accuracy on forest plant population types generated from the deep learning algorithm [10]. Research [11] as the detection of Covid-19 virus infection using deep learning as a model with CT images as input,

The way CNN works is similar to MLP, but in CNN each neuron is represented in two dimensions, unlike MLP where each neuron is only one-dimensional in Fig 3.

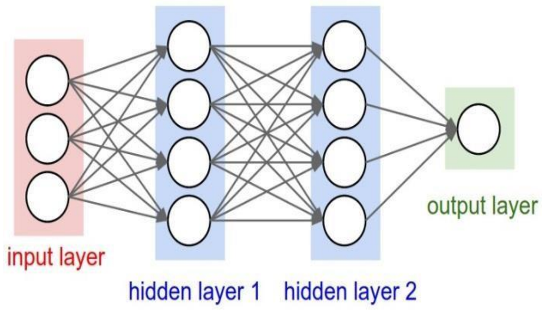

Fig 3. Simple MLP Architecture

An MLP as shown in Fig 3 has i layers (red and blue squares) with each layer containing ji neurons (white circles). MLP accepts one-dimensional input data and propagates that data on the network to produce output. Each connection between neurons in two adjacent layers has a one-dimensional weight parameter that determines the quality of the mode. In each input data layer, a linear operation is performed with the existing weight values, then the computational results will be transformed using a non-linear operation called the activation function. In CNN, the data propagated on the network is two-dimensional data, so the linear operations and weight parameters on CNN are different [20].

Operation linear CNN is using convolution operations, while the weights are no longer just one dimension, but are in the form of four dimensions which are a collection of convolution kernels as shown in Fig 4. The dimensions of the weights on CNN are: input neuron x output neuron x height x width. Due to the nature of the convolution process, CNN can only be used on data that has a two-dimensional structure such as images and sounds.

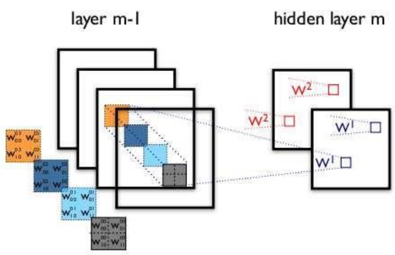

Fig 4. Process CNN

III. RESULTS AND DISCUSSION

Training will stop if you get an MSE from CNN error, where the CNN error is the desired error target, which is the difference between the target data and the network output. If MSE is not met then training will stop at the maximum entered iteration. Each network architecture has a final weight that will be used for the initial weighting of the testing process. The results of the training are shown in Tables 2.

Table 2. Conclusions of the results of training with training 1 to 7

Trial	Training	Learning rate	Iteration to	MSE
1	1	0.3	393	0.022099
2	2	0.3	451	0.021954
3	3	0.4	519	0.022058
4	4	0.4	1020	0.022045
5	5	0.2	2198	0.022096
6	6	0.1	3155	0.022093
7	7	0.3	4999	0.022119

By adding and subtracting search intervals and still using the same other parameter values. After different experiments, results such as Table 3 were obtained by changing at the first search interval.

Table 3. Effects of search interval parameters on the first search

First Search	Second search	Iteration to	MSE
[-100, 100]	[-2, 2]	445	0.022138
[-90, 90]	[-2, 2]	580	0.022142
[-80, 80]	**[-2, 2]**	**427**	**0.022011**
[-70, 70]	[-2, 2]	452	0.022269
[-60, 60]	[-2, 2]	478	0.022129
[-50, 50]	[-2, 2]	451	0.022037
[-40, 40]	[-2, 2]	408	0.022189
[-30, 30]	[-2, 2]	420	0.022101
[-20, 20]	[-2, 2]	415	0.022029
[-10, 10]	[-2, 2]	383	0.022145

The next experiment is to increase the number of iterations and still use the same param ether values as in the previous experiment. After a different experiment, the results obtained as in Table 4 by changing the maximum iteration on the first search.

Table 4. Effect of maximum iteration parameters on the first search

First Search	Second search	Iteration to	MSE
100	1000	428	0.022324
200	1000	440	0.022640
300	1000	437	0.022104
400	1000	423	0.022069
500	1000	406	0.022188
600	1000	382	0.022650
700	1000	435	0.022253
800	1000	493	0.022141
900	1000	450	0.021943
1000	**1000**	**400**	**0.021112**

IV. CONCLUSIONS

Deep learning has good capabilities with the smallest MSE result of 0.021112 with 400 times iterations. Thus the deep learning approach to the COVID-19 spread model can have a significant on the training process.

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REFERENCES

[1] Y. Yuliana, “Corona virus diseases (Covid-19): Sebuah tinjauan literatur,” *Wellness Heal. Mag.*, vol. 2, no. 1, pp. 187–192, 2020, doi: 10.30604/well.95212020.

[2] A. Susilo *et al.*, “Coronavirus Disease 2019: Tinjauan Literatur Terkini,” *J. Penyakit Dalam Indones.*, vol. 7, no. 1, p. 45, 2020, doi: 10.7454/jpdi.v7i1.415.

[3] T. K. Roy and B. P. Singh, “A Data Driven Model for Prediction of COVID-19 Outbreak in Bangladesh,” *Bangladesh J. Infect. Dis.*, vol. 7, no. 1, pp. 22–26, 2020, doi: 10.3329/bjid.v7i1.48673.

[4] I. W. Wiryawan, “Kebijakan Pemerintah Dalam Penanganan Pandemi Virus Corona Disease 2019 (Covid-19) Di Indonesia,” *Pros. Semin. Nas. Webinar Nas. Univ. Mahasaraswati Denpasar “Percepatan Penanganan COVID-19 Berbas. Adat di Indones.*, vol. 2019, no. 6, pp. 179–188, 2020.

[5] J. Craig and V. Patterson, “Introduction to the practice of telemedicine,” *J. Telemed. Telecare*, vol. 11, no. 1, pp. 3–9, 2005, doi: 10.1258/1357633053430494.

[6] J. W. G. Putra, “Pengenalan Konsep Pembelajaran Mesin dan Deep Learning,” *Comput. Linguist. Nat. Lang. Process. Lab.*, vol. 4, pp. 1–235, 2019, [Online]. Available: https://www.researchgate.net/publication/323700644.

[7] L. Syafa and M. Lestandy, “Penerapan Deep Learning untuk Prediksi Kasus Aktif Covid-19,” *J. Sains Komput. Inform.*, vol. 5, no. 1, pp. 453–457, 2021.

[8] S. M. Ayyoubzadeh, S. M. Ayyoubzadeh, H. Zahedi, M. Ahmadi, and S. R. Niakan Kalhori, “Predicting COVID-19 incidence through analysis of Google trends data in Iran: Data mining and deep learning pilot study,” *JMIR Public Heal. Surveill.*, vol. 6, no. 2, pp. 1–6, 2020, doi: 10.2196/18828.

[9] D. Ezzat, A. E. Hassanien, and H. A. Ella, “An optimized deep learning architecture for the diagnosis of COVID-19 disease based on gravitational search optimization,” *Appl. Soft Comput.*, vol. 98, no. xxxx, p. 106742, 2021, doi: 10.1016/j.asoc.2020.106742.

[10] R. T. Prasetio and E. Ripandi, “Optimasi Klasifikasi Jenis Hutan Menggunakan Deep Learning Berbasis Optimize Selection,” *J. Inform.*, vol. l, no. 1, pp. 100–106, 2019, doi: 10.31311/ji.v6i1.5176.

[11] W. Swastika, “Studi Awal Deteksi COVID-19 Menggunakan Citra CT Berbasis Deep Learning,” *J. Teknol. Inf. dan Ilmu Komput.*, vol. 7, no. 3, p. 629, 2020, doi: 10.25126/jtiik.2020733399.

[12] A. L. Lloyd, “Destabilization of epidemic models with the inclusion of realistic distributions of infectious periods,” *Proc. R. Soc. B Biol. Sci.*, vol. 268, no. 1470, pp. 985–993, 2001, doi: 10.1098/rspb.2001.1599.

[13] H. Andersson, “Epidemics in a population with social structures,” *Math. Biosci.*, vol. 140, no. 2, pp. 79–84, 1997, doi: 10.1016/S0025-5564(96)00129-0.

[14] M. K. Ã, “The implications of network structure for epidemic dynamics,” vol. 67, pp. 1–8, 2005, doi: 10.1016/j.tpb.2004.08.002.

[15] R. O. Y. M. Anderson and R. M. May, “Spatial , Temporal , and Genetic Heterogeneity in Host Populations And the Design of Immunization Programmes,” pp. 233–266, 1984.

[16] A. Dobson, “Population Dynamics of Pathogens with Multiple Host Species,” vol. 164, 2012.

[17] U. Michelucci, *Applied deep learning: A case-based approach to understanding deep neural networks*. 2018.

[18] J. M. Czum, “Dive Into Deep Learning,” *J. Am. Coll. Radiol.*, vol. 17, no. 5, pp. 637–638, 2020, doi: 10.1016/j.jacr.2020.02.005.

[19] P. Wang, X. Zheng, G. Ai, D. Liu, and B. Zhu, “Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: Case studies in Russia, Peru and Iran,” *Chaos, Solitons and Fractals*, vol. 140, 2020, doi: 10.1016/j.chaos.2020.110214.

[20] A. Zeroual, F. Harrou, A. Dairi, and Y. Sun, “Deep learning methods for forecasting COVID-19 time-Series data: A Comparative study,” *Chaos, Solitons and Fractals*, vol. 140, 2020, doi: 10.1016/j.chaos.2020.110121.