The object of the study is epidemiological grouping using the SEIR mathematical model on a machine learning-based multilayer network. The problems in this research are related to managing epidemiological data on a large scale to determine disease patterns and identification such as the number of recovered cases, number of infected cases and number of deaths and demographic factors. In the process, traditional methods make it difficult to carry out processes such as determining patterns and identifying diseases. So, it is necessary to use machine learning and the SEIR (Susceptible-Exposed-Infectious-Recovered) mathematical model which can be integrated with multilayer networks to increase accuracy and effectiveness in identifying diseases and determining patterns. The results obtained from this research are a model that can identify and determine patterns of disease spread in large-scale epidemiological data. In its application, the SEIR mathematical model combined into a social layer and an environmental layer in a multilayer network. This research is research with a level of novelty in the application of the SEIR mathematical model to multilayer networks and machine learning so that the model formed can be used to view the distribution of epidemiological data for disease-related information. Machine learning aims to process large-scale data in minimal time resulting in clustering and identification of diseases such as flu, Covid-19 and pneumonia. This research has an accuracy of 94 % using the MAPE evaluation technique. It is hoped that the resulting model can be used in the world of health for disease mapping in certain areas as a reference for mitigating the spread of disease

Keywords: SEIR mathematical models, clustering, epidemiology, multilayer networks, machine learning

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DETERMINING EPIDEMIOLOGICAL PATTERNS IN DISEASE IDENTIFICATION USING MATHEMATICAL MODELS ON MACHINE LEARNING BASED MULTILAYER STRUCTURES

Riah Ukur Ginting
Corresponding author
Doctor of Computer Science*
E-mail: riahukur@students.usu.ac.id
Muhammad Zarlis
Information System Management
Department of BINUS Graduate Program Master of Information System Management
BINUS University
K. H. Syahdan str., 9, Kemanggisan, Palmerah Jakarta, Indonesia, 11480
Poltak Sihombing
Doctor of Computer Science*
Syahril Efendi
Doctor of Computer Science*
*Department of Information Technology
Universitas Sumatera Utara
Dr. T. Mansur str., 9, Kampus Padang Bulan, Medan, Sumatera Utara, Indonesia, 20155

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1. Introduction

The integration of geospatial data in epidemiological grouping using mathematical models in group-based multilayer networks is a topic that combines several important scientific fields in modern public health studies to be able to find patterns and identify diseases [1, 2]. Currently, with the increasingly advanced development of information technology, there are several challenges that require a multidisciplinary approach to determine disease and find patterns [3, 4]. Traditional epidemiological grouping in determining patterns and analyzing data statistically and then observing conditions that occur in the field in identifying diseases traditionally has limitations such as time complexity in analyzing larger and more complex data [5, 6]. With the increasingly rapid development of information technology, the emergence of various techniques that are integrated with technology able to carry out data processing with large and complex capacities. One technological development that can be integrated is a mathematical model in a multilayer network based on machine learning which can be used for data processing and data analysis on a large scale [7, 8]. The use of mathematical models will provide a theoretical framework so that it can be used for epidemiological phenomena by using equations and algorithms that can provide complex relationships between variables and related parameters [9, 10]. In the context of a multilayer network, integration of mathematical models used for the relationship between input and output through processes in interconnected layers. In this network there are hidden layer and an output layer that will process information through epidemiological data [11, 12].

In modern conditions like today, it is necessary to see patterns of disease spread and disease identification so that to apply this context the SEIR mathematical model will be applied. The SEIR model will be processed on a multilayer network so that it can process large-scale data. The results of such studies will be used for a more accurate prediction model in identifying disease patterns by integrating mathematical models and machine learning in multilayer networks and will be used by government institutions and Health Institutions in mitigating the spread of disease from various layers. Therefore, such studies are significant relevance for increasing the effectiveness and efficiency of managing disease epidemiological data in identifying and determining distribution patterns. By using mathematical models and machine learning, research can provide information about the dynamics of disease spread.

2. Literature review and problem statement

Research [13] presents the research results on spatial and temporal computational models in the spread of epidemics in epidemiology which will apply a dynamics approach to understanding networks in the spread of infectious diseases. This research shows that the dynamics approach is able to interpret networks in the distribution of infectious diseases. However, there are problems that have not been resolved regarding the temporal model for the spread of epidemics because the temporal model has a complex architecture in finding patterns. One way to resolve these difficulties is with the SEIR model which utilizes the multilayer structure of the network to find patterns. This approach is widely used in [14] but has not been applied to multilayer networks so it is recommended to carry out studies on multilayer networks using the SEIR model.

Research [15] presents research results on the SIR and SEIR (Susceptible-Expose-Infectious-Recovered) mathematical models which use differential equations in simulating the spread of disease. This research shows that the differential equation approach is capable of simulating the spread of disease using the SIR model. However, there are problems that have not been resolved in the SEIR model because the SEIR model has a long time and process complexity. One way to solve this problem is to use a multilayer network structure to solve time complexity problems. This approach is widely used but has not been applied to simulate the spread of disease so it is recommended to study the application of multilayer networks to simulate the spread of disease in the SEIR model.

Research [16] presenting research results using a machine learning approach for temporal and spatial forecasting models for the Covid-19 virus. This research shows that the machine learning approach can be applied to spatial models. However, there are problems that have not been resolved in the temporal forecasting model because the temporal model has difficulty dealing with large amounts of data. One way to solve this problem is to use the SEIR model in a multilayer network. This approach is widely used for large data but has not been applied to forecasting Covid-19 disease, so it is recommended to carry out analytical studies on SEIR network models for multilayer networks in Covid-19 disease.

Research [17] presenting research results by evaluating artificial neural networks (ANN) using multilayer perceptrons in predicting the geographic distribution of tuberculosis. This research shows that the multilayer perceptron algorithm is able to predict tuberculosis. However, there are problems that have not been resolved in the artificial neural network architecture because the artificial neural network structure has layers that are difficult to interpret with disease data. One way to solve this problem is to utilize a multilayer network approach with the SEIR mathematical model. This approach is widely used but has never been applied to tuberculosis, so it is recommended to conduct a case study for the SEIR model on multilayer networks.

Research [18] presents research results using a neural network-based machine learning approach to predict the Lyme disease epidemic. This research shows that neural networks can make predictions about Lyme disease. However, there are problems that have not been resolved related to the architecture of neural networks because the architecture has time complexity which is difficult to use on small amounts of data. One way to solve this problem is by utilizing the SEIR mathematical model in combination with a multilayer network. This approach is widely used but has never been applied to large scale data so it is recommended to conduct a study for the SEER model on multilayer networks on large scale data.

Research [19] presenting research results using the CNN algorithm approach in predicting the spread of SARS-CoV-2 disease. This research shows good accuracy in predicting spread. However, there are problems related to the time complexity of finding disease patterns, making it difficult to use data on a large scale. One way to solve this problem is by utilizing the SEIR mathematical model approach which is able to find patterns in large-scale data and combinations in multilayer networks. This approach is widely used so it is recommended to carry out studies on SEIR models with a combination of multilayer networks.

The study [20] presents the results using an epidemiological model approach in understanding the spread of disease by applying mathematical modeling. Mathematical modeling shows that the epidemiological model is able to find distribution patterns. This research has unresolved problems related to big data management. The solution offered to solve this problem is by applying the SEIR model to a multilayer network.

All this allows to assert that it is expedient to conduct a study on applying the SEIR model to a multilayer network for determine epidemiological patterns in disease identification.

3. The aim and the objectives of the study

The aim of this study is to determine epidemiological patterns in disease identification.

To achieve this aim, the following objectives are accomplished:

– to apply the SEIR mathematical model to multilayer networks;

– to the integration of geospatial data in mathematical models;

– to apply machine learning so that it can predict epidemiological data.

4. Materials and methods

The object of the study is epidemiological grouping using the SEIR mathematical model on a machine learning-based multilayer network. In this study, there is a research hypothesis, namely the use of the SEIR (Susceptible-Expose-Infectious-Recovered) mathematical model to be integrated into machine learning with multilayer networks. Several problems such as the use of traditional methods and the difficulty of processing data on a large scale are the basis for using mathematical models in machine learning-based multilayer networks. In this research there are problems related to managing epidemiological data on a large scale. In large-scale data there are many parameters such as the number of recovered cases, the number of infected cases and the number of deaths as well as data on demographic factors. In the traditional method, it is difficult to carry out processes such as analyzing, grouping and making predictions for the future. So, it is necessary to use machine learning and the SEIR (Susceptible-Exposed-Infectious-Recovered) mathematical model which can be integrated with multilayer networks to increase accuracy and effectiveness in analyzing the spread of disease [21, 22]. In the context of using machine learning, it used to identify patterns and trends in epidemiological data. In this case, machine learning used to process large-scale data. In this case, it used to identify the spread of disease and predict future disease transmission. In terms of the spread of disease, this research will use geospatial data which will utilize information related to geographical location, in this information there coordinate values. In this case, data in epidemiology will carry out mapping and analysis of disease distribution patterns spatially. By using geospatial data, it is possible to identify and map areas with high risks [23, 24].

This research will use the SEIR model which integrated with a machine learning-based multilayer network. In this approach each category of the model is symbolized by (S) – susceptible, (E) – exposed, (I) – infected, (R) – recovered. Then it represented in a multilayer network layer using epidemiological data and geospatial data. This layer will work structurally to carry out the process and will produce output in the categories that have been determined. In this context, let's utilize the LSTM algorithm in the use of good machine learning in handling time series data. The multilayer layers of the LSTM algorithm can analyze data patterns and complexity so that it can effectively predict changes in vulnerable, exposed, infected and recovered populations based on historical data and geographic factors. Therefore, this research aims to develop a SEIR mathematical model on a multilayer network which is very relevant in integrating geospatial data in mathematical models in determining patterns of disease spread and disease identification in machine learning-based epidemiological data.

In this research, theoretical methods used, namely the mathematical model used is SEIR which integrated into a multilayer network. The main hypothesis in this research is the use of the SEIR mathematical model to be integrated into machine learning with multilayer networks. Several problems such as the use of traditional methods and the difficulty of processing data on a large scale are the basis for using mathematical models in machine learning-based multilayer networks. The problem to be solved in this research is related to managing epidemiological data on a large scale. In large-scale data there are many parameters such as the number of recovered cases, the number of infected cases and the number of deaths as well as data on demographic factors. In traditional methods, it is difficult to carry out processes such as analyzing, grouping, and making predictions for the future. By applying stages such as the use of the SEIR mathematical model and geospatial data integration, it is hoped that machine learning-based epidemiological data can be modeled. For hardware use, used a laptop with Core i5 processor specifications with 256 GB SSD storage and used software such as Microsoft Word version 2019, Google Collaboratory and Anaconda software which uses the Jupiter editor. This research used data from the North Sumatra Health Service. Validation of the proposed solution is to apply the SEIR mathematical model to a multilayer network which uses utilize machine learning in discovering epidemiological patterns and disease identification.

In this research there is a framework architecture in Fig. 1.

In Fig. 1, the architectural framework for using the SEIR mathematical model displayed which used in machine learning-based multilayer layers. In this model let's pay attention to the parameters symbolized by (S) – vulnerability, (E) – exposed, (I) – infected, (R) – recover. In this model, there are interactions such as transitions between compartments S, E, I and R. To be able to describe the spread of disease, geospatial data analyzed to take into account geographical factors such as transmission rates and population transitions, individual mobility.

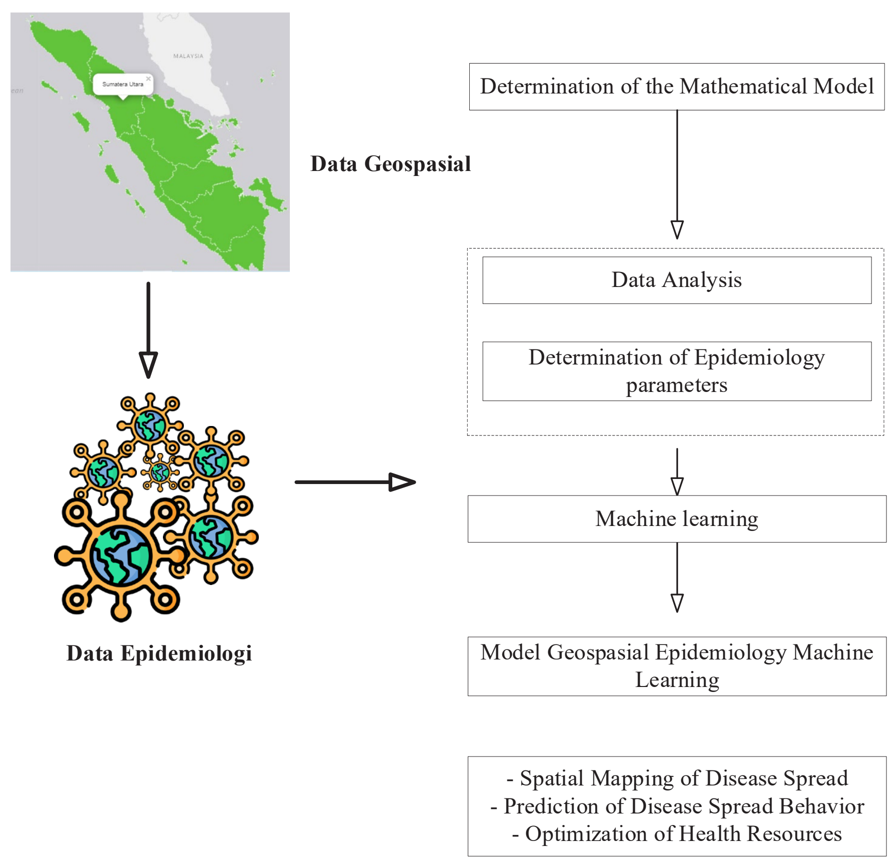

Fig. 1. Proposed architecture

The following is the formulation of the mathematical model expressed by the formula:

$$\frac{dS}{dt}=-\beta\frac{SI}{N}, \quad (1)$$

$$\frac{dE}{dt}=\beta\frac{SI}{N}-\sigma E, \quad (2)$$

$$\frac{dI}{dt}=\sigma E-\gamma I, \quad (3)$$

$$\frac{dR}{dt}=\gamma I. \quad (4)$$

Equations (1)-(4) will present interrelated symbols in the mathematical model of a multilayer network. In this context the number of vulnerable individuals symbolized by *S*, for exposed individuals symbolized by *E*, for the number of infected symbolized by *I*, for recovered individuals it symbolized by *R*, for the level of transmission it symbolized by β, and individuals who are exposed and then move symbolized by σ while the recovery rate symbolized by ϒ. Then the mathematical model integrated with geospatial data which will then use the mathematical formula contained in the following equation:

$$\beta_{ij}=\beta_0\cdot f\left(Density_i, Mobility_{ij}\right). \quad (5)$$

In (5) there mathematical formula for the transmission transition which is symbolized by β_{ij} which is the level of transmission between regions *i* and *j*, β_0 is a basic parameter in geospatial data and $f(Density_i, Mobility_{ij})$ will illustrate the influence of population density and mobility between regions on the data. Then there is a transition from *E* to *I*(σ) and from *I* to *R* (ϒ) with the following equation:

$$\sigma_i=\sigma_0\cdot g\left(Environment_i\right), \quad (6)$$

$$\gamma_i=\gamma_0\cdot h\left(Environment_i\right). \quad (7)$$

In (6), (7) there are symbols σ_i and Υ_i which is a parameter for the region *i* whereas for σ_0 and Υ_0 is a basic parameter that will describe the influence of the environment and transition on recovery which is symbolized by *g* and *h*. then the mathematical model placed on a multilayer network to be able to model epidemiology. In a multilayer network structure, there is dynamic equation like the following:

$$\frac{dS_i}{dt}=-\sum_j\beta_{ij}\frac{s_iI_j}{N_i}, \quad (8)$$

$$\frac{dE_i}{dt}=-\sum_j\beta_{ij}\frac{s_iI_j}{N_i}-\sigma_iE_i, \quad (9)$$

$$\frac{dI_i}{dt}=\sigma_iE_i-\gamma_iI_i, \quad (10)$$

$$\frac{dR_i}{dt}=\gamma_iI_i. \quad (11)$$

In equations (8)–(11) there parameters used, but this model will make it easier to analyze the spread of disease in the context of interactions in various multilayer layers with the Susceptible equation (*S*), Exposed (*E*), Infectious (*I*), and Recovered (*R*) within each layer allows a more accurate calculation of transitions between compartments based on local and global dynamics.

5. Results of mathematical models on multilayer networks in epidemiological grouping

5. 1. SEIR mathematical model in multilayer networks

In this case, the interactions between layers must be analyzed first so that the overall grouping of disease spread on large-scale data can be understood and can be carried out by a multilayer network. In a multilayer network structure, there is a social layer and a workplace layer. This layer has its own characteristics, the social layer analyzed based on individual relationships, family and friends, while for the workplace layer the work environment analyzed. Then, in integrating the SEIR mathematical model in a multilayer network, it is necessary to carry out analysis between layers. In the interaction layer it is symbolized η*lm* which will interpret the individual odds on the layer *l* in influencing individuals at layers *m*. The following is the application of a mathematical model to multilayer layers which formulated between layers as follows:

$$\frac{dS_l}{dt}=-\beta l\frac{S_lI_l}{N_l}-\sum\nolimits_{m\neq l}\eta lm\frac{S_lI_m}{N_l}, \quad (12)$$

$$\frac{dE_l}{dt}=-\beta_l\frac{S_lI_l}{N_l}-\sigma_lE_l, \quad (13)$$

$$\frac{dI_l}{dt}=\sigma_lE_l-\gamma_lI_l, \quad (14)$$

$$\frac{dR_l}{dt}=\gamma_lI_l. \quad (15)$$

On the symbol β_l determined at the level of transmission in the layer *l*, on the symbol σ_l is exposure which will refer to individual exposure or risks that influence the spread of disease, while in symbols Υ_l is the rate of recovery from disease. Then there is η_{lm} which will describe the interactions between layers then for symbols N_l is the total number of individuals in the layer *l*. The SEIR mathematical model which is developed using a multilayer network can model or group the spread of disease by looking at interaction factors between layers in the network. Then the application of the SEIR mathematical model to a multilayer network simulated with 6 populations, each population using 100 individuals, resulting in the model shown in Fig. 2.

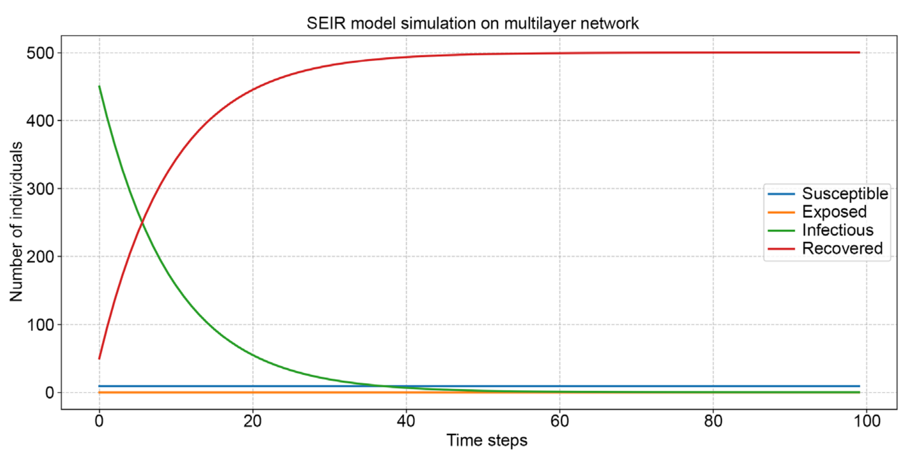

Fig. 2. SEIR model in multilayer networks

In Fig. 2, it explained that in a multilayer network using the SEIR mathematical model there an explanation of the number of individuals who are susceptible to exposure depicted in blue, the number of exposed individuals depicted in yellow, the number of infected individuals depicted in green and the number of individuals who have recovered depicted in red. In Fig. 2, the simulation uses data from 100 individuals which produces an increasing graph for grouping individuals in a multilayer network for the parameters of individuals who have successfully recovered.

5. 2. Geospatial data integration in mathematical models

In the application of mathematical models, aka tone analysis, the process of analyzing geographic data information with parameters from epidemiology so that predictions of the spread of disease can be carried out more effectively. The use of geographic data will provide structured information from a mapping perspective and can influence epidemic dynamics. In data integration, there a map of the distribution and location of health facilities that can be used by individual interactions, then with the parameters of the SEIRD mathematical model, it is possible to group transmission and healing based on interactions carried out by individuals in a population. In Fig. 2, there a mapping of individuals who are susceptible to exposure in 6 populations in the geographical data of the city of Medan, North Sumatera.

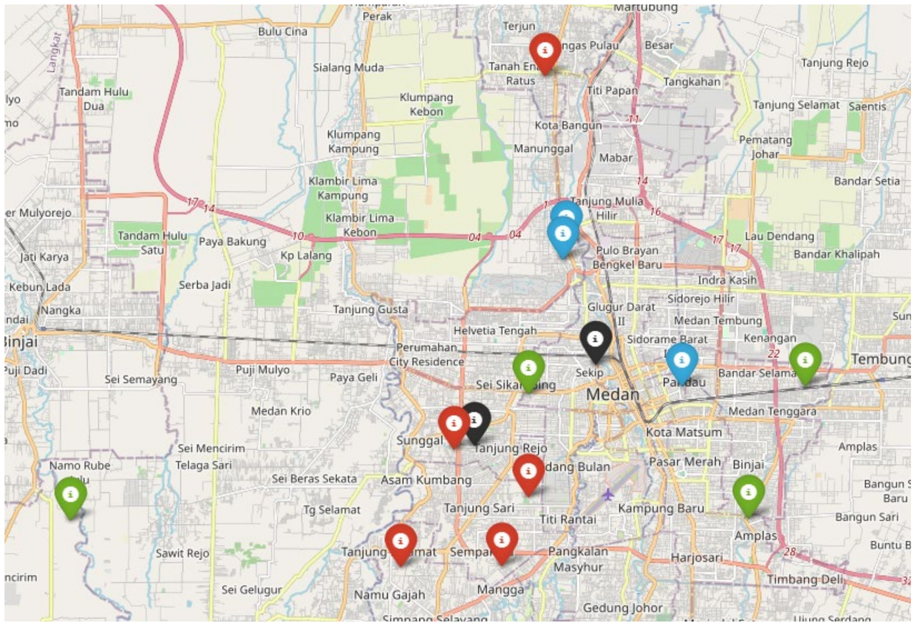

Fig. 3. Epidemiological clustering

Table 1

Distribution of epidemiological data clustering

Latitude	Longitude	Population	Susceptible	Exposed	Infected	Recovered
3,112338	99,0951465	8000000	1000	10	23	15
3,563675	98,6207887	4000000	1000	12	24	14
3,588719	98,6581788	8000000	1000	13	25	16
3,156515	98,5067037	4000000	1000	14	26	15
3,295698	99,1108512	2700000	1000	10	29	18
3,599677	98,6374932	2300000	1000	10	30	17
3,561354	98,7056034	4000000	1000	10	22	15
3,602117	98,723007	4000000	1000	12	21	15
3,560707	98,4962917	8000000	1000	13	20	15
3,582104	98,7049969	4000000	1000	13	34	11
3,805626	98,36412	2700000	1000	15	34	9
3,625978	98,6693942	8700000	1000	16	20	10
3,621431	98,66836	8700000	1000	17	20	11
3,568002	98,6575291	8700000	1000	18	25	20
3,582653	98,6347141	8700000	1000	20	25	20
3,697772	98,6626122	8700000	1000	13	28	15
3,546785	98,649524	8700000	1000	14	28	13
3,510828	99,1795358	8700000	1000	14	28	12
3,546457	98,6180949	8700000	1000	15	30	10

Fig. 3 explains that there is an epidemiological grouping based on geospatial data, where the grouping is divided into 4 categories, namely the number of susceptible individuals, the number of exposed individuals, the number of infected and the number of recovered individuals. Geospatial data that uses geographic data combined with the SEIR mathematical model produces the number of recovered individuals with red markers, the number of exposed individuals with black markers, the number of susceptible individuals with blue markers while the number of infected individuals with red markers. and the number of susceptible individuals with a green marker. In the epidemiological grouping there a data distribution which can be seen in Table 1 below.

In Table 1, it explained that applying the SEIR mathematical model will produce the numbers of Susceptible, Exposed, Infected and Recovered. This number is based on the population at each coordinate point.

5. 3. Application of machine learning to predict epidemiology data

In this section, let's explain the application of machine learning to epidemiological data in predicting the spread of disease, early detection of disease and epidemiological grouping with large-scale data. In the spread of disease there influencing factors such as mobility, population, conditions and weather. In this research, the SEIR mathematical model combined with a machine learning algorithm which can provide projections that are more dynamic and responsive to changing conditions. The following are the results of applying machine learning which displays predictions of cases of disease spread in Fig. 4.

In Fig. 4, it explained that the use of machine learning can predict the spread of disease using actual and predicted data. The trained model produces predictions with an accuracy level of 0.94 % using the Mean Absolute Percentage

Error (MAPE) evaluation technique. Then, for disease detection, there machine learning model that can group early detection of diseases such as Covid-19, flu and pneumonia. The following are the results of the disease detection model using machine learning in Fig. 5.

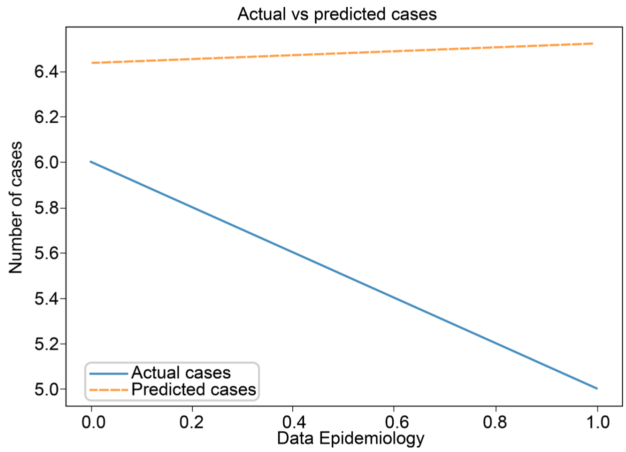

Fig. 4. Prediction of the spread of disease

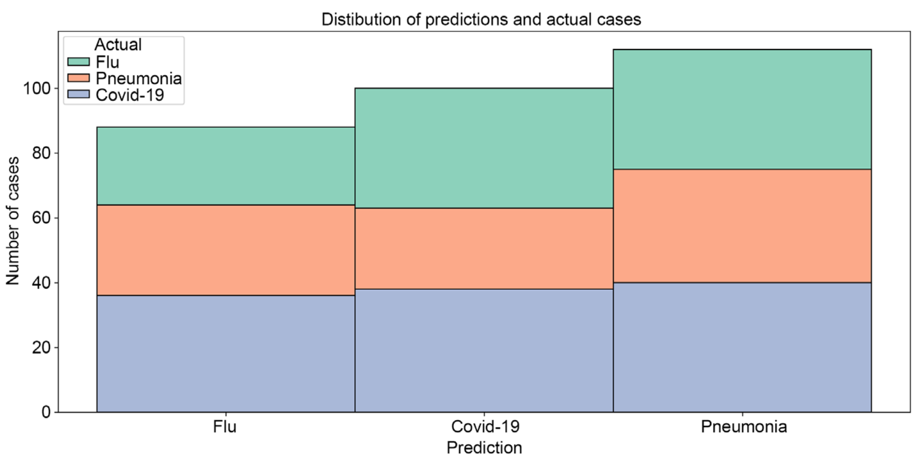

Fig. 5. Prediction of disease detection

In Fig. 5, there are predictions of disease detection using a mathematical model utilizing a machine learning approach where there actual data and predicted data which will explain the performance of the model. This model allows better predictions with an accuracy of up to 94 %. Regarding the spread of disease. This model can also identify spread risks quickly by combining machine learning with mathematical models on multilayer networks on large-scale data.

6. Discussion of machine learning-based mathematical models in determining disease patterns and identification

The application of mathematical models and machine learning in determining disease patterns and identification is the most important component of the results. This research is novel in the field of artificial intelligence. The mathematical model has significant novelty in the use of the SEIR model. The SEIR model combined with machine learning on a multilayer network so that it is able to manage large-scale epidemiological data to identify diseases and be able to understand what parameters are used to be applied to the SEIR mathematical model such as the parameters denoted with (S) – Susceptible, (E) – exposed, (I) – infectious, (R) – recovered. This research has features for solving problems that have solutions for the model. This model provides solutions and results if interactions occur such as transitions between compartments S, E, I and R to describe the spread of disease. This model provides benefits on geospatial data such as transmission rates and population transitions, individual mobility.

This research produces a model that can be used to identify disease and determine distribution patterns. In the model there where there is an interaction between the level of transmission which symbolized by β, and individuals who are exposed and then move symbolized by σ, while the recovery rate symbolized by ϒ. In the transmission transition which is symbolized by β_{ij} which is the level of transmission between regions i and j, β_0 is a basic parameter in geospatial data and $f(Density_i, Mobility_{ij})$ describes the influence of population density and mobility between regions on data.

Then there is a transition from E to I (σ) and from I to R (ϒ). This research aims to produce a model that can group, predict the spread of disease and predict early detection. In this case, the application of mathematical models is very relevant by combining SEIR models in multilayer networks coupled with the use of machine learning. Machine learning is used to apply mathematical models to produce models that can apply equations (1)–(5) to SEIR models, apply equations (6)–(8) to geospatial models and apply equations (9)–(11) for multilayer networks. The results of the mathematical model depicted in Fig. 2 in the SEIR mathematical model which uses (1)–(5). Then, based on this model, there is created a machine learning model that can process large data in (12)–(15) which is then explained by regularities of disease with individual exposure parameters and recovery rates on social networks.

Then in Fig. 3 there are the results of geospatial data grouping by mathematical models of epidemiological grouping and in Fig. 4 there are the results of machine learning model groupings with an accuracy of up to 94 %, prediction and distribution of disease on large scale data. Applying the SEIR mathematical model to a multilayer network can achieve the stated goals of integrating geospatial data and machine learning so that it can solve research problems. This is different from research [14] whose results only apply the SEIR model traditionally, so there are shortcomings such as requiring complex time to process large amounts of data. The proposed solution can cover and resolve these problem areas by applying a multilayer network and a machine learning approach by utilizing the SEIR mathematical model in formulas (12)–(15) which will explain the identification of distribution patterns with the parameters of exposed individuals and social networks.

This research has limitations such as the need for better data processing from a geographical perspective because currently the spread of disease with geographical data is still limited. Then this research has a weakness in terms of multilayer networks which require complex processing time because they have to carry out processing from the social layer and the environmental layer. This research can be expanded and developed by integrating medical records at each public hospital in an area so that it can be empowered to mitigate the spread of epidemiology.

7. Conclusions

1. The results obtained in this research are a SEIR mathematical model for identifying diseases and identifying spread patterns based on machine learning. In this context the aim is to provide knowledge about multilayer networks that can carry out data processing on a large scale. In the mathematical model there are characteristics such as population compartments which contain parameters S (Susceptible), E (Exposed), I (Infectious) and R (Recovered) and characteristics such as transitions between compartments.

2. This research has data integration to combine location or geographic distribution information with mathematical analysis for the accuracy of a prediction model, grouping clusters and being able to identify geographic risk factors which allows the model to consider geographic aspects to increase accuracy in making predictions.

3. This research has an accuracy of 94 % using the MAPE evaluation technique. It is hoped that the resulting model can be used in the world of health for disease mapping in certain areas as a reference for mitigating the spread of disease.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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