Telemedicine Technology Application for COVID-19 Patient Tracing Using Smartphone GNSS

Cahyadi, M. N.,[1] Susanto, L. O. F.,[1] Rokhmana, C. A.,[2] Sulistiawan, S. S.,[3,4] Waloejo, C. S.,[5] Raharjo, A. B.,[6] Endroyono[7] and Atok, M.[8]
[1]Geomatics Engineering Department, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
E-mail: cahyadi@geodesy.its.ac.id, levianasusanto.206016@mhs.its.ac.id
[2]Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta 5581, Indonesia, E-mail: caris@ugm.ac.id
[3]Graduate Institute of Biomedical Sciences-China Medical University, Taiwan 40402, R.O.C.
[4]Department of Anesthesiology and Reanimation, Faculty of Medicine, Universitas Airlangga-Dr. Soetomo Hospital, Surabaya 60132, Indonesia, E-mail: soni.sunarso.s@gmail.com
[5]Master Program in Disaster Management, Postgraduate School, Universitas Airlangga-Dr. Soetomo Hospital, Surabaya 60132, Indonesia, E-mail: christrijogo@fk.unair.ac.id
[6]Department of Informatics Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
E-mail: Lagus.budi@its.ac.id
[7]Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
E-mail: endroyono@ee.its.ac.id
[8]Department of Statistics, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
E-mail: moh_atok@statistika.its.ac.id
Corresponding Author

DOI: https://doi.org/10.52939/ijg.v18i2.2159

Abstract

In order to cope with a pandemic COVID-19, Indonesia has implemented various measures of public health including contact tracing. This research will integrate three aspects, namely the use of telemedicine for geographic information system, tracking COVID-19 patients using smartphones and diagnosed persons. The three aspects are wrapped in interactive and informative application where users can track their journeys, and communicate directly with the doctors. The geographic information system was built based on statistical analysis of the coronavirus disease (COVID-19) pandemic to determine the factors that affect the number of COVID-19 patients in an area using geographically weighted regression. Later on, this application can provide information about the current conditions, increase data transparency, and used as a tool in assessing a particular policy. This telemedicine application utilizes a map-based geographic information system (GIS) feature to display information. This system also has high security so that it can protect user information and can be accessed easily by users.

1. Introduction

Corona virus or Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is a virus that attacks the respiratory system. The disease caused by infection with this virus is called coronavirus disease 2019 (COVID-19). SARS-CoV-2 infection can produce a wide range of symptoms, including moderate upper respiratory tract infection symptoms, life-threatening sepsis, or even asymptomatic infection. COVID-19 initially surfaced in December 2019, when a group of patients in Wuhan, China, were diagnosed with pneumonia of unknown origin. SARS-CoV-2 has infected over 200 nations as of July 1, 2020 (Wiersinga et al., 2020).

Based on the information published on Worldometers website, until May 18, 2021, positive cases of COVID-19 continued to increase, in Indonesia it reached 1,744,045 cases and was in the top 20 most cases in the world (Worldometers, 2021). COVID-19 is a disease with a high transmission rate and has been declared as pandemic by World Health Organization (World Health Organization, 2020). In order to cope with a pandemic COVID-19, Indonesia has implemented various measures of public health, including PSBB (Large-Scale Social Restriction) in accordance with Minister of Health Regulation Number 9 of 2020 concerning Guidelines for Large-Scale Social

Restrictions in the Context of Handling Corona Virus Disease 2019 (COVID-19) and PPKM (Enforcement of Restrictions on Micro-Based Community Activities) in accordance with Indonesian Ministry of Internal Affair's Instruction number 10 of 2021 (INMENDAGRI Nomor 10 Tahun 2021 Tentang Pemberlakuan Pembatasan Kegiatan Masyarakat Berbasis Mikro Dan Mengoptimalkan Posko Penanganan COVID-19 Di Tingkat Desa Dan Kelurahan, 2021; Permenkes No. 9 Tahun 2020 Tentang Pedoman PSBB Dalam Rangka Percepatan Penanganan COVID-19, 2020). In the subsequent development of the pandemic, Indonesian Ministry of Health issued a guide that provides recommendations based on data on the adjustment of economic and social activities in the community where one of the surveillance mechanisms carried out is contact tracing (Keputusan Menteri Kesehatan Republik Indonesia Nomor HK.01.07/MenKes/413/2020 Tentang Pedoman Pencegahan Dan Pengendalian Corona Virus Disease 2019 (COVID-19), 2020).

Currently, smartphone-based applications related to tracing people, telemedicine, and epidemic modelling have been successfully created, but the integration of the three concepts has not been carried out, so their utilization is still not optimal enough to support handling this pandemic. As in the research conducted by Hong et al which applies telemedicine to provide medical information for diagnosis, therapy, and education about COVID-19 disease (Hong et al., 2020). The COVID-19 telemedicine system can improve the accuracy of diagnosis and improve the treatment of COVID-19 cases that are quite critical for people in Western China at a relatively lower cost. One of the work systems in the application of this research that is quite useful for handling COVID-19 is the free consultation or psychological intervention from medical staff to users. This telemedicine system is considered quite helpful in handling COVID-19 in West China. However, the COVID-19 telemedicine system has not been integrated with tracing, and epidemic model concepts. Tracing using a smartphone concept is used in Ferretti et al research, by utilizing the Bluetooth feature on a smartphone to identify "proximity events", when two smartphones are in a relatively close distance for a relatively long time, the server will record this event for later analysis if one of the smartphone owners is confirmed positive for COVID-19 (Ferretti et al., 2020). However, the application developed in this study have some drawbacks. Users can only get information in a small area around them while when they are going to travel to other areas they will have difficulty getting information about the pandemic conditions in the destination area, also the tracing feature in this application has not been integrated with any telemedicine and epidemic model. The concept of epidemic modelling has been carried out by many researchers, one of which is Middya and Roy (Middya and Roy, 2021). However, the results of this modelling are still presented in journal and have not been integrated with any telemedicine or other GIS platforms. Ordinary least squares (OLS) and geographically weighted regression (GWR) approaches were used in this work to evaluate the geographic distribution of COVID-19 deaths and their association to various potential drivers.

This research will integrate three aspects, namely the use of telemedicine for consultation and disease diagnosis, the use of smartphones for tracing people, and epidemic model. This integration is essential for comprehensively handling COVID-19, the three integrated features are able to support decision making for individuals and policy makers in handling COVID-19 optimally. For application users, they can find out the potential and risks of COVID-19 in the surrounding environment from the results of tracing and epidemic model feature. In addition, there is also a telemedicine feature that is used for consultation and early detection if the user experiences symptoms that refer to the COVID-19 disease. As for policy holders, where in this case the telemedicine application will also be tested in hospitals in Surabaya, the results of this integration in epidemic modelling, and spatial information from application users can be taken into consideration for taking policies to deal with COVID-19.

2. Methodology

Two working groups will be conducted in this study, which are Geographic Information System based on patient database and Tracing & diagnosing COVID-19 patients using an integrated smartphone to Smartphone telemedicine.

2.1 Tracing and Diagnosing

COVID-19 virus, according to the World Health Organization (WHO), can cause respiratory disorders such as cough, fever, and pneumonia. In this case, doctors and health workers is trying to withhold the spread of the disease. Some of the methods that is being used to withhold the spread are intensifying lock-downs, mass quarantines to city closures, and conducting contact tracing by using data collection in crowded areas. Contact tracing is the main way to control infectious diseases such as tuberculosis (TB), human immunodeficiency virus (HIV), and COVID-19.

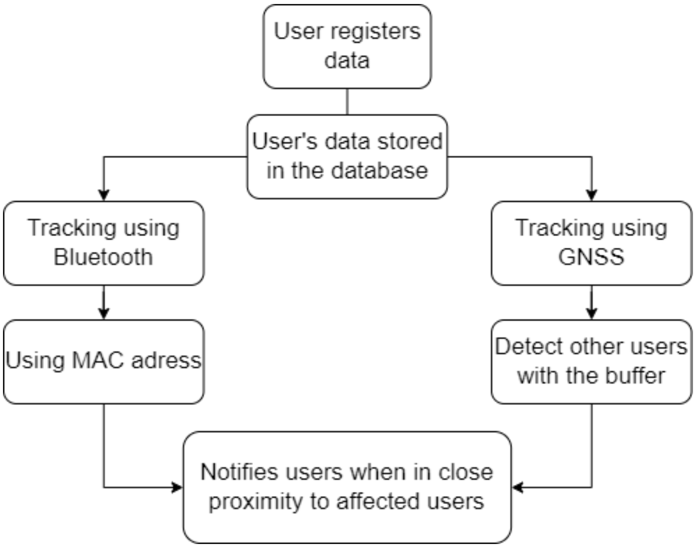

Figure 1: Tracing concept in telemedicine application

However, only few steps have been taken to determine the optimal level of investment in contact tracking systems. The tracing in this study is done using smartphone technology by utilizing its GNSS and Bluetooth technology to track positions and contacts between smartphones.

The tracing concept is using a smartphone application with the daily activity concept with the flow described in Figure 1. The user will provide personal data manually in the application system where the data will be entered into the data base server. The data is used to track the user's journey and to record the user's medical history (especially for COVID-19). The following are the detailed steps in implementing the concept:

a. Android smartphones are being used to develop a telemedicine application. This program allows users to enter details such as their name, postal code, phone number, birthdate, Bluetooth MAC address, gender, and COVID-19 status into the proposed model. The Bluetooth MAC address (similar to a phone's serial number) is automatically acquired by the program without the need for user intervention. COVID-19, no COVID-19, and cured are the three alternatives for the COVID-19 status.

b. Tracking. After the user completes the registration process, the user can enter a position tracking model that utilise GNSS feature in the smartphone. This tracking model was made to send the information about the user's position into the system database and then showing their position on an online map. The GNSS accuracy varies depending on the smartphone brand and variations in landscape settings. In our experiments in a residential environment with open sky conditions using the Redmi Note 8 Pro device, Smartphone GNSS accuracy ranged from 5-12 meters. Similar results also found in Merry & Bettinger study that shows smartphone 7–13 m range accuracy using iPhone 6 in urban area (Merry and Bettinger, 2019).

c. Users receive related notifications when they are in areas that have been visited by other users which have been infected with COVID-19, even when the application is not in use, because the application is always working/online. The notice and alert dialog models are also configured in outdoors and indoors. When the user is outside, the user's position information based on the smartphone's GNSS will be used to calculate the gap between two different user spots. Afterwards, a buffer technique is performed based on this distance for each application user. If the distance is less than 5 m, the user will receive a notification. When the user is in a particular room, it will cause interference with the user's position information based on GNSS. Thus, this application is equipped with a scanning feature using a Bluetooth device which will scan other Bluetooth users. This scanning process is utilizing the MAC address that has been pre-registered in the system. If the Bluetooth MAC user who has registered in the application has a history of COVID-19, then notifications and warning dialog in this application will notify the user regarding COVID-19 cases in the scanning area. Governments are currently preparing for the worst by quickly realising the effect of COVID-19 on healthcare and global economy.

Aside of tracing, fast responses in handling symptoms or diagnosis is very important to withhold the spread of COVID-19. Therefore, telemedicine is ideal for the management of infectious diseases. A key factor in slowing the transmission of the virus is social distancing, thereby reducing face-to-face contact. For patients with COVID-19 or those who are concerned that they may be infected, telemedicine can assist remote consultation and provision of care. For people who are not infected with COVID-19 virus, especially those who are at a higher risk of contracting it (e.g. older adults with pre-existing medical conditions), telemedicine can provide easy access to routine care without the risk of exposure to overcrowded hospitals or in the waiting room of medical practice (Smith et al., 2020).

One of the benefits of telemedicine application is to provide diagnoses toward the users related to the symptoms of the disease that has been experienced, including comparatively by analysing the clinical characteristics of viral infections from COVID-19. This application will be combined with the position of the tracing feature on hospital patients in Surabaya. This research method is carried out in the form of consultations in text and video calls. The data used for early detection of symptoms experienced by patients is by obtaining information from health experts or expert doctors, and is also supported by other information about COVID-19 and other diseases.

2.2 Telemedicine Application

There are several steps that need to be done in the making process of telemedicine applications, including creating designs, code generation, application testing and maintenance. The design process translates requirements into a representation of the form of software that can be seen for its quality before entering the coding stage. The first step is to create a data or information model that will be displayed, and then architectural design was made to create an overall picture of the application to be built. The data flow design will be made at this stage, namely the process of describing the system flow, the relationship between the entities of the system, application algorithms and database design (Kristanto, 2018). After the application architecture is formed, and then the interface design is carried out to describe the specifications of the application to be made in detail.

After the application design is formed, the next step is Code Generation. This is a coding activity and testing errors in the code. Construction begins with the preparation stage including what is needed such as basic design concepts, ranging from programming language selection, programming environment, to testing units. The programming is done by applying algorithms, selecting data structures, creating variable names, and creating code for easy understanding. The testing is done after writing the program code. Testing is the process of executing the program with the intention of finding errors. A good testing is the one that has a high probability of finding errors that have not been found, checking the correctness of syntax and logic, conducting tests and correcting errors (Pressman and Maxim, 2019). After the application can run without errors, the next step is maintenance and development, and the software that has been delivered to the user will definitely experience changes. These changes can happen due to an error, adjustment to a new environment, or because the user needs functional development.

2.3 Geographic Information System Based on Patient Database

The Geographic Information System is built based on geospatial and spatial-statistical analysis of the geographic dimensions of the coronavirus disease (COVID-19) pandemic. Understanding the dynamics of COVID-19 is very important to help clarify the impact of the pandemic and can aid community decision-making, planning, and action (Franch-Pardo et al., 2020). In addition to carrying out patient disease and tracing to monitor movement and study the spread of disease, investigation of the geographic relationship between positive cases of COVID-19 and potential related factors needs to be done. Spatial modelling of COVID-19 epidemiology was carried out to determine the vulnerability level of the region to the COVID-19 outbreak using Geographic Information System. The Geographically Weighted Regression (GWR) method was used to investigate the geographic distribution of COVID-19 positive cases as well as the possibility for correlating socioeconomic, demographic, and health aspects. In addition, comparisons of local (OLS) and global (GWR) models were made to ensure that they were both suitable.

1) Data collection. The dependent variable used in this study is the number of COVID-19 cases of each urban village in the City of Surabaya, retrieved from Surabaya City COVID-19 Information and Coordination Centre website as of July 15, 2021. The demographic, socio-economic, and health factors was chosen from the data collection to explain the variation of COVID-19 cases.

In demographic factors, data on population density (X1), population (X2) and number of elderly people per 1000 population (X3) are used. In the health factor, data on the number of health facilities per 10000 populations (X4) is used. In socio-economic factors, data on the number of economic centres (X5) is used. For the record, the independent variable is taken from the 2019 data, which was last recorded by the Central Bureau of Statistics of Surabaya.

2) The making of OLS (Ordinary Least Square) modelling. The OLS method estimates the relationship between one or more independent variables and one dependent variable (Wu and Zhang, 2021). Mathematically, Equation 1 represents the OLS global regression model as follows:

$$y_i = \eta_0 + \sum_{k=1}^{n} \eta_k X_{ik} + \delta_i$$

Equation 1

y_i shows the dependent variable or respond, X_{ik} is the i-number observation from the independent variable of k-number, η_k shows global regression coefficient for the independent variable of k, η_0 shows the intercept parameter and δ shows the error term (Middya and Roy, 2021).

3) The making of GWR (Geographically Weighted Regression) model includes classification stage of each parameter, calculation analysis of COVID-19 spread factors using GWR and weighting each parameter. Geographically Weighted Regression (GWR) is one of the analyses which form a regression analysis but it is local to each location. This approach yields a regression model with attribute values for each observation spot. The GWR model can be represented as follows (Fotheringham et al., 2002):

$$y_i = \xi_{i0} + \sum_{k=1}^{n} \xi_k(\mu_i, v_i) X_{ik} + \delta_i$$

Equation 2

y_i, X_{ik}, and δ_i shows the dependent variable (or responds), independent variable (or predictor) of k-number, and error in i location, (μ_i, v_i) shows the location coordinates of i; $\xi_k(\mu_i, v_i)$ representing the local coefficient for k-number predictor in i location. The weighted matrix element W(i) is used in GWR with the magnitude depends on the proximity between locations. Closer location indicates greater weight of influence.

The weighting function for GWR is the Kernel Gaussian function. The Global Regression Model (GWR) is a progression of the global regression model. In contrast to global regression, which uses the Weighted Least Square (WLS) approach to produce local model parameter values for each observation location, GWR uses the Weighted Least Square (WLS) method to provide local model parameter values for each observation location, namely (Wu and Zhang, 2021):

$$\hat{\xi}(i) = (X'W(i)X)^{-1}X'W(i)Y$$

Equation 3

$$W(i) = \mathrm{diag}[w_1(i), w_2(i), \dots, w_n(i)]$$

Equation 4

Where X shows the matrix of independent variable value, Y indicates the vector value from dependent variable; $\hat{\xi}$ is the local regression parameter vector, W(i) is the spatial weighting matrix of the i-location, whose he distance of diagonal factor affects the appearance of the i-location toward other locations (j-location). The bigger the weighted value on the related element, the closer the location would be. The following is one of the spatial weighting factors in GWR, which is based on the Gaussian Kernel function:

$$w_j(i) = \exp\left[-{}^1/_2\left({}^{d_{ij}}/_b\right)^2\right]$$

Eqaution 5

with dij as the is the distance from location-i to location-j and b is the bandwidth, which is a value that must be set to describe the longest distance of a particular location that still impacting other locations.

4) Result comparison of OLS and GWR model. While GWR focuses on spatial heterogeneity and does not accurately represent spatial homogeneity, OLS is frequently used when the dependent and independent variables do not differ or have spatial homogeneity. (Shoff et al., 2014). Brunsdon offer the GWR model, which is an extended form linear regression model that combines geographic location data as a regression component. (Brunsdon et al., 1996). Three metrics including R^2, Adj R^2, and AICc, are used to evaluate the model's performance. The Akaike Information Criterion (AICc) is a corrected version of Akaike Information Criterion (AIC).

Model accuracy is measured by AICc, with a smaller AICc indicating better model quality and the best model (Fotheringham et al., 2002). The R^2 number reflects how well the model can explain the variance in the dependent variable, and a higher R^2 indicates superior model performance. It is calculated using the dependent variable's estimation and actual value. In addition, the Moran I index was constructed to look into the residual model's spatial autocorrelation (Middya and Roy, 2021).

5) Significant test of linear regression parameters. The t-test is conducted to identify the significance of each regression coefficient to show the effect of independent variable, whether individual or partial toward dependent variable (significant) or is it only obtained coincidentally (Sujana et al., 2020).

3. Result and Discussion

3.1 Telemedicine Application

The application has been designed with 3 main features, which are Geographic Information System, Tracing COVID-19 patients using smartphone and Diagnosed People which wrapped as an interactive and informative application with the following display:

3.1.1 Main page

Main Page is the initial page (home) which will be shown after a user has logged in. The page is started by notifying user to turn on their GNSS for tracing feature. Figure 2 shows that on the main page there are several features such as tips and information related to health, user location, map button, travel history button, and Bluetooth search button.

3.1.2 Tracing and GIS Map feature

The tracing feature used on Telemedicine Smartphones is using GNSS and Bluetooth. The GNSS feature will automatically track user's location by pressing the activate button on the GNSS usage permit notification on the main page. Meanwhile, Bluetooth tracing can be activated by accessing it from the main page. The user will obtain some information about the proximity of other infected users around them after activating Bluetooth from this page. Aside of tracing the user's current location, the user can also access their trip history on the main page,as shown in Figure 3.

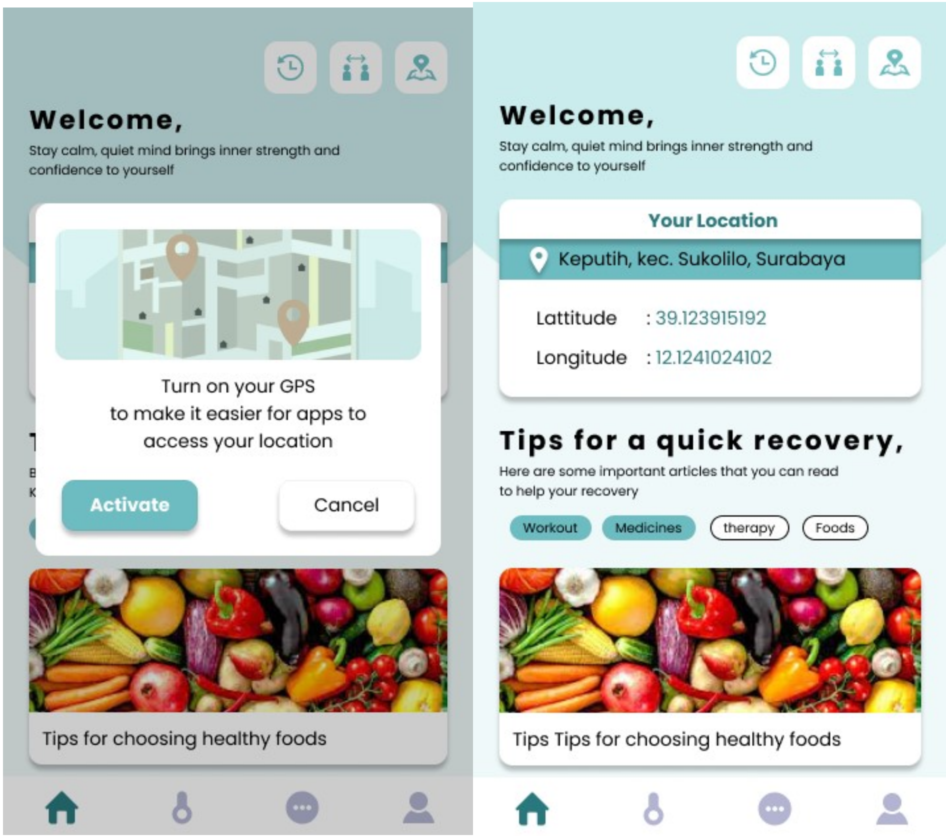

Figure *2:* Home page of smartphone telemedicine

ISSN 2673-0014 (Online) / © Geoinformatics International

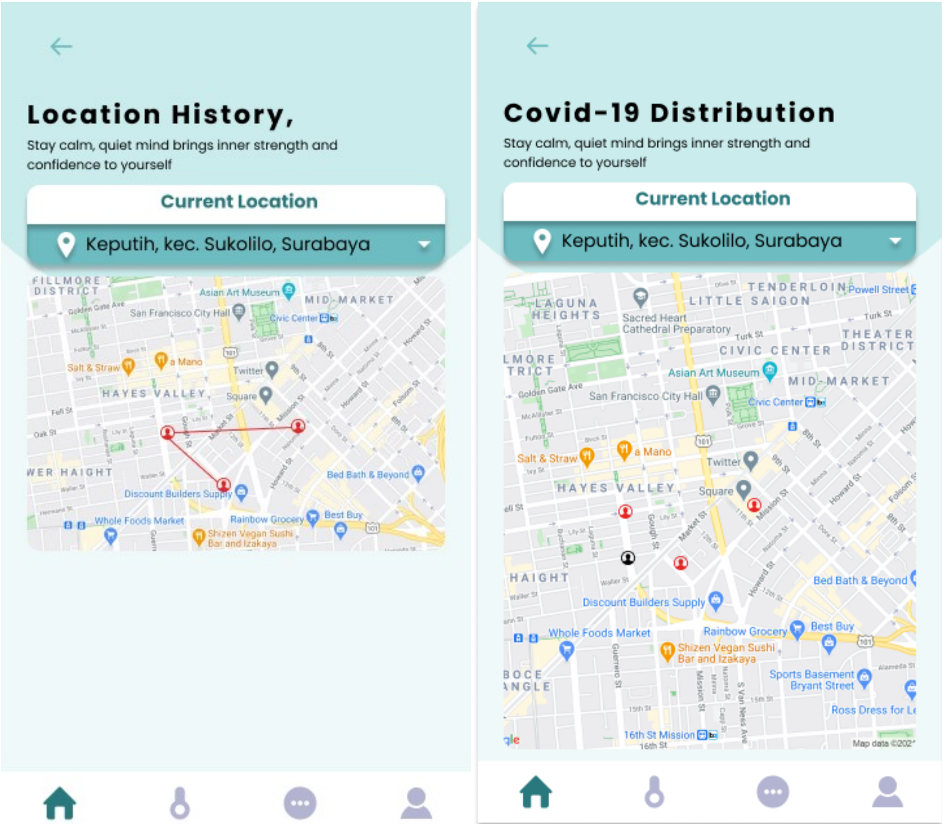

Figure 3: GNSS tracking

By accessing the trip history, the user is able to do self-isolation if they feel any COVID-19 symptoms, and it can also be useful additional information for doctor consultation. Telemedicine smartphones are not only used by individuals in tracing contacts with other individuals who are confirmed to have COVID-19. This application can also be used to study the characteristics of community mobility in a particular area based on the tracing people database. One of the processes is by making an epidemiological model or a vulnerability model of an area which then can be utilised by the government to determine the right strategy in dealing with COVID-19 pandemic. The spread of COVID-19 can be observed through the map feature by accessing it from the main page. On this page, users will be presented with information about the condition around them, such as health facilities around the user, COVID conditions in the area where the user is located, and patients affected by COVID-19 around the user.

3.1.3 Diagnosis

There are two menus that can be used for diagnostic features, namely early symptom check and consultation. In the early symptom check menu, the user will be given several questions regarding the early symptoms of COVID-19 as shown in Figure 4. In the consultation menu, the user can choose a doctor according to the symptom that they currently feel and interact directly via chat and telephone. Users can also find out the diagnosis result from online consultation so that it can be used as a reference for necessary medical actions and drugs. On the early symptom check page, the questionnaire is divided into 3, namely the symptom questionnaire, contact history and mobility history which contain questions related to COVID-19 that must be answered with yes or no. The result will appear at the end of the questionnaire form by showing the user's status and the required action.

On the consultation page (Figure 5), the user can choose the doctor based on the symptom that they felt and then interacting directly by chat, voice call or video call features. After the consultation, the user can immediately find out the results of the diagnosis concluded by the doctor on the diagnosis page feature.

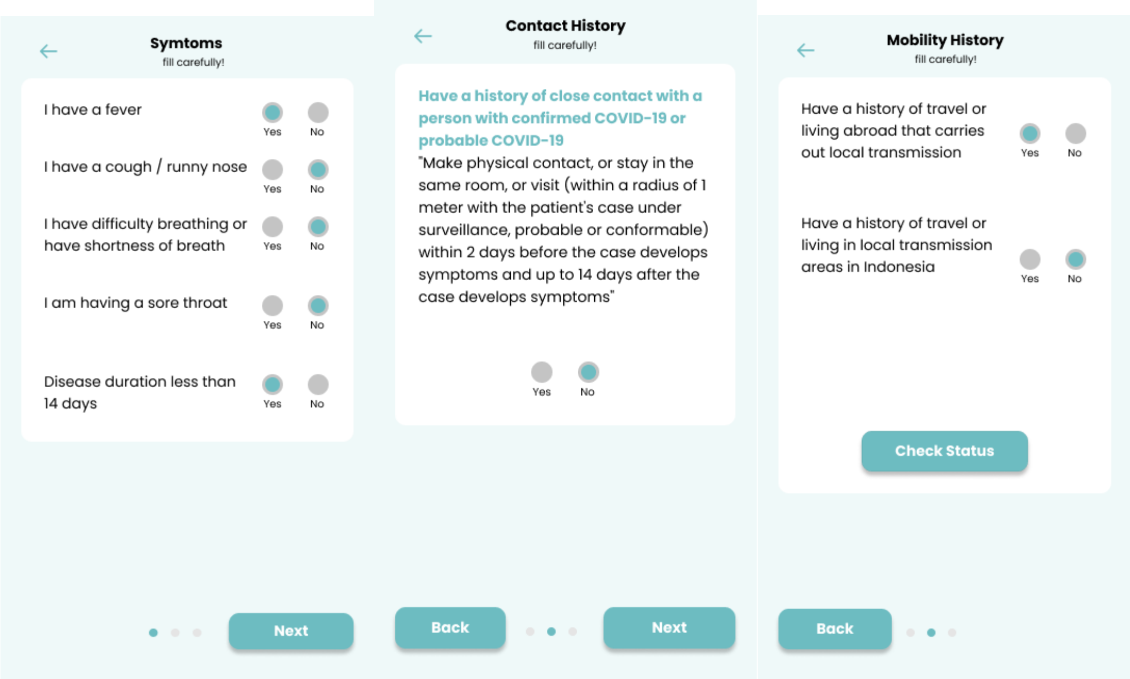

Figure 4: Early symptoms checks

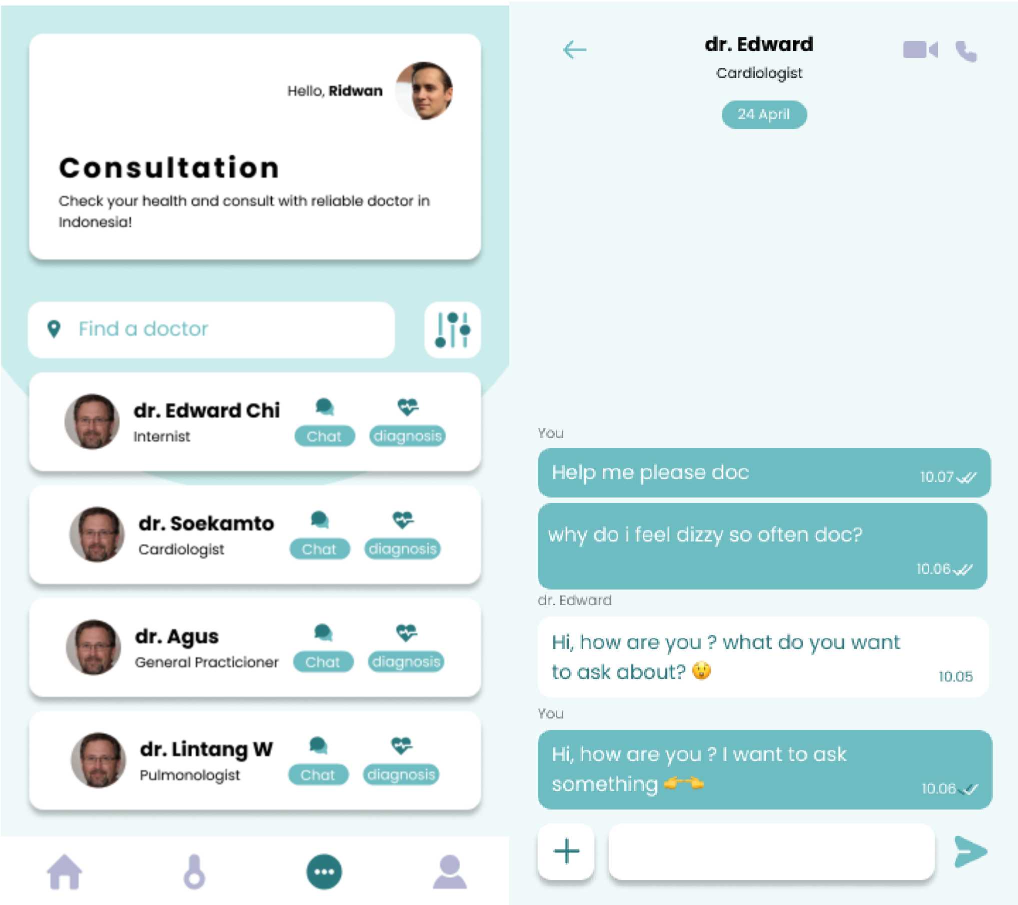

Figure 5: Consultation page

3.2 Geographic Information System Based on Patient Database

3.2.1 Performance comparison of OLS and GWR method

The city of Surabaya consists of 154 villages. Based on data from the website against COVID-19 Surabaya, the highest number of COVID-19 confirmed cases happened in Mojo Village with 769 confirmed cases and the lowest number of cases happened in Romokalisari Village with 17 confirmed cases, and the spread of COVID-19 in Surabaya is shown on the map in Figure 6.

The OLS model produces a significant t-value of population density, total population, number of elders per 1000 population, number of health facilities per 10000 populations, and number of economic centres as presented in Table 1. In addition, the Moran's I of the global OLS model residuals were also analysed. It was found that there was a significant spatial auto correlation (Moran's I = 0.20 and $p < 0.05$). Based on the spatial dependence test, it was concluded that the data on the cumulative number of COVID-19 events in Surabaya contained spatial auto correlation. Lastly, the GWR model was used to show the geographic variation of the relationship with different factors. A detailed summary of GWR model for local parameter estimation is presented in Table 2. The performance of OLS and GWR models in terms of R^2, Adj R^2, and AICc are also presented in Table 3. It can be seen that the GWR model produces a better fit than the global OLS model. At the village level, the global model only explains 59.27 percent of the variance in the number of COVID-19 instances, which rises to 86.6 percent when the model is calibrated as GWR and the local influence of independent variables is taken into account. Meanwhile, based upon this AICc comparison models, it is revealed that dropping the AICc value from 1788.66 (OLS model) to 1711.96 considerably improves the model's fit (GWR model). This demonstrates GWR's applicability in comparison to the global model (OLS).

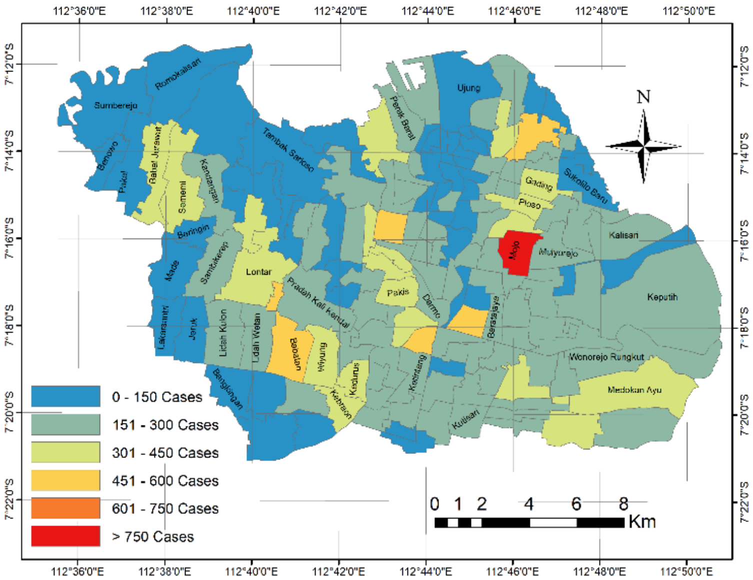

Figure 6: Distribution of COVID-19 in Surabaya

Table 1: Summary of OLS Model

Variable	Coefficient	Std Error	t- statistic	p-value
Intercept	42.94442	14.458964	2.97009	0.003479*
Population Density (X1)	-0.00179	0.000496	-3.60565	0.000434*
Total Population (X2)	0.00858	0.000764	11.23766	0.000000*
Number of Elders per 1000 population (X3)	-0.00513	0.003019	-1.6996	0.091315
Number of Healthcare facility per 10000 population (X4)	9.28147	1.726368	5.3763	0.000000*
Number of economic centres (X5)	0.08651	0.069715	-1.241	0,216598

*significant at the 95% confidence level

Table 2: Summary of GWR Model

Variable	Min	Median	Max	Global
Intercept	-0.94093	26.018	163.12	38.1803
Population Density (X1)	-0.00776	-0.001652	0.000347	-0.0020
Total Population (X2)	0.002825	0.011475	0.017861	0.0096
Number of Elders per 1000 population (X3)	-1.1101	-0.12535	0.62860	-0.0682
Number of Healthcare facility per 10000 population (X4)	-1.2314	5.5147	24.096	10.6082
Number of economic centres (X5)	-0.32467	0.000791	0.41809	-0.0704

Table 3: Comparison of OLS and GWR performance model in terms of R^2, Adj R^2, and AICc

Performance metrics	OLS	GWR
AICc	1788.66875	1711.9675
R^2	0.592708	0.866301
Adj R^2	0.578948	0.802165

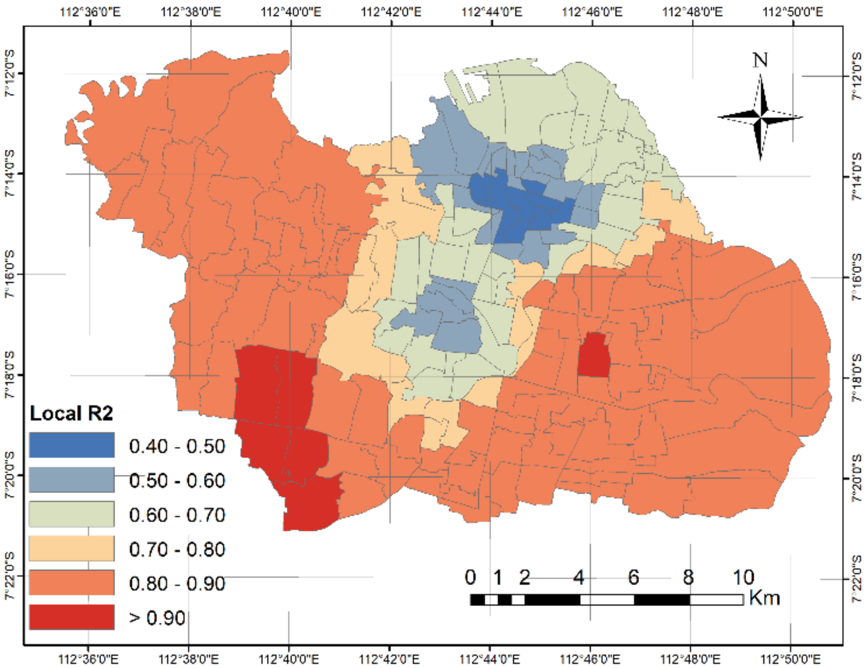

Figure 7: Local R2 for GWR model

3.2.2 Geographically weighted regression

The geographic distribution of R^2 value is presented in Figure 7 which shows the variation in the range of 0.4 to 0.93. From the figure below, high R^2values are mostly found in the eastern, western and southern areas of Surabaya. R^2 is an indication if a selected model has been successful in explaining the variation of the object of observation, R^2describes the proportion of variation in the object of observation that can be explained by multiple regression models of independent variable data. The greater the value of R2, the higher the fit of a model (Brunsdon et al., 1996). Figure 8 shows local coefficients distribution of GWR model to explain the relationship between the variables and the accumulation of COVID-19 cases. The distribution of local coefficients not only shows whether a relationship is positively or negatively, but also to show its strength and weaknesses (Wu and Zhang, 2021). The positive association implies that the cumulative number of COVID-19 cases tends to increase when the value of the relevant independent variable rises. The negative association indicates that the cumulative number of COVID-19 cases tends to decrease when the value of the relevant independent factor rises (Franch-Pardo et al., 2020).

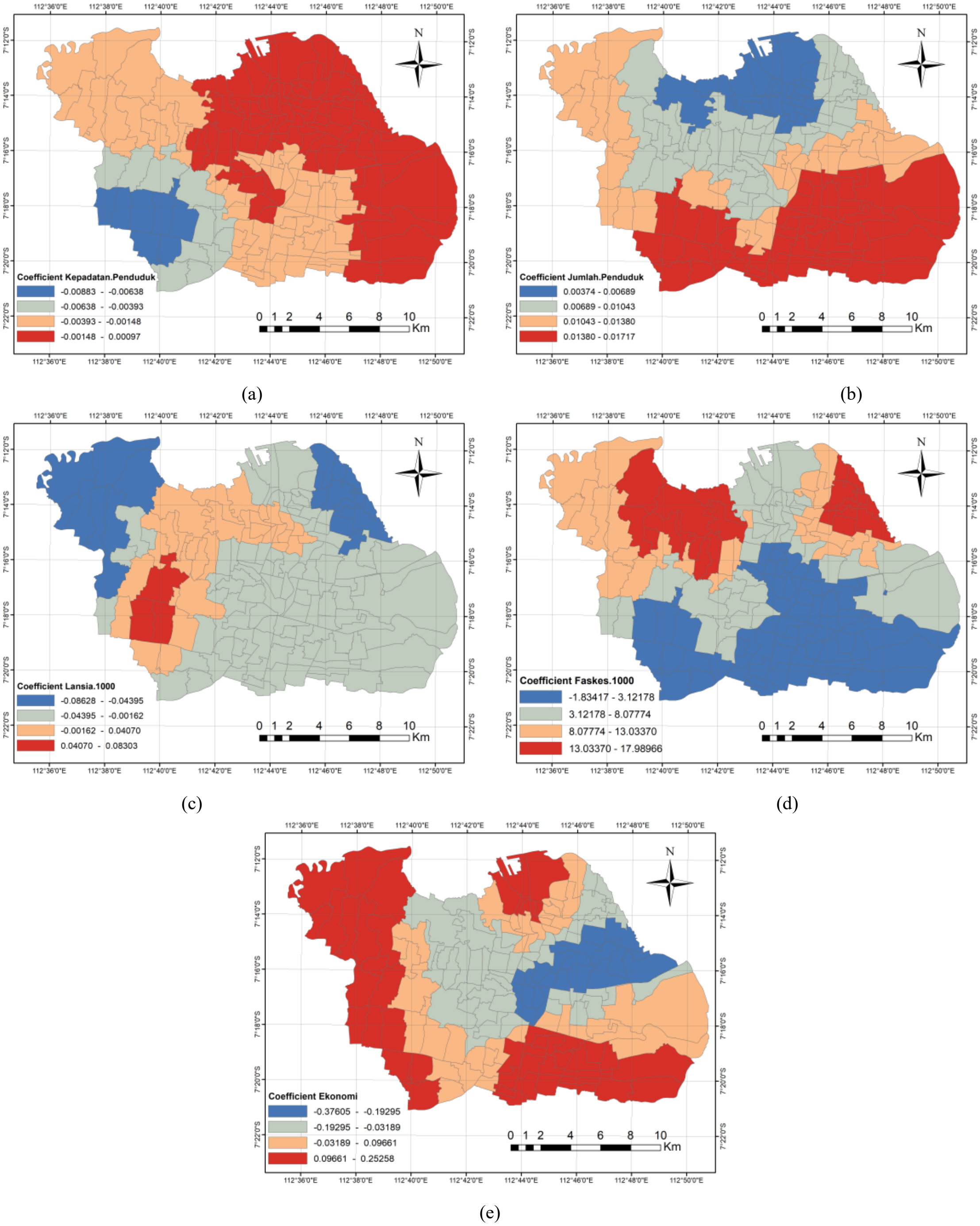

Figure 8: Local Coefficient of GWR Variable (a) Population density (b) Total population (c) Number of Elders per 1000 population (d) Number of healthcare facility per 1000 population (e) Number of economic centers

The locations shown in dark red on Figure 8's map indicate places where the specified parameter has a significant positive influence (i.e. a positively significant correlation) on the total number of COVID-19 cases. Since one of the focuses in this study is the usage of the epidemic model in order to make the policies related to COVID-19, a partial significance test of GWR model was carried out to determine the independent variables that significantly affect each village.

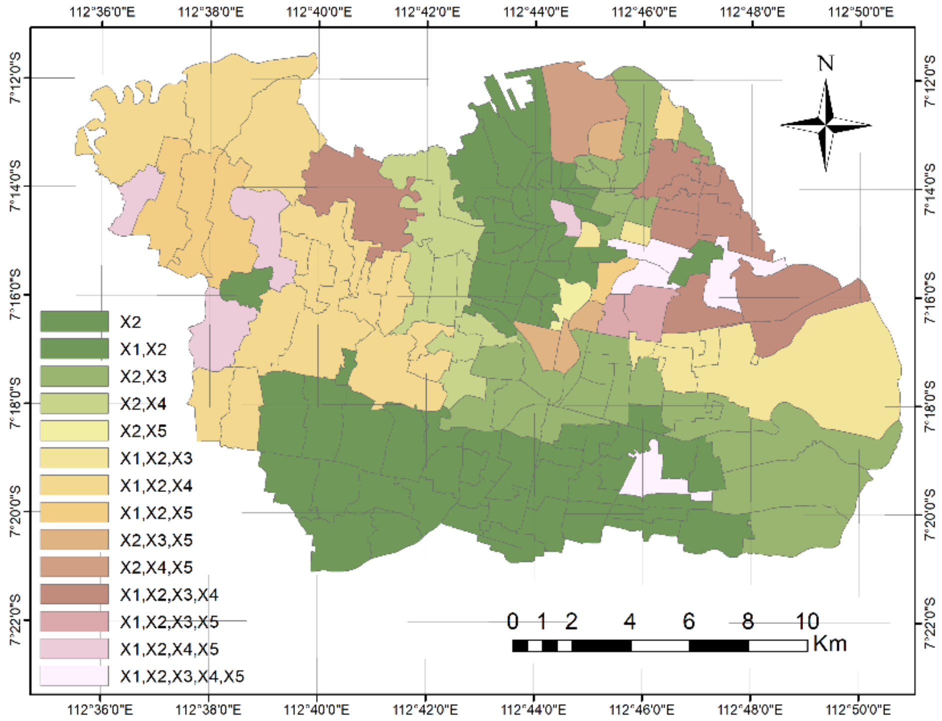

Figure 9: Parameter of GWR modeling which significantly affect each village

Coefficient values and standard errors are used in the calculation of the t-statistic to find the p-value. The results of calculations with a significance level of 0.05 show that the population density variable (X1) has a significant effect on 64 villages, the population variable (X2) has a significant effect on all villages, the variable number of elderly per 1000 population (X3) has a major impact on 51 urban villages, the variable number of health facilities per 1000 population (X4) has a significant effect on 45 urban villages. and the variable number of economic centres (X5) has a significant effect on 20 urban villages. Regions are then grouped based on independent variables that have a significant effect on that area in Figure 9.

Population density reveals a negative association between population numbers from every city with COVID-19 cases, according to the modelling results. This negative correlation among population numbers and COVID-19 instances has been discovered as well in Cahyadi et. al (2022) which studied about COVID-19 delta variant spatiotemporal analysis using air parameters and spatial modelling (Cahyadi et al., 2022). The varied levels of severe lockdown measures could explain the correlation of population density. Distinct places in the world have different lockdown regulations. Similar result to the study by Byass and Sun et al., which indicates that there is a contradictory association in China between population numbers and COVID-19 incidence (Byass, 2020 and Sun et al., 2020). The efficiency of focused infection management in highly populated urban areas is shown in certain regions' extraordinary lockdown policies. In Wong and Li (2020) study also stated that during the initial period of the epidemic, the area with the main transportation centre and its surroundings was the area where infected travellers or disease vectors were most likely to be discovered in the early instances. However, these transportation hubs along their surroundings may not have the largest population number (Wong and Li, 2020). These situation is relatively same with Surabaya COVID-19 cases.

The number of residents shows a positive relationship with the accumulation of COVID-19 cases. This is supported by one study which showed that SARS-CoV-2 in USA countries, areas with high population density had a higher rate of spread in compared to areas with low population density (Chen and Li, 2021). However, paradoxically, COVID-19 cases were higher in urban villages with lower numbers of elderly people, which is interesting. As a result, a thorough investigation into the association between the old population and the occurrence of COVID-19 is required.

For the record, there are some limitations to this research. First, result shows that paradoxical modelling might happened due to various unobserved factors or other factors that were not taken into account in the analysis due to unavailability of data such as age, gender, nationality, and other biological traits. Furthermore, because this research was based on intelligence information, a significant association between socio-demographic variables and COVID-19 incidence could not be confirmed. In its development, the usage of this telemedicine application through the patient tracking feature and patient diagnosis database will be able to provide more in-depth knowledge about the relationship between modelling results and provide better data in subsequent modelling, such as the location and number of COVID-19 hotspots, crowd locations, health background for deaths, COVID-19 sufferers, population distribution and population mobility patterns. Later on, this application can provide information for the government about the current conditions, increase data transparency, help authorities to spread the information and can be used as a tool in assessing a particular policy. Moreover, communication via map-based dashboards offers information that can be accessed by not only patients but also residents who want to protect them and their communities because telemedicine application is using modern GIS features in it (Kamel Boulos and Geraghty, 2020).

4. Conclusion

There are two working group conducted in this research, including Tracing and COVID-19 patient diagnosing and Geographic Information System based on patient database integrated in telemedicine Smartphone. This application enables the user to submit their information into the system and activating the tracing mode using GNSS and Bluetooth. The GNSS feature will automatically detect the user's location, and it will inform the user about other users which has been infected with COVID around them after activating Bluetooth. Through the feature of diagnose the telemedicine application can provide diagnoses to the users related to the symptoms of the disease that they felt through the diagnostic feature with doctors by accessing early symptom check menu and consultation and interacting directly with the doctor in question using the chat, voice call and video call features available. Geographically Weighted Regression (GWR) method is used to explore geographic variations of the potential association of socio-economic, demographic, and health-related aspect for positive cases of COVID-19. In addition, a comparative models of local (OLS) and global (GWR) was carried out as well to validate their suitability. Based on the performance of the OLS and GWR models in terms of R^2, Adj R^2, and AICc, it can be seen that GWR model produces a better fit than the global OLS model. According to the modeling results, the total population of each city has a negative association with COVID-19 instances, while the number of people has a positive relationship with the accumulation of COVID-19 cases. Testing the significance of the GWR model was carried out partially to determine the independent variables that significantly affect each village. Regions are then grouped based on independent variables that have a significant effect on that area. Further application development is carried out by developing a system to reduce the large power consumption due to the use of GNSS and bluetooth systems running in the background. In its development, the usage of this telemedicine application through the patient tracking feature and patient diagnosis database can provide a deeper knowledge about the relationship between modelling results and provide better data in developing epidemic models. Moreover, since the telemedicine applications have modern GIS features in them, the map-based dashboards can provide information for the government about the current conditions, increase data transparency, and help authorities to spread the information which can be accessed by both COVID-19 patients and the residents who would like to protect themselves and their communities from the pandemic.

Funding

This work was supported by Badan Riset dan Inovasi Nasional (Southeast Asia-Europe Joint Funding Scheme for Research and Innovation Program): 2243/PKS/ITS/2021; Indonesian Collaborative Research Program-Program Riset Kolaborasi Indonesia (PPKI): 1328/PKS/ITS/2021.

References

Brunsdon, C., Fotheringham, A. and Charlton, M., 1996, Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geogr. Anal*, Vol. 28, 281–298.

Byass, P., 2020, Eco-Epidemiological Assessment of the COVID-19 Epidemic in China, January–February 2020. *Global Health Action*, Vol. 13(1), doi: 10.1080/16549716.2020.1760490.

Cahyadi, M. N., Handayani, H. H., Warmadewanthi, I. and Rokhmana, C. A. 2022, *Spatiotemporal Analysis for COVID-19 Delta Variant Using GIS-Based Air Parameter and Spatial Modeling*. *Int. J. Environ. Res. Public Health,* Vol. 19(3), 1614; https://doi.org/10.3390/ijerph19031614.

Chen, K. and Li, Z., 2021, The Spread Rate of SARS-CoV-2 is Strongly Associated with Population Density. *Journal of Travel Medicine*, Vol. 27(8), https://doi.org/10.1093/JTM/TA-AA186.

Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D. and Fraser, C., 2020, Quantifying SARS-CoV-2 Transmission Suggests Epidemic Control with Digital Contact Tracing. *Science*, Vol. 368(6491), 1–13. https://doi.org/10.11-01/2020.03.08.20032946.

Fotheringham, A. S., Brunsdon, C. and Charlton, M., 2002, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships* (1 edition). John Wiley & Sons.

Franch-Pardo, I., Napoletano, B. M., Rosete-Verges, F. and Billa, L., 2020, Spatial Analysis and GIS in the Study of COVID-19. A Review. *Science of the Total Environment*, Vol. 15(739), doi: 10.1016/j.scitotenv.2020.140033.

Hong, Z., Li, N., Li, D., Li, J., Li, B., Xiong, W., Lu, L., Li, W. and Zhou, D., 2020, Telemedicine during the COVID-19 Pandemic: Experiences from Western China. *Journal of Medical Internet Research*, Vol. 22(5), 1–5. https://doi.org/10.2196/19577.

INMENDAGRI Nomor 10 Tahun 2021 Tentang Pemberlakuan Pembatasan Kegiatan Masyarakat Berbasis Mikro dan Mengoptimalkan Posko Penanganan COVID-19 di Tingkat Desa dan Kelurahan, (2021).

Kamel Boulos, M. N. and Geraghty, E. M., 2020, Geographical Tracking and Mapping of Coronavirus Disease COVID-19/severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) Epidemic and Associated Events around the World: How 21st Century GIS Technologies are Supporting the Global Fight Against Outbr. *International Journal of Health Geographics*, Vol. 19(1), 1–12. https://doi.org/10.1186/s-12942-020-00202-8.

Keputusan Menteri Kesehatan Republik Indonesia Nomor HK.01.07/MenKes/413/2020 Tentang Pedoman Pencegahan dan Pengendalian Corona Virus Disease 2019 (Covid-19), Pub. L. No. HK.01.07/MenKes/413/2020 (2020). https://c-ovid19.go.id/storage/app/media/Regulasi/KMK No. HK.01.07-MENKES-413-2020 ttg Pedoman Pencegahan dan Pengendalian COVID-19.pdf.

Kristanto, A., 2018, *Perancangan Sistem Informasi dan Aplikasinya*. Gava Media.

Merry, K. and Bettinger, P., 2019, Smartphone GPS Accuracy Study in an Urban Environment. *PLoS ONE*, Vol. 14(7), 1–19. https://doi.org/10.13-71/journal.pone.0219890.

Middya, A. I. and Roy, S., 2021, Geographically Varying Relationships of COVID-19 Mortality with Different Factors in India. *Research Square*, Vol. 11(1), 1–12. https://doi.org-/10.1038/s41598-021-86987-5.

Permenkes No. 9 Tahun 2020, tentang Pedoman PSBB Dalam Rangka Percepatan Penanganan COVID-19, Pub. L. No. Permenkes No. 9 Tahun, 2020 (2020).

Pressman, R. and Maxim, B., 2019, *Software Engineering (A Practitioner's Approach)* (9th ed.). McGraw-Hill Education.

Shoff, C., Chen, V. Y. J. and Yang, T., 2014, When Homogeneity Meets Heterogeneity: The Geographically Weighted Regression with Spatial Lag Approach to Prenatal Care Utilization. *Geospat. Health*, Vol. 8(2), 557-568, doi: 10.4081/gh.2014.45.

Smith, A. C., Thomas, E., Snoswell, C. L., Haydon, H., Mehrotra, A., Clemensen, J. and Caffery, L. J., 2020, Telehealth for Global Emergencies: Implications for coronavirus Disease 2019 (COVID-19). *Journal of Telemedicine and Telecare*, Vol. 26(5), 309–313. https://doi.org/10.1177/1357633X20916567.

Sujana, E., Saputra, K. A. K. and Manurung, D. T. H., 2020, Internal Control Systems and Good Village Governance to Achieve Quality Village Financial Reports. *International Journal of Innovation, Creativity and Change*, Vol. 12(9), 98–108.

Sun, Z., Zhang, H., Yang, Y., Wan, H. and Wang, Y., 2020, Impacts of Geographic Factors and Population Density on the COVID-19 Spreading Under the Lockdown Policies of China. *Science of The Total Environment*, Vol. 746, https://doi.org/10.1016/j.scitotenv.2020.141347.

Wiersinga, W. J., Rhodes, A., Cheng, A. C., Peacock, S. J. and Prescott, H. C., 2020, Pathophysiology, Transmission, Diagnosis, and Treatment of Coronavirus Disease 2019 (COVID-19): A Review. *JAMA - Journal of the American Medical Association*, Vol. 324(8), 782–793. https://doi.org/10.1001/jama.2020.12839.

Wong, D. W. S. and Li, Y., 2020, Spreading of COVID-19: Density Matters. *PLoS ONE*, Vol. 15(12), 1–16. https://doi.org/10.1371/jou-rnal.pone.0242398.

World Health Organization, 2020, *WHO Director-General's Opening Remarks at the Media Briefing on COVID-19 - 11 March 2020*. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

worldometers, 2021, *COVID-19 Coronavirus Pandemic Reported Cases and Deaths by Country or Territory*. https://www.worldometers.info/coronavirus/.

Wu, X. and Zhang, J., 2021, Exploration of Spatial-Temporal Varying Impacts on COVID-19 Cumulative Case in Texas using Geographically Weighted Regression (GWR). *Environ. Sci. Pollut. Res. Int.,* Vol. 28(32), 43732-43746. doi: 10.1007/s11356-021-13653-8.