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Research Paper

Bayesian Mixture Statistical Modeling Perspective in the Series of Diabetes Mellitus Disaster Mitigation in Malang Regions

Ani Budi Astuti[1*], Nur Iriawan[2], Suci Astutik[1], Viera Wardhani[3], Ari Purwanto Sarwo Prasojo[4], Tiza Ayu Virania[5]

[1]*Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Brawijaya, Malang, Jawa Timur, 65145, Indonesia*
[2]*Department of Statistics, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Surabaya, Jawa Timur, 60111, Indonesia*
[3]*Faculty of Medicine, Universitas Brawijaya, Malang, Jawa Timur, 65145, Indonesia*
[4]*Research Center for Population, National Research and Inovation Agency, Jakarta, 10340, Indonesia*
[5]*Master Student of Statistics Department, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Surabaya, Jawa Timur, 60111, Indonesia*
*Corresponding author: ani_budi@ub.ac.id

Abstract
Statistical modeling is one of the most important activities in Statistics in order to simplify complex problems in society, to make it easy, simple, and useful. The perspective of statistical modeling is very useful for society in various fields. Probabilistic-based statistical modeling concept is strongly influenced by the shape of the data distribution, data validity, and data availability. Bayesian concept approach in the statistical modeling has advantages compared to the non-Bayesian approach, which is any sample and any distribution of the data and in this case it often occurs in data in the community. In particular, the Bayesian mixture concept discusses the Bayesian approach with data specifications having a mixture (multimodal) distribution. Diabetes Mellitus (DM) is a disease that is not contagious but the side effects are very dangerous for humans and require large costs to handle. Indonesia ranks seventh in the world for the number of DM sufferers and it is estimated that in 2045, the number of DM sufferers in Indonesia will reach approximately 16.7 million people. Mitigation of DM disease in various regions in Indonesia continues to be pursued, including Malang regions. One of the efforts made is through the statistical modeling perspective of the Bayesian approach which can be used for efforts to control, prevent, treat, and overcome DM. The purpose of the study was to build a suitable Bayesian model for DM cases in Malang regions in order to map the DM case areas in Malang. The results showed that in each district area in the city of Malang it was divided into three groups based on the severity of DM sufferers. The three groups are DM sufferers in the categories of not yet severe, moderate, and severe with the model validation indicator using the smallest Kolmogorov-Smirnov value. Sukun District and Klojen District in the Malang region are two districts that need serious attention from the local government of Malang City in dealing with DM cases. Through the perspective of Bayesian statistical modeling, DM cases in five districts in the Malang area showed a mixture distribution with a different number of mixture components as the basis for regional mapping.

Keywords
Bayesian Mixture, Diabetes Mellitus, Regional Mapping, Statistical Modeling

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1. INTRODUCTION

The Chairperson of the Indonesian Endocrinology Association (PERKENI) stated that Indonesia is a country in the emergency status of Diabetes Mellitus (DM) in 2020. Because based on data from the International Diabetes Federation (IDF), Indonesia has a Diabetes Mellitus alert status. Furthermore, according to the IDF, Indonesia is the country with the fifth largest number of DM sufferers in the world, where Indonesia is the only country in Southeast Asia that is included in the group of five countries in the world. Based on a report by the International Diabetes Federation (IDF), there are 19.5 million Indonesians aged 20-79 years who suffer from DM in 2021. In this case, it means that the contribution of the number of DM diseases in Indonesia has a very large influence on the prevalence value of DM in Southeast Asian countries, where prevalence is the number of people in the population who experience certain diseases, disorders or conditions at a time associated with the population from which the cases originate (Riskesdas Jatim, 2020; Infodatin, 2020).

The contribution of the number of DM in Indonesia has a very large influence on the prevalence of DM in countries in Southeast Asia. The number of DM in Indonesia in 2020 is 10,681,400 (± 10.7 million) with a prevalence of 8.5% per year. This figure is expected to continue to increase to ± 16.7 million people in 2045. IDF information means that in 2020, 1 in 25 Indonesian population (8.5% of Indonesia's population) suffers from DM and the number continues to increase rapidly. Before 2018, the prevalence rate of DM was 6.2% and now it is 8.5% per year. This increase in prevalence rates causes the life expectancy for the people of Indonesia to be reduced by five to ten years. However, what happens is that in 2021 there will be as many as 19.5 million Indonesians aged 20-79 years who suffer from DM and this has exceeded the estimated number of DM in Indonesia in 2020 by 8.5% per year (Riskesdas Jatim, 2020; Infodatin, 2020).

The above certainly must be vigilance for the Indonesian state because DM causes premature death worldwide and also causes blindness, heart disease, and kidney failure. Even though DM is a non-communicable disease, the effects of this disease are very dangerous and chronic that can threaten human safety and other consequences can damage human cognitive function (Hazari et al., 2015; Safitri et al., 2022). Based on the WHO report, DM is ranked the 6th largest in the world as a disease that causes human death. Treatment of DM requires a very large cost, in addition to the complications of chronic disease it causes (American Diabetes Association, 2010). Therefore, the study of DM from the perspective of statistical modeling is very important to do to control, prevent, treat, and overcome this DM disease so that the number of diseases continues to decrease significantly from time to time.

In various previous studies, many researchers have carried out DM disease, two of which are Suharjo's research in 2003 as research reference Astuti et al. (2015a); Astuti et al. (2015b); Astuti et al. (2016); Astuti et al. (2017) which examined DM cases in Surabaya where the distribution of DM case data was proven to have a normal mixture distribution. Furthermore, research by Astuti et al. (2015a); Astuti et al. (2015b); Astuti et al. (2016); Astuti et al. (2017) carried out statistical modeling with a normal Bayesian mixture approach for DM cases in the Malang city area in various districts. The results of research by Astuti et al. (2015a); Astuti et al. (2015b); Astuti et al. (2016); Astuti et al. (2017) also show that the distribution of DM case data in each of the five districts in Malang city follows the normal mixture distribution and the form of the normal mixture distribution varies between regions one district to another. Based on the normal mixture model obtained, it can be used to determine the condition of each district in the Malang city area for DM cases. Based on these two studies, the Bayesian approach is used because the Bayesian concept has several advantages, namely, it can overcome the availability of data with a small sample size (n) (any sample) and for any form of data distribution (any distribution), the concept of data-driven, and working directly on the data (Aitkin, 2001; Box and Tiao, 1973; Carlin and Chib, 1995; Gelman et al., 1995; Bernardo and Smith, 2000; Congdon, 2006; Gosh et al., 2006). Regarding the DM model, Agustina et al. (2020) conducted research on the implementation of DM prevention behavior using the Health Belief Model. Safitri et al. (2022) also conducted a study on the model of the relationship between depression and cognitive function in DM sufferers of Type II in the Assisted Area of the Sedayu 2 Health Center, Bantul. Irwansyah and Kasim (2021) build models to identify the relationship between lifestyle and the risk of DM. Furthermore, Supriyadi and Ridja (2021) conducted a model to find out the relationship between medication adherence and fasting blood glucose levels in DMT 2 sufferers at Puskesmas X Malang city. Research from Syahid (2021) concerning factors related to adherence to DM treatment. Meanwhile, Okosun and Lyn (2015) conducted research on a linkage model between prediabetes awareness, health care provider advice, and lifestyle changes in American adults.

Based on the description in previous research, the researcher found a gap to conduct further research to form a Bayesian mixture model in each district in Malang city as an aggregate model of a mixture model for the Malang area so that the model formed in the Malang area can be used for regional mapping. Malang city is based on DM cases in each district.

2. EXPERIMENTAL SECTION

2.1 Materials

2.1.1 Bayesian Analysis

The basic Bayesian concept can be explained by the following illustration, for example, given observation data x with a probability function $f(x|\theta)$ then the known parameter information θ before the observation is made is referred to as prior θ i.e $p(\theta)$. Furthermore, determining the posterior probability distribution θ, which is $p(\theta|x)$ based on the probability rule in the Bayes theorem according to Gelman et al. (1995) and Bernardo and Smith (2000) is shown in Equation (1).

$$p(\theta|x) = \frac{f(x|\theta)p(\theta)}{f(x)} \text{wherever}$$

$$f(x) = E[f(x|\theta)] = \int_{\theta\in R} f(x|\theta)f(\theta)d\theta \text{ if } \theta \text{ continuous and}$$

$$f(x) = E[f(x|\theta)] = \sum_{\theta\in B} f(x|\theta)p(\theta) \text{ if } \theta \text{ discrete} \tag{1}$$

$f(x)$ is a constant called the normalized constant according to Gelman et al. (1995) and Bernardo and Smith (2000) so that Equation (1) can be written as in Equation (2).

$$p(\theta|x) \propto f(x|\theta) \times p(\theta) \tag{2}$$

Posterior ∝ (Likelihood Function) × (Prior)

2.1.2 Mixture Models

The mixture model is a specific model for data that has a multimodal distribution. Multimodal distribution is a distribution for data that has subpopulations in which each subpopulation is a component of the mixture model with different proportions. The mixture model is a specific model because of this model can mix data but still maintain the properties of the real data. A flexible parametric framework for statistical modeling and

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analysis is an advantage of the mixture distribution (Gelman et al., 1995; Mc Culloch and Searle, 2000).

According to Mc Lachlan and Basford (1988); Gelman et al. (1995); McLachlan and Peel (2000); Stephens (2000); Iriawan (2001); Marin et al. (2005); Gosh et al. (2006), probabilistic model of an observation as a mixture probability function x= $(x_1, x_2, ..., x_n)$ retrieved from several k subpopulations are as follows.

$$f_{mixture} = f(x|\theta, w) = \sum_{j=1}^{k} w_j g_j(x|\theta_j) \tag{3}$$

wherever $f(x|\theta, w)$ is a mixture probability function, $g_j(x|\theta_j)$ is one of the probability functions of as many as k components that make up the mixture model which has model parameters θ_j which are parameter vectors with elements $(\theta_1, \theta_2, ..., \theta_k)$ where the parameters θ depend on the shape of the distribution g_j for each component in the mixture model, while w is the vector parameter proportion (weighting) of the mixture model with elements $(w_1, w_2, ..., w_k)$, wherever $0 < w_j < 1, \forall j$ and $\sum_{j=1}^{k} w_j = 1, j = 1, 2, ..., k$ for each model parameter θ_j.

2.1.3 Bayesian Analysis of Mixture Models

The view of all parameters in the Bayesian approach mixture model is that all parameters are random variables that have a certain prior distribution. Therefore, a very important part of this analysis process as in Equation (3) is to determine the most suitable prior distribution specification. This forms the following set of hierarchies (Green, 1995):

- The number of components of the mixture in the model, which is equal to k
- Proportion w = $(w_1, w_2, ..., w_k)$ wherever $0 < w_j < 1, \forall j$ and $\sum_{j=1}^{k} w_j = 1, j = 1, 2, ..., k$
- The specific parameters of the components, θ_j

According to Marin et al. (2005), in compiling the mixture model, they view that each observation x_i in each sub-population is unknown. If the variable z is the allocation variable for each observation for each sub-population of the mixture model in Equation (3), then the probality of z_i as the probality of allocation of each observation can be calculated as the formula presented in Equation (4).

$$p(z_i = j) = w_j, j = 1, 2, ..., k \tag{4}$$

Therefore, if any value of z_i and there are observational data x_i comes from the sub-population that is distributed in Equation (5).

$$x_i|z_i \sim f(x|\theta_{zi}), i = 1, 2, ..., n \tag{5}$$

Accordingly, the posterior distribution of the mixture model is a joint distribution of all the mixture model variables in Equation (3) which is stated in Equation (6).

$$p(k, w, z, \theta, x) = p(k)p(w|k)p(z|w, k)p(\theta|z, w, k)p(x|\theta, z, w, k) \tag{6}$$

Estimation of each parameter in Equation (6) is carried out as a follow-up process by forming a full conditional distribution of each model parameter (Stephens, 2000).

2.1.4 Gibbs Sampler Approach to MCMC Algorithm

There are three steps to implementing the Gibbs Sampler approach to MCMC algorithm, which are as follows (Ntzoufras, 2009).

Step 1. Define the initial value of $\theta^{(k)}$ at k=0 in order to $\theta^{(0)} = (\theta_1^{(0)}, ..., \theta_r^{(0)})$

Step 2. Carry out the sampling process to get the value of θ_j as a conditional distribution with sampling for $\theta^{(k+1)}$ with the r steps presented below

(1) Sampling $\theta_1^{(k+1)}$ from $p(\theta_1|X, \theta_2^{(k)}, ..., \theta_r^{(k)})$

(2) Sampling $\theta_2^{(k+1)}$ from $p(\theta_2|X, \theta_1^{(k)}, \theta_3^{(k)}, ..., \theta_r^{(k)})$

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(r) Sampling $\theta_r^{(k+1)}$ from $p(\theta_r|X, \theta_1^{(k)}, \theta_2^{(k)}, ..., \theta_{r-1}^{(k)})$

Step 3. Iterate over step (2) M times with M $\to \infty$

2.2 Methods

The data used in this study were data on Diabetes Mellitus (DM) cases in various districts of Malang City taken from data sources from the Ministry of Health of the Republic of Indonesia or Malang City data sources. Government Hospital namely Dr. Saiful Anwar Malang, East Java. The stages carried out in this study included literature studies, surveys, data collection, exploratory and descriptive data, data diagnostics and data analysis, as well as interpretation of the results of the analysis. The analytical method used in this research was Bayesian mixed modeling. The variables measured in this study were fasting blood sugar levels in adults measuring 100–125 mg/dL, declared pre-Diabetes Mellitus and if fasting blood sugar levels were more than 125 mg/dL, it was stated that they had diabetes. The method includes the following stages of analysis is as follows.

1. The data to be analyzed is prepared, videlicet DM case data in each district in the Malang City area which consists of five districts namely Blimbing, Kedungkandang, Klojen, Lowokwaru, and Sukun.
2. Descriptive statistics analysis was carried out on DM case data in each district in the city of Malang.
3. The pattern of distribution of DM case data is identified in each district in the Malang City area.
4. If the distribution of the mixture is identified in the data in step 3, then the best number of components of the mixture must be determined.
5. The prior distribution of the parameters of the DM case model is identified in each district in the Malang City area.
6. Posterior mixture distribution or non-mixture distribution (univariate distribution) is determined and depends

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on the results of identification in step 3 and identification of model parameter estimators.

7. The best model is evaluated and validated to get the best model in each district.
8. The selected model from each district is used to form a Bayesian mixture model in DM case data in Malang City.
9. The model formed in step 8 is evaluated and validated.
10. The boundary value of the model formed in step 9 is determined using the HPD concept.
11. The magnitude of the contribution of DM cases in each district in the Malang City area to the DM prevalence in the Malang area is calculated.
12. The districts that make the largest contribution to the prevalence of DM in the Malang area are determined.
13. A map of DM disease areas based on district in the City of Malang East Java was made.

In this study required statistical software related to the needs of data analysis according to the method used. These software were EASYFIT 5.2, MAPLE 5 R-4, MATLAB 7.11, WINBUGS 1.4, R Studio, and R2WINBUGS.

3. RESULT AND DISCUSSION

The results of the exploration of research data on Diabetes Milletus (DM) show that the value of Current Blood Sugar (GDS) in the Malang area from five districts can be presented in Figure 1.

Based on Figure 1, it can be seen that the form of distribution of the GDS value data for DM patients in each district is multimodal, that is, there are groups that have different characteristics in each district data. This indicates that the data on the GDS value of DM patients in each district in the city of Malang has a mixture distribution. An indication of this mixture can also be seen from the results in Figure 2, where fittings with a normal univariate distribution have many data that are not recorded in the distribution. Figure 3 below presents descriptive statistics values of the GDS of DM patients in each district in the Malang City area.

Figure 3 shows that the highest average GDS value is occupied by DM patients from Sukun district and the lowest GDS values are occupied by DM patients from Blimbing Regency. The most heterogeneous distribution of DGS data is in the Lowokwaru district and the most homogeneous is in the Blimbing district. In general, the average value of GDS data for the Malang city area from five districts is 273.434 mg/dL with a standard deviation of 95.592 mg/dL. Table 1 shows the number of normal mixture components for GDS data in each district.

Table 1 shows that for the GDS data model in every district spread over the city of Malang, it is possible to define two components normal mixture model or three components normal mixture model. The smallest Kolmogorov-Smirnov (KS) value is used as an indicator to determine the most appropriate model.

Table 1. Number of Mixture Components of Each District Based on RJMCMC Test

Districts	Normal Mixture Component Number
Blimbing	2 or 3 Components
Kedung Kandang	2 or 3 Components
Klojen	2 or 3 Components
Lowokwaru	2 or 3 Components
Sukun	2 or 3 Components

Furthermore, the estimation of the parameters of the normal Bayesian mixture model of DGS data with two components for each district in Malang city is carried out as presented in Table 2 to Table 6.

In Table 2 it can be shown that Blimbing district show that GDS data are grouped into two groups, namely 66.92% of GDS data with moderate and severe DM status and 33.08% of GDS data with moderate and severe DM status. The average value of GDS data for DM status is not severe at 170.5835 mg/dL and the average value for GDS data for moderate and severe DM status is 312.1899 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 3, the results of modeling GDS data with two-component normal Bayesian mixture for Kedung Kandang district show that GDS data are grouped into two groups, namely 82.28% of GDS data with moderate and severe DM status and 17.72% of GDS data with moderate and severe DM status. The average value of GDS data for non-severe DM status is 218.0057 mg/dL and the average value for moderately severe and severe GDS data is 421.2386 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 4, the results of modeling GDS data with two-component normal Bayesian mixture for Klojen district show that GDS data are grouped into two groups, namely 50.03% of GDS data with moderate and severe DM status and 49.97% of GDS data with moderate and severe DM status. The average value of GDS data for DM status is not severe at 239.86 mg/dL and the average value for GDS data for moderate and severe DM status is 393.08 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 5, the results of modeling GDS data with two-component normal Bayesian mixture for Lowokwaru district show that GDS data are grouped into two groups, namely 42.45% of GDS data with moderate and severe DM status and 57.55% of GDS data with moderate and severe DM status. The average value of GDS data for DM status is not severe at 150.369 mg/dL and the average value for GDS data for moderate and severe DM status is 330.698 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 6, the results of modeling GDS data with two-component normal Bayesian mixture for Sukun district show that GDS data are grouped into two groups, namely 59.81%

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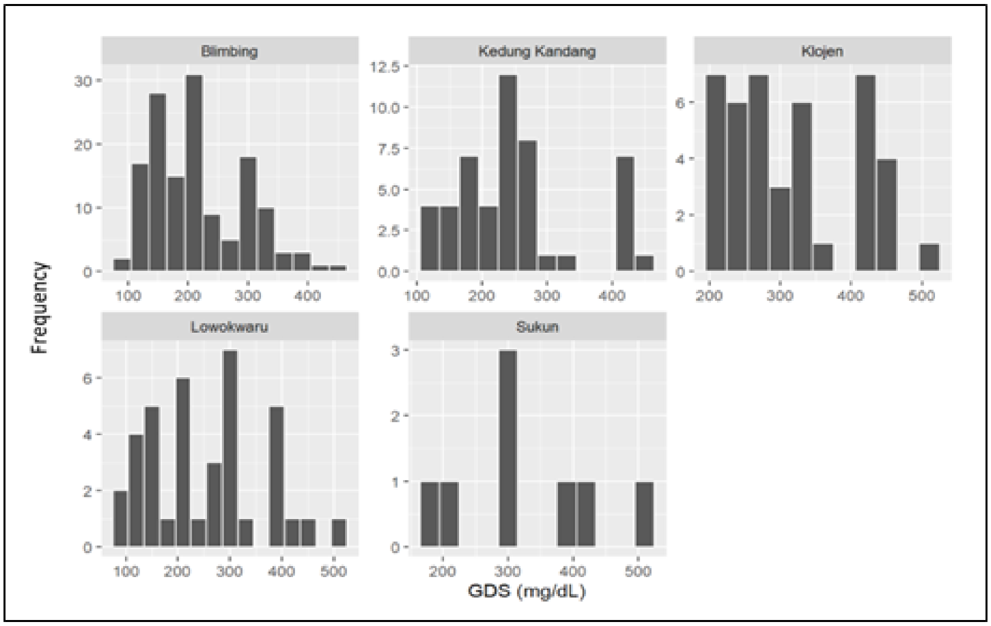

Figure 1. Histogram of DGS Value Data in Five Districts of Malang City

Table 2. Parameter Estimator Model with Two Mixture Components for Blimbing District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Blimbing	deviance	10,000	1648.6862	3.01712	1645	1646	1648	1650	1656
Blimbing	w[1]	10,000	0.6692	0.0388	0.5896	0.6437	0.6700	0.6963	0.7434
Blimbing	w[2]	10,000	0.3308	0.0388	0.2566	0.3037	0.3300	0.3563	0.4104
Blimbing	lambda[1]	10,000	170.5835	3.3069	164.200	168.30	170.60	172.80	177
Blimbing	lambda[2]	10,000	312.1899	6.7861	298.700	307.70	312.20	316.73	325.60
Blimbing	tau[1]	10,000	0.0007	0.0001	0.0005	0.0006	0.0007	0.0008	0.0009
Blimbing	tau[2]	10,000	0.0005	0.0001	0.0003	0.0004	0.0005	0.0005	0.0007
Blimbing	sigma[1]	10,000	37.8722	2.7393	33.0299	35.923	37.659	39.612	43.819
Blimbing	sigma[2]	10,000	46.1776	4.8224	37.8801	42.799	45.729	49.159	56.806

of GDS data with moderate and severe DM status and 40.19% of GDS data with moderate and severe DM status. The average value of GDS data for DM status is not severe at 261.087 mg/dL and the average value for GDS data for moderate and severe DM status is 442.042 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

The values of the estimation results of the normal Bayesian mixture model parameters for DGS data with three components for each district in Malang city are presented in Table 7 to Table 11.

In Table 7, the results of modeling GDS data with a three-component normal Bayesian mixture for Blimbing district show that GDS data are grouped into three groups, namely 34.89% of GDS data with moderate DM status, 32.22% GDS data with moderately severe DM status, and 32.89% GDS data with moderate DM status. Severe DM. The average value of GDS data for non-severe DM status is 139.225 mg/dL and the value of average for moderately severe DM is 205.626 mg/dL, and the value of average GDS data for severe DM status is 311.943 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 8, the results of modeling GDS data with a three-component normal Bayesian mixture for Kedung Kandang district show that GDS data are grouped into three groups, namely 38.45% of GDS data with moderate DM status, 44.22% GDS data with moderately severe DM status, and 17.34% of GDS data with severe DM status. The average value of GDS data for non-severe DM status is 164.393 mg/dL and the value of average GDS data for moderately severe DM status is 263.444 mg/dL, and the value of average GDS data for severe DM status is 421.284 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 9, the results of modeling GDS data with a three-component normal Bayesian mixture for Klojen district show that GDS data are grouped into three groups, namely 17.74% of GDS data with moderate DM status, 53.27% GDS data with

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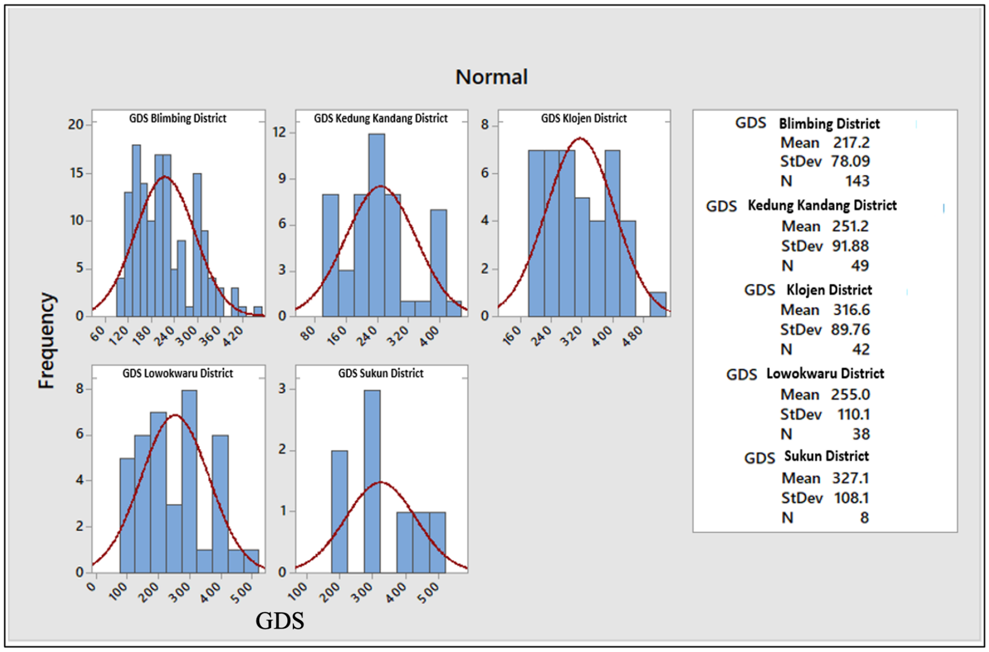

Figure 2. GDS Fitting Value Data Pattern Normal Univariate Distribution in the Five Districts of Malang City

Table 3. Parameter Estimator Model with Two Mixture Components for Kedung Kandang District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Kedung Kandang	deviance	10,000	559.2231	2.8983	555.50	557.10	558.60	560.70	566.60
Kedung Kandang	w[1]	10,000	0.8228	0.0529	0.7053	0.7895	0.8274	0.8609	0.9132
Kedung Kandang	w[2]	10,000	0.1772	0.0529	0.0868	0.1391	0.1726	0.2105	0.2947
Kedung Kandang	lambda[1]	10,000	218.0057	5.6812	206.80	214.20	218	221.80	229.20
Kedung Kandang	lambda[2]	10,000	421.2386	5.4862	410.40	417.80	421.20	424.70	432
Kedung Kandang	tau[1]	10,000	0.0003	0.0001	0.0002	0.0003	0.0003	0.0004	0.0005
Kedung Kandang	tau[2]	10,000	0.0055	0.0026	0.0016	0.0036	0.0051	0.0069	0.0116
Kedung Kandang	sigma[1]	10,000	55.5497	6.2277	45.029	51.138	54.989	59.308	69.454
Kedung Kandang	sigma[2]	10,000	14.7554	4.0324	9.2728	11.983	13.997	16.611	24.922

moderately severe DM status, and 28.99% GDS data with moderate DM status. Severe DM. The average value of GDS data for non-severe DM status is 205.4253 mg/dL and the value of average GDS data for moderately severe DM is 287.1367 mg/dL, and the value of average GDS data for severe DM status is 438.1715 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 10, the results of modeling GDS data with a three-component normal Bayesian mixture for Lowokwaru district show that GDS data are grouped into three groups, namely 29.21% of GDS data with moderate DM status, 48.88% GDS data with moderately severe DM status, and 21.90% of GDS data with moderate DM status. Severe DM. The average value of GDS data for non-severe DM status is 130.964 mg/dL and the value of average GDS data for moderately severe DM status is 257.094 mg/dL, and and the value of average GDS data for severe DM status is 421.315 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

In Table 11, the results of modeling GDS data with a three-component normal Bayesian mixture for Lowokwaru district show that GDS data are grouped into three groups, namely 27.28% of GDS data with moderate DM status, 36.37% GDS data with moderately severe DM status, and 36.35% of GDS data with moderate DM status. Severe DM. The average value of GDS data for non-severe DM status is 195.004 mg/dL and the value of average GDS data for moderately severe DM status is 300.677 mg/dL, and the value of average GDS data for severe DM status is 442.184 mg/dL. The results of this parameter estimation are carried out with 10,000 iterations.

The goodness of two components and three components normal Bayesian mixture model evaluation that has been formed is carried out to obtain the best model for GDS data in each district in the Malang city area. For Goodness of fit the model uses the Kolmogorov-Smirnov (KS) value indicator with the

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Table 4. Parameter Estimator Model with Two Mixture Components for Klojen District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Klojen	deviance	10,000	490.7600	2.8500	487.100	488.700	490.100	492.200	497.800
Klojen	w[1]	10,000	0.5003	0.0749	0.3551	0.4491	0.4998	0.5521	0.6459
Klojen	w[2]	10,000	0.4997	0.0749	0.3541	0.4479	0.5002	0.5509	0.6449
Klojen	lambda[1]	10,000	239.86	3.9225	232.30	237.20	239.80	242.50	247.60
Klojen	lambda[2]	10,000	393.08	12.733	367.89	384.70	393	401.50	418.30
Klojen	tau[1]	10,000	0.0014	0.0004	0.0007	0.0011	0.0014	0.0017	0.0024
Klojen	tau[2]	10,000	0.0003	0.0001	0.0002	0.0003	0.0003	0.0004	0.0005
Klojen	sigma[1]	10,000	27.3983	4.2746	20.571	24.398	26.880	29.881	37.101
Klojen	sigma[2]	10,000	57.5712	9.0950	43.323	51.149	56.424	62.650	78.811

Table 5. Parameter Estimator Model with Two Mixture Components for Lowokwaru District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Lowokwaru	deviance	10,000	468.278	2.8714	464.60	466.20	467.70	469.70	475.50
Lowokwaru	w[1]	10,000	0.4245	0.0775	0.2753	0.3712	0.4235	0.4773	0.5772
Lowokwaru	w[2]	10,000	0.5755	0.0775	0.4228	0.5227	0.5765	0.6288	0.7247
Lowokwaru	lambda[1]	10,000	150.369	4.8187	140.90	147	150.40	153.60	159.80
Lowokwaru	lambda[2]	10,000	330.698	17.001	297.09	319.50	330.70	341.80	363.80
Lowokwaru	tau[1]	10,000	0.0009	0.0003	0.0004	0.0007	0.0009	0.0011	0.0016
Lowokwaru	tau[2]	10,000	0.0002	0.0001	0.0001	0.0001	0.0002	0.0002	0.0003
Lowokwaru	sigma[1]	10,000	34.261	6.0802	24.7008	29.975	33.479	37.692	48.359
Lowokwaru	sigma[2]	10,000	77.854	12.068	58.6002	69.288	76.449	84.788	105.60

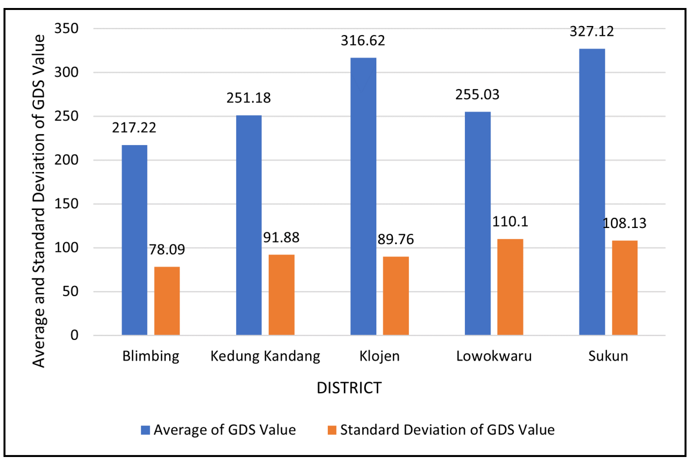

Figure 3. Average Value and Standard Deviation of GDS Data in Malang City Area

smallest value being the value for the best model. Table 12 shows the KS values for two components and three components normal Bayesian mixture model for each district in the Malang region.

Table 12 shows that the smallest KS value in the three-component normal Bayesian mixture model in each district in the Malang city area. Therefore, the three-component Bayesian mixture model was chosen in mapping the area of DM sufferers based on districts. But before applying the model for mapping the district area, it is necessary to identify the fulfillment of ergonic Markov chains, namely Markov chains that have irreducible, recurrent, aperiodic, and transient properties. As an example of the nature for Ergodic Markov chain properties can be seen through trace plots, autocorrelation plots, and Kernel density plots of each parameter of the three-component normal Bayesian mixture model. The results of the evaluation and identification for the fulfillment of ergodic Markov chains, namely recurrent, irreducible, aperiodic, and transient for some model parameters in the Blimbing and Klojen Districts for the three-component Bayesian mixed model are shown in Figure 4 and Figure 5.

Based on Figure 4, it can be shown that the plot of ergodic characteristics of Markov chain in Figure 4(a), Figure 4(b), and Figure 4(c) are irreducible, recurrent, aperiodic, and transient for the Bayesian mixture model of three components in Blimbing district.

Based on Figure 5, it can be shown that the plot of ergodic characteristics of Markov chains in Figure 5(a), Figure 5(b), and Figure 5(c) are irreducible, recurrent, aperiodic, and transient for the Bayesian mixture model of three components in Klojen district. Likewise with Kedung Kandang district, Lowokwaru district, and Sukun district also have the plot of ergodic characteristics of Markov chains are irreducible, recurrent, aperiodic, and transient for the Bayesian mixture model of three

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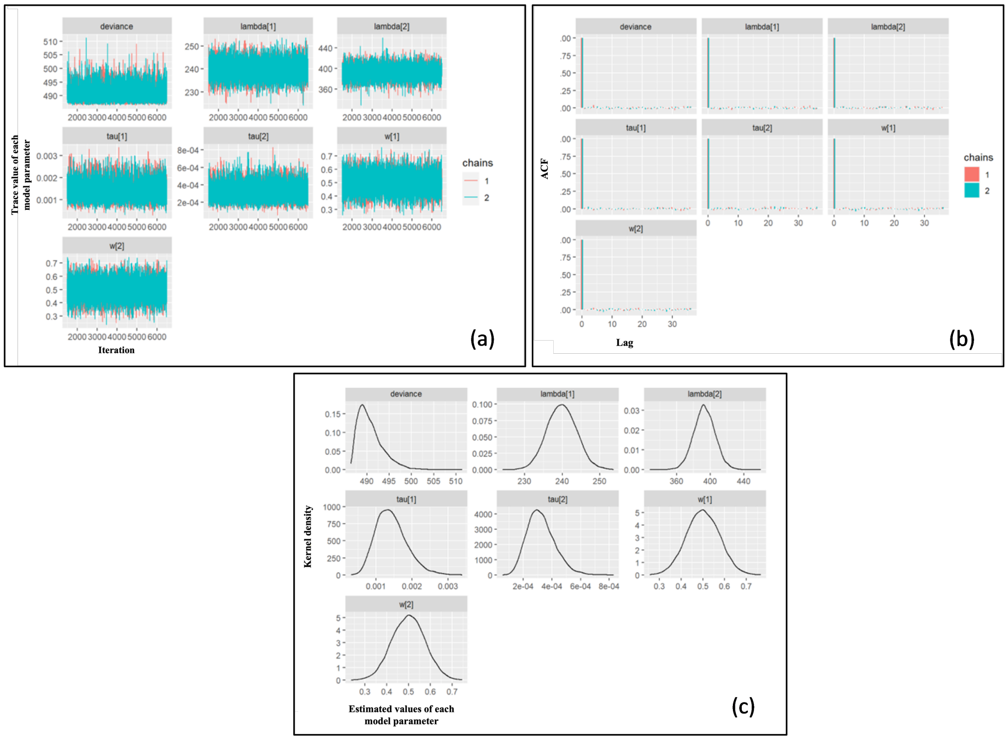

Figure 4. Plot of Ergodic Characteristics of Markov Chain (a) Trace Plots of Blimbing District, (b) Auto-correlation Plots of Blimbing District, and (c) Kernel Density Plots of Blimbing District: Irreducible, Recurrent, Aperiodic, and Transient of some Model Parameters for the Bayesian Mixture of Three Components in Blimbing District

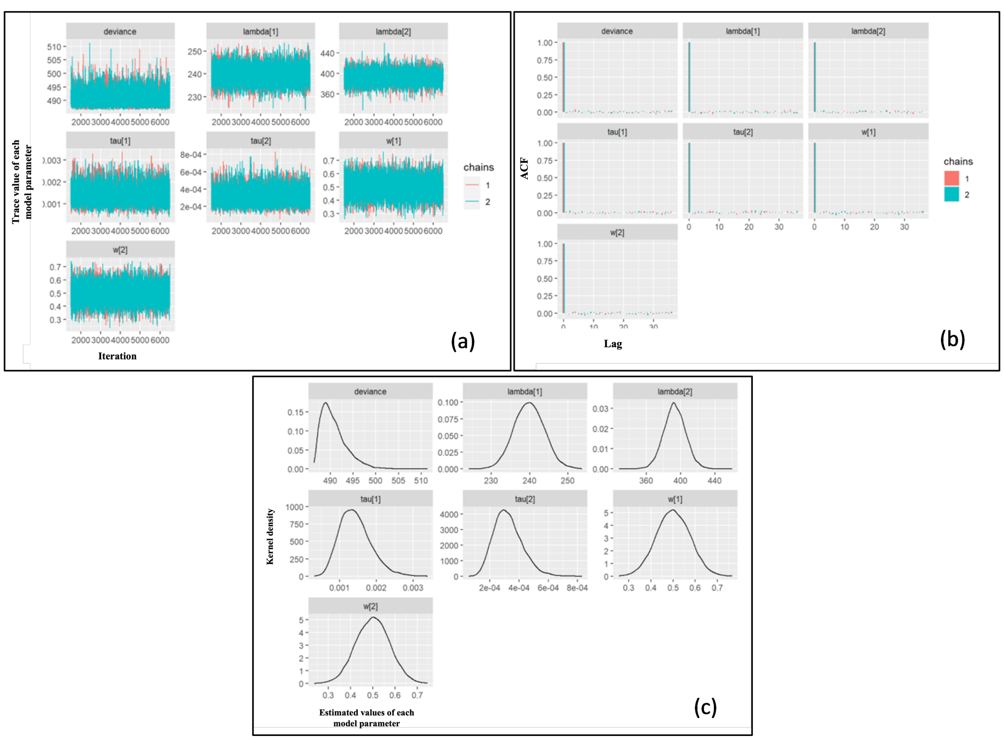

Figure 5. Plot of Ergodic Characteristics of Markov Chain (a) Trace Plots of Klojen District, (b) Autocorrelation Plots of Klojen District, and (c) Kernel Density Plots of Klojen District: Irreducible, Recurrent, Aperiodic, and Transient of some Model Parameters for the Bayesian Mixture of Three Components in Klojen District

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Table 6. Parameter Estimator Model with Two Mixture Components for Sukun District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Sukun	deviance	10,000	99.258	2.7195	95.820	97.250	98.630	100.600	106.100
Sukun	w[1]	10,000	0.5981	0.1487	0.2989	0.4939	0.6041	0.7074	0.8656
Sukun	w[2]	10,000	0.4019	0.1487	0.1344	0.2926	0.3959	0.5060	0.7012
Sukun	lambda[1]	10,000	261.087	7.0467	247	256.40	261.10	265.800	274.900
Sukun	lambda[2]	10,000	442.042	29.674	385.70	425.70	441.80	457.800	499.603
Sukun	tau[1]	10,000	0.0005	0.0003	0.0001	0.0003	0.0005	0.0007	0.0012
Sukun	tau[2]	10,000	0.0007	0.0005	0.0001	0.0004	0.0006	0.0009	0.0021
Sukun	sigma[1]	10,000	49.825	16.206	29.309	38.818	46.494	56.689	89.522
Sukun	sigma[2]	10,000	46.055	23.823	21.821	31.759	40.441	52.853	106.662

Table 7. Parameter Estimator of Three Components Bayesian Mixture Model for Blimbing District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Blimbing	deviance	10,000	1636.869	3.9064	1631	1634	1636	1639	1646
Blimbing	w[1]	10,000	0.3489	0.0395	0.2739	0.3215	0.3483	0.3753	0.4277
Blimbing	w[2]	10,000	0.3222	0.0386	0.2487	0.2953	0.3219	0.3479	0.3984
Blimbing	w[3]	10,000	0.3289	0.0388	0.2553	0.3023	0.3280	0.3548	0.4065
Blimbing	lambda[1]	10,000	139.225	2.3198	134.800	137.700	139.200	140.800	143.800
Blimbing	lambda[2]	10,000	205.626	2.3941	200.900	204.100	205.600	207.200	210.400
Blimbing	lambda[3]	10,000	311.943	6.7614	299.000	307.400	311.900	316.900	325.200
Blimbing	tau[1]	10,000	0.0028	0.0006	0.0018	0.0024	0.0028	0.0032	0.0040
Blimbing	tau[2]	10,000	0.0040	0.0008	0.0025	0.0034	0.0039	0.0045	0.0058
Blimbing	tau[3]	10,000	0.0005	0.0001	0.0003	0.0004	0.0005	0.0005	0.0007
Blimbing	sigma[1]	10,000	19.0827	1.9254	15.7661	17.7269	18.9321	20.2735	23.2812
Blimbing	sigma[2]	10,000	16.0603	1.7059	13.1749	14.8655	15.9132	17.0772	19.8811
Blimbing	sigma[3]	10,000	46.1127	4.7993	37.8749	42.7364	45.7055	49.0822	56.6504

components.

Because of the parameter estimation results for each district have met the ergodic characteristics of Markov chains, that is irreducible, recurrent, aperiodic, and transient, then the three-component Bayesian mixture model have been met for each district. These shows that the model formed with the Bayesian approach has fulfilled the Bayesian concept principles so that the model is in accordance with the data challenges. Therefore, the parameter estimator from the model that has been built, namely the three-component normal Bayesian mixture for each district, can be used for district-based mapping in the Malang city area.

Mapping of Diabetes Milletus (DM) based on the district of Malang city based on a mixture of three components. The results of regional mapping for DM based on districts in the Malang area are shown in Table 13 and Figure 6. Table 13 shows that the Malang area based on each district can be grouped into three groups based on the severity of DM suffered by the population, namely group one is a group of people with DM who are not yet severe (GDS values range from 100 mg/dL to 235 mg/dL), group two was a group with moderately severe DM (GDS values ranged from over 155 mg/dL to 341 mg/dL), and group three was a group with severe DM (GDS values ranged from over 250 mg/dL) up to 520 mg/dL). The depiction of regional mapping with maps is presented as shown in Figure 6.

Figure 6 shows that the group of severe DM patient (dark red) occurs in all sub-districts in Malang City and the largest dark red color occurs in Sukun District, which is 40%. Kedung Kandang district and Lowokwaru district, the lowest severe DM patient, namely 20%. Klojen district and Blimbing district, 30% of severe DM patient. DM patient with moderate severity (moderately severe/group of two/red flag) also occur in all districts. Lowokwaru and Klojen districts were ranked first for patient with moderate severity DM, which was 50%. In Blimbing District, DM sufferers with moderate severity are the smallest, which is 30%. For DM patient with mild scabies, most occur in Kedung Kandang and Blimbing districts, which is 40%. Sukun District and Klojen District, DM patient with the least mild severity, namely 20%. The results of this study indicate that Sukun District and Klojen District in the Malang region are two districts that need serious attention from the local government of Malang city in dealing with DM cases because in these two districts the percentage of DM sufferers

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Table 8. Parameter Estimator of Three Components Bayesian Mixture Model for Kedung Kandang District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Kedung Kandang	deviance	10,000	558.111	3.7922	552.700	555.300	557.400	560.200	567.100
Kedung Kandang	w[1]	10,000	0.3845	0.0675	0.2582	0.3372	0.3830	0.4293	0.5212
Kedung Kandang	w[2]	10,000	0.4422	0.0689	0.3119	0.3932	0.4402	0.4890	0.5785
Kedung Kandang	w[3]	10,000	0.1734	0.0517	0.0842	0.1364	0.1695	0.2062	0.2848
Kedung Kandang	lambda[1]	10,000	164.393	3.8613	156.800	161.800	164.400	167	172
Kedung Kandang	lambda[2]	10,000	263.444	5.8799	252	259.500	263.400	267.300	275.400
Kedung Kandang	lambda[3]	10,000	421.284	5.4044	410.500	417.975	421.300	424.500	432
Kedung Kandang	tau[1]	10,000	0.0015	0.0005	0.0007	0.0012	0.0015	0.0018	0.0026
Kedung Kandang	tau[2]	10,000	0.0015	0.0004	0.0008	0.0012	0.0015	0.0018	0.0026
Kedung Kandang	tau[3]	10,000	0.0055	0.0026	0.0016	0.0036	0.0051	0.0069	0.0115
Kedung Kandang	sigma[1]	10,000	26.7545	4.3717	19.8027	23.7006	26.2251	29.1729	36.9869
Kedung Kandang	sigma[2]	10,000	26.7012	4.1551	19.9799	23.7473	26.1891	29.1235	36.1388
Kedung Kandang	sigma[3]	10,000	14.7562	4.0304	9.3168	11.9842	14.0083	16.6028	24.6557

Table 9. Parameter Estimator of Three Components Bayesian Mixture Model for Klojen District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Klojen	deviance	10,000	475.059	3.7881	469.600	472.300	474.400	477.100	484.100
Klojen	w[1]	10,000	0.1774	0.0562	0.0813	0.1363	0.1728	0.2132	0.2992
Klojen	w[2]	10,000	0.5327	0.0737	0.3899	0.4820	0.5328	0.5836	0.6755
Klojen	w[3]	10,000	0.2899	0.0665	0.1659	0.2433	0.2863	0.3347	0.4246
Klojen	lambda[1]	10,000	205.4253	0.9496	203.500	204.800	205.400	206	207.300
Klojen	lambda[2]	10,000	287.1367	8.5870	270.100	281.600	287.100	292.800	304
Klojen	lambda[3]	10,000	438.1715	8.7844	420.700	432.600	438.200	443.625	455.103
Klojen	tau[1]	10,000	0.1307	0.0637	0.0375	0.0839	0.1204	0.1667	0.2797
Klojen	tau[2]	10,000	0.0007	0.0002	0.0003	0.0005	0.0006	0.0008	0.0011
Klojen	tau[3]	10,000	0.0013	0.0005	0.0005	0.0009	0.0012	0.0016	0.0025
Klojen	sigma[1]	10,000	3.0438	0.8481	1.8908	2.4492	2.8826	3.4531	5.1655
Klojen	sigma[2]	10,000	40.3978	6.1704	30.5995	36.0089	39.6059	43.8624	54.7176
Klojen	sigma[3]	10,000	29.4274	6.3829	20.0845	24.9280	28.4498	32.7477	44.7549

Table 10. Parameter Estimator of Three Components Bayesian Mixture Model for Lowokwaru District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Lowokwaru	deviance	10,000	463.096	3.6342	457.900	460.400	462.400	465.100	471.900
Lowokwaru	w[1]	10,000	0.2921	0.0706	0.1657	0.2423	0.2876	0.3384	0.4409
Lowokwaru	w[2]	10,000	0.4888	0.0775	0.3407	0.4351	0.4885	0.5415	0.6403
Lowokwaru	w[3]	10,000	0.2190	0.0634	0.1093	0.1733	0.2147	0.2601	0.3540
Lowokwaru	lambda[1]	10,000	130.964	3.4956	124.100	128.600	131	133.300	137.900
Lowokwaru	lambda[2]	10,000	257.094	11.3754	234.900	249.500	257	264.600	279.600
Lowokwaru	lambda[3]	10,000	421.315	12.8480	395.995	413.300	421.300	429.300	446.500
Lowokwaru	tau[1]	10,000	0.0029	0.0012	0.0011	0.0021	0.0028	0.0037	0.0057
Lowokwaru	tau[2]	10,000	0.0005	0.0001	0.0002	0.0003	0.0004	0.0005	0.0008
Lowokwaru	tau[3]	10,000	0.0009	0.0003	0.0003	0.0006	0.0009	0.0012	0.0020
Lowokwaru	sigma[1]	10,000	19.4569	4.2111	13.2605	16.4935	18.7779	21.6118	29.5659
Lowokwaru	sigma[2]	10,000	49.1937	8.0749	36.1549	43.5607	48.2019	53.8538	68.1053
Lowokwaru	sigma[3]	10,000	35.2379	9.4695	22.2605	28.6652	33.4947	39.7716	58.3415

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Table 11. Parameter Estimator of Three Components Bayesian Mixture Model for Sukun District

District	Parameter	Iteration	Mean	SD	Q0025	Q025	Q05	Q075	Q0975
Sukun	deviance	10,000	75.3127	3.4376	70.3098	72.800	74.720	77.210	83.450
Sukun	w[1]	10,000	0.2728	0.1294	0.0653	0.1768	0.2588	0.3563	0.5621
Sukun	w[2]	10,000	0.3637	0.1388	0.1213	0.2616	0.3555	0.4583	0.6535
Sukun	w[3]	10,000	0.3635	0.1406	0.1208	0.2583	0.3555	0.4589	0.6524
Sukun	lambda[1]	10,000	195.004	1.7749	191.500	193.800	195	196.200	198.500
Sukun	lambda[2]	10,000	300.677	0.8837	299	300.200	300.700	301.100	302.400
Sukun	lambda[3]	10,000	442.184	29.2605	385.098	426.200	441.700	458	500.900
Sukun	tau[1]	10,000	0.0698	0.0495	0.0080	0.0332	0.0588	0.0940	0.1966
Sukun	tau[2]	10,000	0.8479	0.6043	0.1040	0.4006	0.7096	1.1370	2.3921
Sukun	tau[3]	10,000	0.0007	0.0005	0.0001	0.0004	0.0006	0.0009	0.0021
Sukun	sigma[1]	10,000	4.7712	2.5659	2.2553	3.2612	4.1234	5.4924	11.1552
Sukun	sigma[2]	10,000	1.3619	0.7115	0.6466	0.9378	1.1871	1.5799	3.1009
Sukun	sigma[3]	10,000	46.1645	23.1443	21.9158	31.8348	40.2993	53.3305	104.2844

Table 12. Kolmogorov Smirnov (KS) Values for Two and Three Components Normal Mixture Bayesian Models

Districts	KS Values	
	Two Components	Three Components
Blimbing	0.0918	0.0544
Kedung Kandang	0.1300	0.1230
Klojen	0.1300	0.1230
Lowokwaru	0.1390	0.1080
Sukun	0.2180	0.1360

Table 13. Mapping of DM Disease Area in Malang City Based on District

Districs	GDS Citizen Values Data Group of Malang		
Blimbing	Group 1 (40%) GDS 100-GDS 184	Group 2 (30%) GDS>184-GDS 250	Group 3 (30%) GDS>250-GDS 450
Kedung Kandang	Group 1 (40%) GDS 134-GDS 235	Group 2 (40%) GDS>235-GDS 302	Group 3 (20%) GDS>302-GDS 458
Klojen	Group 1 (20%) GDS 202-GDS 230	Group 2 (50%) GDS>230-GDS 341	Group 3 (30%) GDS>341-GDS 520
Lowokwaru	Group 1 (30%) GDS 100-GDS 155	Group 2 (50%) GDS>155-GDS 340	Group 3 (20%) GDS>340-GDS 500
Sukun	Group 1 (20%) GDS 190-GDS 200	Group 2 (40%) GDS>200-GDS 302	Group 3 (40%) GDS>302-GDS 500

Information:
Group 1 : Group of Low Severe DM Patient
Group 2 : Group of Moderately Severe DM Patient
Group 3 : Group of Severe DM Patient

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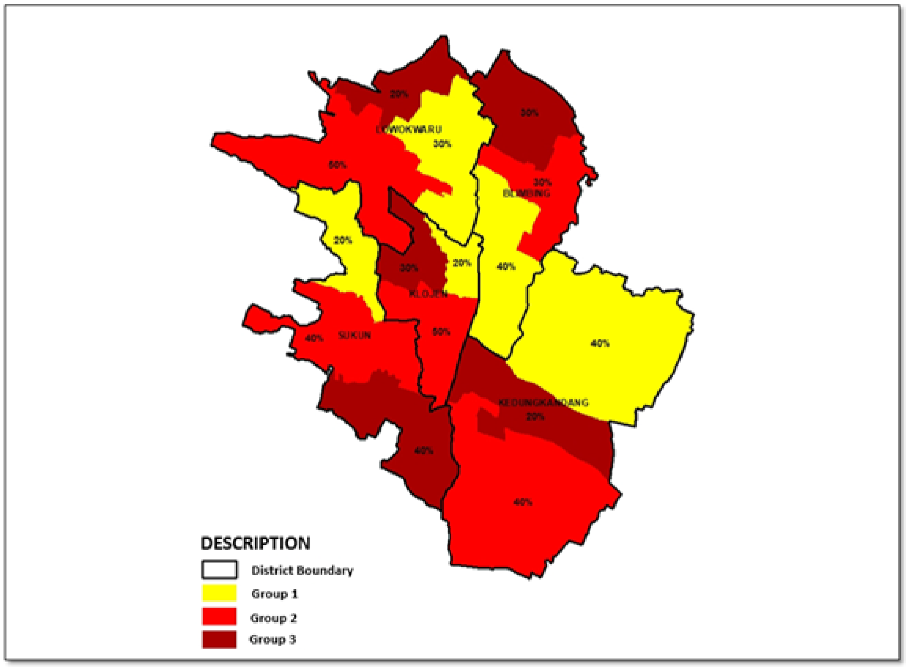

Figure 6. Mapping of DM Disease Area in Malang City Based on District

Information:
Group 1 : Group of Low Severe DM Patient
Group 2 : Group of Moderately Severe DM Patient
Group 3 : Group of Severe DM Patient

with very high blood sugar levels, namely the GDS value >302 mg/dL up to a GDS value of 520 mg/dL is the largest.

Research conducted by Supriyadi and Ridja (2021) regarding the compliance of DM sufferers in Malang city to undergo treatment can control fasting blood sugar levels under normal conditions. This can be one of the solution steps in managing the DM disease disaster in Malang city which is related to the results of this regional mapping research based on DM cases in Malang city, namely especially for areas group 3 and group 2 with regional characteristics that have severe and moderate DM cases. In addition to medication adherence that must be carried out by DM patients, to preserve fasting blood sugar levels at normal conditions, DM sufferers must also maintain the amount and type of food intake and physical activity according to the advice and recommendations of the doctor. This has been proven from the results of research from Seran et al. (2022) for cases of DM patient at two health centers in Malang city. Research from Irwansyah and Kasim (2021) regarding DM patients shows that lifestyle also greatly influences the risk of DM.

4. CONCLUSION

The conclusion that can be drawn from this study is a regional map based on DM disease in each district based on the order of severity of DM patients divided into three groups. Namely, group one is a patient with moderate DM, group two is a patient with moderately severe DM, and group three is a patient with severe DM. The normal Bayesian mixture model for DM in the Malang area shows that the area is divided according to the districts in the Malang area with each district having a different percentage of contribution to the number of DM patient. The highest to lowest rankings for the percentage contribution of DM patient in each district are Blimbing 50%, Kedung Kandang 18%, Klojen 15%, Lowokwaru 14%, and Sukun 3%. The non-severe DM patient group, the districts that need to be considered sequentially are Kedung Kandang, Klojen, Sukun, Blimbing, and Lowokwaru; in the group of patient with moderately severe DM, the districts that need to be considered sequentially are Klojen, Lowokwaru, Kedung Kandang, Sukun, and Blimbing; and in the group of severe DM patient, the districts that need to be considered sequentially are Klojen, Lowokwaru, Sukun, Kedung Kandang, and Blimbing. Sukun District and Klojen District in the Malang region are two districts that need serious attention from the local government of Malang City in dealing with DM cases. DM sufferers in group 3 and group 2 areas must comply with treatment, maintain the amount and type of food intake, lifestyle, and physical activity recommended by doctors so that DM disaster mitigation in the two regional groups can be controlled and controlled properly. In further research, modeling using the Bayesian mixture of mixture approach for DM cases in Malang can be carried out because in this study it has been proven that every region in

Malang district has a mixture distribution pattern.

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REFERENCES

Agustina, V., R. E. Rayanti, and N. Hidayah (2020). Penerapan Perilaku Pencegahan Penyakit Diabetes Mellitus Menggunakan Health Belief Model Di Puskesmas Sidorejo Lor–Salatiga. *Jurnal Keperawatan Muhammadiyah*, **5**(2); 61–69 (in Indonesia)

Aitkin, M. (2001). Likelihood and Bayesian Analysis of Mixtures. *Statistical Modelling*, **1**(4); 287–304

American Diabetes Association (2010). Diagnosis and Classification of Diabetes Mellitus. *Diabetes Care*, **33**(1); 62–69

Astuti, A. B., N. Iriawan, Irhamah, H. Kuswanto, and L. Sasiarini (2015a). *Modeling of Blood Sugar Levels in Patients with Diabetes Mellitus through the Development of the Bayesian Mixture Model Averaging Algorithm*. PUPT-BOPTN Research Report Year I. Universitas Brawijaya, Malang

Astuti, A. B., N. Iriawan, Irhamah, H. Kuswanto, and L. Sasiarini (2015b). *Modeling of Blood Sugar Levels in Patients with Diabetes Mellitus through the Development of the Bayesian Mixture Model Averaging Algorithm*. PUPT-BOPTN Research Report Year II. Universitas Brawijaya, Malang

Astuti, A. B., N. Iriawan, H. Kuswanto, and L. Sasiarini (2016). Blood Sugar Levels of Diabetes Mellitus Patients Modeling with Bayesian Mixture Model Averaging. *Global Journal of Pure and Applied Mathematics*, **12**(4); 3143–3158

Astuti, A. B., N. Iriawan, H. Kuswanto, and L. Sasiarini (2017). Bayesian Mixture Modeling for Blood Sugar Levels of Diabetes Mellitus Patients (Case Study in RSUD Saiful Anwar Malang Indonesia). *Journal of Physics: Conference Series*, **893**(1); 012036

Bernardo, J. M. and A. F. M. Smith (2000). *Bayesian Theory*. John Willey and Sons

Box, G. E. P. and G. C. Tiao (1973). *Bayesian Inference in Statistical Analysis*. Addison-Wesley, Massachusetts

Carlin, B. P. and S. Chib (1995). Bayesian Model Choice via Markov Chain Monte Carlo Methods. *Journal of the Royal Statistical Society: Series B (Methodological)*, **57**(3); 473–484

Congdon, P. (2006). *Bayesian Statistical Modelling. Second Edition*. John Wiley and Sons

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin (1995). *Bayesian Data Analysis*. Chapman and Hall

Gosh, J. K., M. Delampady, and T. Samanta (2006). *An Introduction to Bayesian Analysis Theory and Methods*. Springer

Green, P. J. (1995). Reversible Jump Markov Chain Monte Carlo Computation and Bayesian Model Determination. *Biometrika*, **82**(4); 711–732

Hazari, M. A. H., B. R. Reddy, N. Uzma, and B. S. Kumar (2015). Cognitive Impairment in Type 2 Diabetes Mellitus. *International Journal of Diabetes Mellitus*, **3**(1); 19–24

Infodatin (2020). *Center for Data and Information Ministry of Health RI*. Kementerian Kesehatan Republik Indonesia (in Indonesia)

Iriawan, N. (2001). Univariable Normal Mixture Model Estimation: A Bayesian Method Approach with MCMC. *Proceedings of National Seminar and Konferda VII on Mathematics in DIY and Central Java Region*; 105–110

Irwansyah, I. and I. S. Kasim (2021). Indentifikasi Keterkaitan Lifestyle Dengan Risiko Diabetes Melitus. *Jurnal Ilmiah Kesehatan Sandi Husada*, **10**(1); 62–69 (in Indonesia)

Marin, J. M., K. Mengersen, and C. P. Robert (2005). Bayesian Modelling and Inference on Mixtures of Distributions. *Handbook of Statistics*, **25**(50); 459–507

Mc Culloch, C. E. and S. R. Searle (2000). *Generalized, Linear, and Mixed Models*. John Willey and Sons

Mc Lachlan, G. J. and K. E. Basford (1988). *Mixture Models Inference and Applications to Clustering*. Marcel Dekker

McLachlan, G. J. and D. Peel (2000). *Finite Mixture Models*. John Wiley and Sons

Ntzoufras, I. (2009). *Bayesian Modeling Using WinBUGS*. John Wiley and Sons

Okosun, I. S. and R. Lyn (2015). Prediabetes Awareness, Healthcare Provider's Advice and Lifestyle Changes in American Adults. *International Journal of Diabetes Mellitus*, **3**(1); 11–18

Riskesdas Jatim (2020). *Main Results of Riskesdas 2019 East Java Province, Surabaya*. Ministry of Health of the Republic of Indonesia, Health Research and Development Agency Center for Humanities and Health Management (in Indonesia)

Safitri, E. S., B. I. Yulitasari, and M. Mulyanti (2022). Depresi Dengan Fungsi Kognitif Pada Penderita Diabetes Mellitus Tipe II Di Wilayah Binaan Puskesmas Sedayu 2 Bantul. *Nursing News: Jurnal Ilmiah Keperawatan*, **6**(3); 124–132 (in Indonesia)

Seran, N. S., V. M. Ardiyani, , and A. Sutriningsih (2022). *Hubungan Jumlah dan Jenis Makanan dan Aktivitas Fisik Dengan Status Kadar Gula Darah Puasa Pada Penderita Diabetes Melitus Tipe 2 di Puskesmas Dinoyo Kota Malang*. Universitas Tribhuwana Tunggadewi (in Indonesia)

Stephens, M. (2000). Bayesian Analysis of Mixture Models with an Unknown Number of Components-an Alternative to Reversible Jump Methods. *Annals of Statistics*, **28**(1); 40–74

Supriyadi, N., Dewi and E. W. Ridja (2021). Kepatuhan Pengobatan Pada Penderita Diabetes Melitus Tipe 2 Di Puskesmas X Kota Malang. *Jurnal Ilmiah Keperawatan*, **5**(1); 9–15 (in Indonesia)

Syahid, Z. M. (2021). Factors Associated with Diabetes Mellitus Treatment Adherence. *Jurnal Ilmiah Kesehatan Sandi Husada*, **10**(1); 147–155

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