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Risk Factors for Anaemia, Iron Deficiency, and Iron Deficiency Anaemia in Women of Reproductive Age Using Logistic Regression

Shaly Wanda Hamzah[1], Muhammad Nur Aidi[2], I Made Sumertajaya[3], Fitrah Ernawati[4]

[123]Department of Statistics, IPB University, Bogor, Indonesia

[4]National Research and Innovation Agency, Bogor, Indonesia

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ABSTRACT

Women of reproductive age (WRA) are vulnerable to anaemia, iron deficiency (ID), or iron deficiency anaemia (IDA). To identify the factors influencing anaemia, ID, and IDA to WRA in Indonesia, logistic regression analysis was employed. This study aims to determine the prevalence of anaemia, ID, and AID among WRA, as well as to identify influencing factors and evaluate the classification results produced by Logistic Regression methods. The data used were obtained from the Research and Development Agency, Ministry of Health of Indonesia. Haemoglobin data, demographic, and socioeconomic data were derived from the Basic Health Research 2013, and ferritin (Fe) and CRP data used stored serum samples collected in 2013 and analyzed in 2016. The results of this study found that the prevalence of anaemia among WRA in Indonesia is 11%, ID 14%, and AID 9%. Significant factors influencing health conditions include BMI, marital status, family size, malaria, and ARI. Individuals with overweight or obesity have a lower chance of experiencing anaemia, ID, and IDA compared to those who are thin, while individuals who are divorced have a higher risk than those who are unmarried. Additionally, individuals affected by malaria or ARI also have a higher risk of experiencing anaemia. Consumption of animal protein and education also emerges as significant factors affecting ID conditions. Although the model using Multinomial Logistic Regression shows higher accuracy than the binary model, both still have weaknesses in identifying cases of anaemia, ID, and IDA with low sensitivity. Model evaluation indicates that despite proficiency in recognizing normal cases, they still struggle to detect cases of anaemia, ID, and IDA.

Keywords: Logistic Regression, Anaemia, Iron Deficiency, Iron Deficiency Anaemia, Reproductive-Age Women

I. INTRODUCTION

Anaemia is a condition in which the body experiences a decrease in haemoglobin concentration. One of the vulnerable groups to anaemia is Women of Reproductive Age (WRA) between the ages of 15-49 years. This is because WRA undergo physiological changes such as menstruation, pregnancy, and postpartum bleeding(Kinyoki et al., 2021). The prevalence of anaemia among WRA in Indonesia is 27.2% (Ministry of Health of the Republic of Indonesia, 2018). This figure has increased since 2007, which was 11.3% (Ministry of Health of the Republic of Indonesia, 2007), and in 2013 it was 16.7% (Ministry of Health of the Republic of Indonesia, 2013).

In the study by Manikam et al. (2022) , anaemia has wide-ranging effects on the life cycle of pregnant women, children, and adolescents. In addition to affecting maternal health, anaemia in pregnant women also increases the risk of anaemia in newborns. Severe iron deficiency in pregnant women can result in decreased iron reserves in fetuses and newborns (Harding et al., 2018). The prevalence of anaemia in children ranges from approximately 55% at ages 0.5-1.9 years to between 10.6 and 15.5% in children aged 2-12 years (Sandjaja et al., 2013) . Ernawati et al (2013) reported that the prevalence among infants aged 0.5-0.9 years was 54.7% in urban areas and 61.9% in rural areas. These figures are higher compared to children aged 9.0-12.9 years, which were 5.0% in urban areas and 11.4% in rural areas. Children who experience anaemia are at risk of experiencing this condition until toddlerhood and even into adulthood. Anaemia in children can affect their cognitive and motor development, which on a larger scale can impact human resources in the future (Ernawati et al., 2018).

One of the commonly encountered causes of anaemia is iron deficiency anaemia (IDA). Iron Deficiency Anaemia (IDA) is anaemia that arises due to a reduced supply of iron because of depleted iron stores, ultimately resulting in decreased haemoglobin formation (Setyorini et al., 2019). Based on the results of research conducted by Nugraheni et al. (2021), the percentage of pregnant women of reproductive age experiencing anaemia is 35.1%, while those with iron deficiency are 10.5%.

According to Ernawati et al. (2018), it needs to be emphasized that Anaemia is not a disease. Anaemia occurs when the number of red blood cells or the haemoglobin level in the blood falls below normal levels. Based on the WHO definition (World Health Organization, 2015), individuals are said to not have anaemia when the haemoglobin (Hb) level is greater than 12 g/dL, and ferritin (Fe) > 15 mcg/dL. Individuals with an Hb level less than 12 g/dL and Fe level greater than 15 mcg/dL are considered to have anaemia, whereas when individuals have an Hb level greater than 12 g/dL but Fe level less than 15 mcg/dL, they can be considered to have iron deficiency (ID). On the other hand, individuals with an Hb level less than 12 g/dL and Fe level also less than 15 mcg/dL can be considered to have iron deficiency anaemia (IDA).

Identifying all factors that affect anaemia is necessary (Aidi, Efriwati, et al., 2022)(Aidi, Ernawati, et al., 2022). Factors influencing the occurrence of anaemia involve complex interactions of social, economic, ecological, and biological factors (Akbar et al., 2020). Household socioeconomic conditions are also related to anaemia. Several studies have shown that the prevalence of anaemia tends to be higher in poor households (Sudikno et al., 2014). In the study by Ernawati et al. (2021), it was found that children from low socioeconomic backgrounds tend to have low haemoglobin (Hb) and ferritin levels. Iron deficiency anaemia is more common in developing countries due to economic limitations and low intake of animal protein (Setyorini et al., 2019). Limited access to food that meets daily nutritional needs can lead to malnutrition (Ayensu et al., 2020). The main source of iron is animal food, such as meat, liver, poultry, and fish. However, Indonesian society tends to consume iron from plant-based sources such as tofu and tempeh due to their lower cost. Therefore, in general, Indonesian society is vulnerable to the risk of anaemia

(Ministry of Health of the Republic of Indonesia, 2018). Additionally, factors such as malaria also contribute to the risk of (Aidi, Ernawati, et al., 2022).

To determine the factors influencing Anaemia, IDA, and ID in WRA in Indonesia, logistic regression analysis can be performed (Pangestika et al., 2021). Silvana (2008) found consistency between logistic regression analysis in the analysis of menarche age factors in junior high school female students. In the study by Atti et al., (2008), logistic regression was used to analyse the risk factors for coronary heart disease, and it was found that the total error for logistic regression analysis was 32.8%.

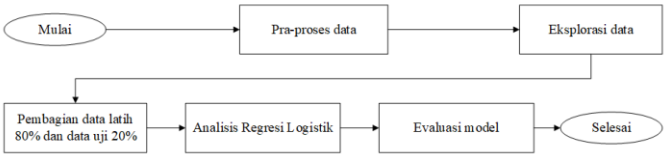
The aim of this study is to determine the prevalence of anaemia, ID, and IDA in WRA, as well as to identify the influencing factors and evaluate the classification results generated from Logistic Regression analysis.

II. METHODS AND MATERIAL

Data

This study utilized secondary data obtained from the National Institute of Health Research and Development, Ministry of Health Republic of Indonesia. Haemoglobin (Hb), demographic, and socio-economic data were sourced from the Basic Health Research (Riskesdas) 2013, while ferritin (Fe) and CRP data were obtained from stored serum samples collected in 2013 and analysed in 2016. The study comprised 9530 respondents. The data analysis process involved the following steps:

Figure 1. Flowchart of the method



Logistic Regression

Regression is a statistical technique used to explore the connection between one or more independent variables and a dependent variable. It can also be applied to forecast the dependent variable's values based on the independent variables. The main aim of regression analysis is to determine the optimal line or model that represents the relationship between variables and use this model to make precise predictions (Kutner et al., 2004).

Logistic regression is a predictive model that uses one or more independent variables to forecast a binary response variable (Aidi & Maulana, 2020). In this study, the dependent variable with binary values is the status of WUS categorized as either anaemia or normal, followed by ID and normal, as well as IDA and normal. The variables utilized are detailed in Table 1.

Table 1 Variables in the study

Variables	
Y_1	WRA's Status (Normal, Anaemia)
Y_2	WRA's Status (Normal, ID)
Y_3	WRA's Status (Normal, IDA)
Y_4	WRA's Status (Normal, Anaemia, ID, IDA)
X_1	Residential Area (Village, City)
X_2	Body Mass Index (Underweight, Normal, Overweight, Obesity)
X_3	Age (Early Teen, Late Teen, Early Adult, Late Adult)
X_4	Education (No Schooling, Elementary School, High School, Higher Education)
X_5	Occupation (Unemployed, Student, Employed)
X_6	Home Ownership Status (Rental, Free Rental, Own)
X_7	Family Size (Small Family, Medium Family, Large Family)
X_8	Marital Status (Single, Married, Divorced)
X_9	Ever Pregnant (Never, Ever)
X_{10}	Weekly Fruit Consumption (Never, Moderate, Frequent)
X_{11}	Weekly Vegetable Consumption (Never, Moderate, Frequent)

Variables	
X_{12}	Daily Meat/Chicken/Fish Consumption (Never, Rare, Moderate, Frequent)
X_{13}	Pneumonia Disease (No, Yes)
X_{14}	Malaria Disease (No, Yes)
X_{15}	Diarrhea Disease (No, Yes)
X_{16}	Tuberculosis Disease (No, Yes)
X_{17}	ARI Disease (No, Yes)
X_{18}	Hepatitis Disease (No, Yes)

The evaluation of model

The assessment of the classification model is conducted through the utilization of a confusion matrix. Marrom et al. (2010) affirm that a confusion matrix provides a comprehensive evaluation of the classification model's performance. As described by Navin (2016), a confusion matrix serves to assess the performance of classification on binary data. The metrics employed for comparing the performance of each model include accuracy, sensitivity, and specificity. Accuracy reflects the overall precision of the classification, sensitivity denotes the accuracy of identifying true positive cases, and specificity indicates the accuracy of identifying true negative cases. In this research, the positive class pertains to teenage girls positively impacted by anaemia, while the negative class encompasses those not affected by anaemia.

The values of accuracy, sensitivity, and specificity are derived from the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. TP and TN signify correctly classified data, whereas FP and FN denote misclassified data. Refer to Table 2 for the depiction of the confusion matrix table.

Tabel 2 Confusion matrix table

Actual	Prediction	
	Positif	Negatif
Positif	True Positive (TP)	False Negative (FN)
Negatif	False Positive (FP)	True Negative (TN)

The most frequently used metric for assessing a model's performance is accuracy, sensitivity, and specificity, which, however, may not always provide a clear indication of its effectiveness. This issue becomes particularly pronounced when there is an imbalance between classes.

$$Sensitivity : \frac{TP + TN}{TP + FP + TN + FN}$$

The sensitivity, or recall, measures the proportion of correctly identified positive instances relative to the total actual positive instances in the dataset. It helps determine how many true positive instances the model failed to identify.

$$Sensitivity : \frac{TP}{TP + FN}$$

The specificity measures the proportion of correctly identified negative instances relative to the total actual negative instances in the dataset. It is akin to recall but focuses on negative instances.

$$Specificity : \frac{TN}{TN + FP}$$

III. RESULTS AND DISCUSSION

Prevalence of anaemia, ID, and IDA

Based on all the available data in this study, data exploration was conducted to get an overview of Women Reproductive Age (WRA) in Indonesia.

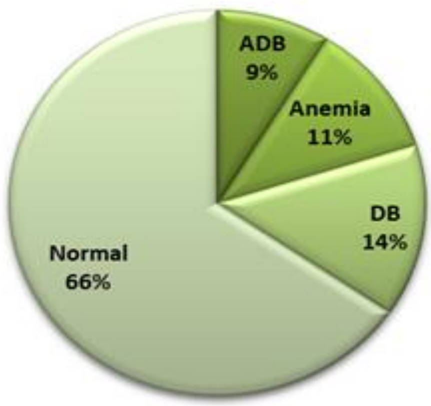


Figure 2: WRA status based on Hb dan Fe value

According to the obtained data (Figure 2), there were 1073 cases of Anaemia, accounting for approximately 11%, 1365 cases of Iron Deficiency (ID), accounting for about 14%, and 832 cases of Iron Deficiency Anaemia (IDA), accounting for around 9%.

Binary Logistic Regression

During the binary logistic regression analysis conducted on Women of Reproductive Age (WRA), the dependent variables include anaemia and normal, Iron Deficiency (ID) and normal, Iron Deficiency Anaemia (IDA) and normal. The "Normal" category is used as the reference point. The aim is to determine the variables that have a significant impact on the outcomes based on their p-values. The results of the binary regression reveal that multiple variables play a significant role in influencing the occurrence of anaemia, ID, and IDA.

Tabel 3 p-values and odds ratio for anaemia status (Y_1)

Variables	Categories	p value	Odds Ratio
Constant		0,001	0,159
(X2) BMI (Body Mass Index)	Underweight (0)		
	Normal (1)	0,787	0,965
	Overweight (2)	0,013	0,690
	Obese (3)	0,007	0,603
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,869	0,975
	Divorced (2)	0,003	1,893
(X14) Malaria Disease	No (0)		
	Yes (1)	0,003	2,158
(X17) ARI Disease	No (0)		1,000
	Yes (1)	0,002	1,396

In the first model, which predicts anaemia status, the body mass index (BMI) variable proved to be significant. Individuals who are overweight or obese have 0.69 and 0.603 times lower odds of experiencing anaemia compared to individuals with normal weight. Furthermore, marital status also influences, with divorced individuals having 1.893 times higher odds of experiencing anaemia compared to unmarried individuals. Malaria disease also proved to be significant, where individuals affected by the disease have 2.158 times higher odds of experiencing anaemia. The next variable is acute respiratory infection (ARI), which indicates that individuals affected by ARI have 1.396 times higher odds of experiencing anaemia.

Tabel 4 p-values and odds ratio for ID status (Y_2)

Variables	Categories	p value	Odds Ratio
Constant		0,099	0,469
(X2) BMI (Body Mass Index)	Underweight (0)		
	Normal (1)	0,064	0,818
	Overweight (2)	0,000	0,593
	Obese (3)	0,000	0,499
(X4) Education	No schooling (0)		
	Elementary School (1)	0,216	1,312
	Junior High School (2)	0,184	1,341
	College (3)	0,037	1,748
(X7) Family Size	Small Family (0)		
	Medium Family (1)	0,784	0,962
	Large Family (2)	0,038	1,376
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,001	0,648
	Divorced (2)	0,084	0,686

In the second model, which predicts iron deficiency (DB) status, the BMI variable once again emerges as a significant variable. Overweight or obese individuals have 0.593 and 0.499 times lower odds of experiencing DB compared to thin individuals. Additionally, education also affects, with women with university education having 1.748 times higher odds of experiencing DB compared to women with no education. Family size variable is also significant, with large families having 1.376 times higher odds of experiencing DB compared to small families. Marital status also influences, where married individuals have 0.648 times lower odds of experiencing DB compared to unmarried individuals.

Tabel 5 p-values and odds ratio for IDA status (Y_3)

Variables	**Categories**	**p value**	**Odds Ratio**
Constant		0,375	0,632
(X2) BMI (Body Mass Index)	Underweight (0)		
	Normal (1)	0,043	0,772
	Overweight (2)	0,000	0,451
	Obese (3)	0,000	0,389
(X7) Family Size	Small Family (0)		
	Medium Family (1)	0,001	0,622
	Large Family (2)	0,769	0,952
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,000	0,577
	Divorced (2)	0,809	1,057
(X14) Malaria Disease	No (0)		
	Yes (1)	0,006	2,202

In the third model, which predicts iron deficiency anemia (ADB) status, a similar pattern is observed in the significance of the BMI variable. Additionally, family size is also significant, with medium-sized families having 0.622 times lower odds of experiencing ADB compared to small families. Marital status also affects, where married individuals have 0.577 times lower odds of experiencing ADB compared to unmarried individuals. Malaria disease also emerges as a significant variable, with individuals affected by the disease having 2.202 times higher odds of experiencing ADB.

Multinomial Logistic Regression

The multinomial logistic regression analysis highlights the influence of variables on the conditions of Anaemia, ID, and IDA compared to the normal condition, with normal as the reference category.

Tabel 6 p-values and odds ratio (Y_4)

Variables	**Categories**	**p value**	**Odds Ratio**
Anaemia			
Constant		0,000	0,080
(X2) BMI (Body Mass Index)	Underweight (0)		
	Normal (1)	0,594	0,921
	Overweight (2)	0,022	0,705
	Obese (3)	0,010	0,613
(X5) Occupation	Not working (0)		
	School (1)	0,008	0,702
	Working (2)	0,757	1,035
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,949	0,976
	Divorced (2)	0,005	1,842
(X14) Malaria Disease	No (0)		
	Yes (1)	0,000	2,587
(X17) ARI Disease	No (0)		
	Yes (1)	0,019	1,300
ID			
Constant		0,014	0,302
(X2) BMI (Body Mass Index)	Underweight (0)		

Variables	Categories	p value	Odds Ratio
	Normal (1)	0,123	0,837
	Overweight (2)	0,000	0,617
	Obese (3)	0,000	0,525
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,000	0,640
	Divorced (2)	0,224	0,758
(X12) Daily Consumption of Meat/Chicken/Fish	Never (0)		
	Rarely (1)	0,007	1,263
	Moderate (2)	0,711	1,049
	Often (3)	0,041	1,273
IDA			
Constant		0,095	0,399
(X2) BMI (Body Mass Index)	Underweight (0)		
	Normal (1)	0,055	0,773
	Overweight (2)	0,000	0,520
	Obese (3)	0,000	0,373
(X8) Marital Status	Unmarried (0)		
	Married (1)	0,001	0,597
	Divorced (2)	0,847	1,069

In the Anaemia category, BMI emerges as a significant variable. Individuals with overweight and obesity have chances 0.705 and 0.613 times lower, respectively, to experience Anaemia compared to those who are underweight. Additionally, employment status proves to have a significant impact on the category of women who are still in school, with the likelihood of experiencing anaemia 0.702 times lower. Furthermore, marital status also affects significantly, where individuals who are divorced have 1.842 times higher chances of experiencing Anaemia compared to those who are unmarried. The factor of malaria is also significant, with individuals affected having 2.587 times higher chances of experiencing Anaemia. Similarly, the variable of Acute Respiratory Infection (ARI) presents a likelihood 1.3 times higher for experiencing anaemia compared to those not affected.

In the ID category, BMI and marital status play significant roles. Individuals with overweight and obesity have chances 0.617 and 0.525 times lower, respectively, to experience ID compared to those who are underweight. Married individuals have 0.64 times lower chances of experiencing ID compared to unmarried ones. Additionally, the consumption of animal protein is also significant, where individuals who rarely and frequently consume it have chances 1.263 and 1.273 times higher, respectively, to experience ID compared to those who never consume it.

In the IDA category, BMI and marital status also have significant effects. Individuals with overweight and obesity have chances 0.52 and 0.373 times lower, respectively, to experience IDA compared to those who are underweight. Married individuals have 0.597 times lower chances of experiencing IDA compared to unmarried ones.

Logistic Regression Model Evaluation

In comparing the effectiveness of binary logistic regression and multinomial regression methods in classifying Anaemia, ID, and IDA conditions against normal conditions, there is a significant difference between the two methods, it can be seen in the table 7.

Tabel 7 Model Evaluation

Model		Acc	Sens	Spec
Biner Logistic Regression	Anaemia	14,88	0,002	1,00
	ID	18,07	0,00	1,00
	IDA	11,82	0,00	1,00
Multinomial Logistic Regression	Normal	65,36	99,82	99,84
	Anaemia		0,00	0,00
	ID		0,00	0,00
	IDA		0,00	0,00

In the first model, anaemia status was assessed using binary logistic regression analysis, yielding an accuracy of only 14.88%. This suggests a tendency for numerous incorrect predictions. With a sensitivity of just 0.161%, the model struggles to accurately identify anaemia cases. Although it exhibits a specificity of 100%, indicating proficiency in identifying non-anaemia cases, its primary weakness lies in the failure to detect anaemia. The second model, assessing ID status through binary logistic regression analysis, similarly demonstrates low accuracy at 18.07%. Zero sensitivity reveals the model's inability to identify ID cases, despite a high specificity of 100% for non-ID cases. Despite its proficiency in identifying normal cases, the model's weakness lies in its inability to detect ID cases. In the third model, analysing IDA status with binary logistic regression, accuracy remains low at 11.82%. Zero sensitivity again indicates failure to identify IDA cases, while high specificity (100%) suggests competence in classifying non-IDA cases. The fourth model, assessing WRA with categories of anaemia, ID, IDA, and normal, using multinomial logistic regression analysis, achieves higher accuracy (65.36%) than the previous three models. However, its sensitivity fails to identify anaemia, ID, and IDA cases, approaching zero. This suggests better identification of normal cases but reduced effectiveness in predicting anaemia, ID, and IDA cases.

Discussion

The results of this study indicate that BMI significantly influences both binary and multinomial logistic regression methods, across all conditions, namely anaemia, ID, and IDA. It is important to understand that BMI is not just a number but also reflects the overall nutritional and health status of an individual. A low BMI may indicate a deficiency in iron and other nutrients, which can increase the risk of ID and IDA. Pasalina et al. (2019) found that individuals with low body weight may not be receiving enough nutrients, leading to anemia. However, it's not only low BMI that we should pay attention to; high BMI or obesity can also increase the risk of Iron Deficiency Anaemia (IDA) through complex inflammatory processes.

Another variable that significantly influences both binary and multinomial logistic regression methods is marital status. Married women are more likely to become pregnant and give birth. During pregnancy, anaemia often occurs due to significant bodily changes, including a 20-30% increase in blood volume. This necessitates additional iron and vitamin intake for the production of haemoglobin (Hb) required by the body, as more blood is needed for the growing fetus (Astriana, 2017). Married women tend to have larger families because the more often a woman becomes pregnant and gives birth, the larger her family will likely be. According to research conducted by Astriana (2017), respondents with more children (higher parity) have a greater risk of experiencing anaemia during pregnancy. Malaria is often a leading cause of anaemia in tropical regions. Malaria infection accelerates the breakdown of red blood cells and disrupts the production of new red blood cells in the bone marrow, slowing down the recovery from anaemia (White, 2018). Additionally, haemoglobin levels can decrease due to respiratory tract infections such as flu and cough. Viruses and bacteria from these diseases can damage the immune system and slow down the blood formation process, leading to anaemia (Darshan et al., 2010).

IV. CONCLUSION

From this study, it can be concluded that the prevalence of anaemia, ID, and IDA among Women of Reproductive Age (WRA) in Indonesia is approximately 11%, 14%, and 9% respectively. Significant factors influencing health conditions include BMI, marital status, family size, malaria, and ARI. Individuals with overweight or obesity have a lower chance of experiencing anaemia, ID, and IDA compared to those who are thin, while individuals who are divorced have a higher risk than those who are unmarried. Additionally, individuals affected by malaria or ARI also have a higher risk of experiencing anaemia. Consumption of animal protein and education also emerges as significant factors affecting ID conditions. Although the model using Multinomial Logistic Regression shows higher accuracy than the binary model, both still have weaknesses in identifying cases of anaemia, ID, and IDA with low sensitivity. Model evaluation indicates that despite proficiency in recognizing normal cases, they still struggle to detect cases of anaemia, ID, and IDA. Therefore, adjustments or improvements to the model are needed to enhance identification capabilities. These findings provide valuable insights for the development of more effective intervention strategies to address anaemia, ID, and IDA issues in Indonesia, thus improving the well-being of WRA and reducing the burden of related conditions.

V. REFERENCES

[1] Aidi, M. N., Efriwati, E., Suryanty, S., Rahman, L. O. A., Nurfadilah, K., & Ernawati, F. (2022). Identifying the Characteristics of Pregnant Women with Inflammation/Infection in Indonesia. *Jurnal Gizi Dan Pangan*, *17*(3), 177–186. https://doi.org/10.25182/jgp.2022.17.3.177-186

[2] Aidi, M. N., Ernawati, F., Efriwati, Nurjanah, N., Rachmawati, R., Julianti, E. D., Sundari, D., Retiaty, F., Fitrianto, A., Nurfadilah, K., & Arifin, A. Y. (2022). Spatial distribution and identifying biochemical factors affecting haemoglobin levels among women of reproductive age for each province in Indonesia: A geospatial analysis. *Geospatial Health*, *17*(2). https://doi.org/10.4081/gh.2022.1118

[3] AIDI, M. N., & MAULANA, S. I. (2020). A SPATIAL MODEL FOR PREDICTING THE OCCURENCES OF DEFORESTATION IN THE ISLAND OF SUMATRA, INDONESIA. *Journal of Sustainability Science and Management*, *15*(6). https://doi.org/10.46754/jbsd.2020.08.007

[4] Akbar, M. I., Rinaningsih, Y. S., Ekawaty, R., Batiari, N. M. P., Abdussalam, I., Suharyanto, E., Widiana, D., & Sulistyowati, Y. (2020). Pelaksanaan Program Keping Emas Pada Ibu Hamil Kekurangan Energi Kalori dan Anemia Di Desa Kronjo Tahun 2019. *Jurnal Bidang Ilmu Kesehatan*, *10*(1), 108–121. https://doi.org/10.52643/jbik.v10i1.866

[5] Astriana, W. (2017). Kejadian Anemia pada Ibu Hamil Ditinjau dari Paritas dan Usia THE OCCURRENCE OF ANEMIA IN PREGNANT WOMEN BASED ON PARITY AND AGE. *Jurnal Aisyah : Jurnal Ilmu Kesehatan*, *2*(2), 123–130. http://ejournal.stikesaisyah.ac.id/index.php/jika/

[6] Atti, A., Sunarlim, B., Utami, ;, & Syafitri, D. (2008). ANALISIS FAKTOR RISIKO PENYAKIT JANTUNG KORONER MENGGUNAKAN METODE REGRESI LOGISTIK DAN CHAID. In *Jurnal Mat Stat* (Vol. 8, Issue 2).

[7] Ayensu, J., Annan, R., Lutterodt, H., Edusei, A., & Peng, L. S. (2020). Prevalence of anaemia and low intake of dietary nutrients in pregnant women living in rural and urban areas in the Ashanti region of Ghana. *PLoS ONE*, *15*(1), 1–15. https://doi.org/10.1371/journal.pone.0226026

[8] Darshan, D., Frazer, D. M., Wilkins, S. J., & Anderson, G. J. (2010). Severe iron deficiency

blunts the response of the iron regulatory gene Hamp and pro-inflammatory cytokines to lipopolysaccharide. *Haematologica*, *95*(10). https://doi.org/10.3324/haematol.2010.022426

[9] Departemen Kesehatan Republik Indonesia. (2007). Riset Kesehatan Dasar 2007. *Laporan Nasional 2007*, 1–384. http://kesga.kemkes.go.id/images/pedoman/Riskesdas 2007 Nasional.pdf

[10] Dinas Kesehatan Republik Indonesia. (2013). Riset Kesehatan Dasar. *Diabetes Mellitus*, 87–90. https://doi.org/1 Desember 2013

[11] Ernawati, F., Octaria, Y., & Khomsan, A. (2018). Peluang Generasi Bangsa yang Terabaikan Anemia Baduta. In *Journal of Materials Processing Technology* (Vol. 1, Issue 1).

[12] Ernawati, F., Sandjaja, N., & Soekatri, M. (2013). Status Vitamin a Dan Zat Besi Anak Indonesia. *Gizi Indonesia*, *36*(2), 123. https://doi.org/10.36457/gizindo.v36i2.140

[13] Ernawati, F., Syauqy, A., Arifin, A. Y., Soekatri, M. Y. E., & Sandjaja, S. (2021). Micronutrient deficiencies and stunting were associated with socioeconomic status in indonesian children aged 6–59 months. *Nutrients*, *13*(6). https://doi.org/10.3390/nu13061802

[14] Harding, K. L., Aguayo, V. M., Namirembe, G., & Webb, P. (2018). Determinants of anemia among women and children in Nepal and Pakistan: An analysis of recent national survey data. *Maternal and Child Nutrition*, *14*(November 2016), 1–13. https://doi.org/10.1111/mcn.12478

[15] Kemenkes RI. (2018). Hasil Riset Kesehatan Dasar Tahun 2018. *Kementrian Kesehatan RI*, *53*(9), 1689–1699.

[16] Kinyoki, D., Osgood-Zimmerman, A. E., Bhattacharjee, N. V., Schaeffer, L. E., Lazzar-Atwood, A., Lu, D., Ewald, S. B., Donkers, K. M., Letourneau, I. D., Collison, M., Schipp, M. F., Abajobir, A., Abbasi, S., Abbasi, N., Abbasifard, M., Abbasi-Kangevari, M., Abbastabar, H., Abd-Allah, F., Abdelalim, A., … Hay, S. I. (2021). Anemia prevalence in women of reproductive age in low- and middle-income countries between 2000 and 2018. *Nature Medicine*, *27*(10), 1761–1782. https://doi.org/10.1038/s41591-021-01498-0

[17] Kutner, M., Nachtsheim, C., & Neter, J. (2004). Applied linear regression models- 4th edition. In *McGraw-Hill Irwin*.

[18] Manikam, R. M., Angesti, A. N., & Mardiyah, S. (2022). FAKTOR YANG BERHUBUNGAN DENGAN KEJADIAN ANEMIA PADA SANTRIWATI DI KOTA BEKASI. *Jurnal Sains Kesehatan*, *29*(2). https://doi.org/10.37638/jsk.29.2.1-11

[19] Marrom ND, Rokach L, Shmilovici A. 2010. Using the confusion matrix for improving ensemble classifiers. IEEE Explore. 978(1):4244-8682

[20] Navin M, Panjaka R. 2016. Performance analysis of text classification algorithms using confusion matrix. International Journal of Engineering and Techmical Research. 6(4):2454-4698.

[21] Nugraheni, A., Prihatini, M., Yuriestia Arifin, A., Retiaty, F., Ernawati, F., Biomedis danTeknologi Dasar Kesehatan Badan Litbang Kesehatan Jalan Percetakan Negara Nomor, P., Pusat, J., & Jakarta, D. (2021). PROFIL ZAT GIZI MIKRO (ZAT BESI, ZINK, VITAMIN A) DAN KADAR HEMOGLOBIN PADA IBU HAMIL Micronutrient Profile (Iron, Zinc, Vitamin A) and Hemoglobin Level in Pregnant Women. *Mgmi*, *12*(2), 119–130.

[22] Pangestika, M. P., Sumertajaya, I. M., & Rizki, A. (2021). Penerapan Synthetic Minority Oversampling Technique pada Pemodelan Regresi Logistik Biner terhadap Keberhasilan Studi Mahasiswa Program Magister IPB. *Xplore: Journal of Statistics*, *10*(2), 152–166. https://doi.org/10.29244/xplore.v10i2.238

[23] Pasalina, P. E., Jurnalis, Y. D., & Ariadi, A. (2019). HUBUNGAN INDEKS MASSA TUBUH

DENGAN KEJADIAN ANEMIA PADA WANITA USIA SUBUR PRANIKAH. *Jurnal Ilmu Keperawatan Dan Kebidanan*, *10*(1). https://doi.org/10.26751/jikk.v10i1.584

[24] Sandjaja, S., Budiman, B., Harahap, H., Ernawati, F., Soekatri, M., Widodo, Y., Sumedi, E., Rustan, E., Sofia, G., Syarief, S. N., & Khouw, I. (2013). Food consumption and nutritional and biochemical status of 0·5-12-year-old Indonesian children: The SEANUTS study. *British Journal of Nutrition*, *110*(SUPPL.3). https://doi.org/10.1017/S0007114513002109

[25] Setyorini, E., Anwar, F., Riyadi, H., & Khomsan, A. (2019). Faktor Risiko Anemia pada Wanita Pemetik Teh. *Media Kesehatan Masyarakat Indonesia*, *15*(3). https://doi.org/10.30597/mkmi.v15i3.7008

[26] Silvana, S. (2008). Pemodelan Usia Menarche dengan Regresi Logistik Ordinal dan Metode CHAID pada Siswi SMP di Kota. *(Tesis) Program Studi Statistika, IPB.*

[27] Sudikno, N., Jus'at, I., Sandjaja, N., & Ernawati, F. (2014). Faktor Risiko Anemia Pada Ibu Menyusui Di Rumah Tangga Miskin. *Gizi Indonesia*, *37*(1), 71. https://doi.org/10.36457/gizindo.v37i1.152

[28] White, N. J. (2018). Anaemia and malaria. In *Malaria Journal* (Vol. 17, Issue 1). https://doi.org/10.1186/s12936-018-2509-9

[29] World Health Organization. (2015). WHO | Iron deficiency anaemia: assessment, prevention and control. *Who.*