EDUMATSAINS
JURNAL PENDIDIKAN MATEMATIKA DAN SAINS
E-ISSN:2527-7235
Volume 9 Issue. 1, July, 2024, pp 62-73
http://ejournal.uki.ac.id/index.php/edumatsains

Identification of Dominant Factors Affecting Study Time and Waiting Time of Mathematics Undergraduate Using the Least Absolute Shrinkage And Selection Operator (LASSO)

Hendra Cipta[1*], Rina Widyasari[2], Linna Syahputri[3]

[1,2,3]Department of Mathematics, Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara, Medan, Indonesia

e-mail: *hendracipta@uinsu.ac.id, rinawidyasari@uinsu.ac.id, linna0703201012@uinsu.ac.id

Article Info
Article history:
Received : July 11, 2024
Revised : July 18, 2024
Accepted : July 24, 2024
Available online : July 31, 2024

https://doi.org/10.33541/edumatsains.v9i1.6069

Abstract
Higher education is a level of education that is able to produce and prepare graduates so that college graduates are able to compete and are ready to face the world of work. The aim of this research is to determine the dominant factors that influence the study period and waiting time for undergraduates in Department of Mathmatics FST UIN Sumatera Utara Medan until they get their first job in less than 9 months. The Least Absolute Shrinkage And Selection Operator (LASSO) method was used in this research, where this method is expected to be able to provide high accuracy results in terms of determining the most dominant factors. From the results of calculations using the LASSO method, the three most dominant factors that greatly influence the study period and waiting time for undergraduates are working status (X_3), organizational participation (X_5), grade point average (X_2), final assignment position (X_2). By producing this most dominant factor, it is hoped that mathematics study programs will care more about their students by making major and minor improvements to future accreditation.

Keywords: Dominant factors, study time, LASSO method, undergraduates, waiting time

1. Introduction

According to Law of the Republic of Indonesia Number 12 in 2012 year concerning Higher Education, it is stated that higher education is part of the national education system which has a role in educating the life of the nation and advancing science and technology while still paying attention to human values and sustainable national empowerment (Azzahra & Zahra, 2023) and (Nurwahida, 2022). Higher education can be obtained through universities and from someone who is studying at a university called a student (Digdowiseiso, 2020). Students are prospective intellectuals in society who are expected to be able to provide change in a more advanced direction and bring benefits to society with the knowledge they have (Fadhil & Sabic-El-Rayess, 2021).

Higher education in Indonesia consists of several programs, namely the Undergraduate Program (S1), Postgraduate Program (S2) and Doctoral Program (S3), cross-track undergraduate program/transfer program from graduates of the Diploma Program (D3), and Diploma IV Program (D4) (Marpi, 2023). The Undergraduate Program (S1) is an academic education program which aims to prepare students to become citizens who believe and are devoted to God Almighty, have the spirit of Pancasila, have high personality integrity, are open and responsive to changes and advances in science. The Undergraduate Program (S1) can be completed in less than 8 semesters and the maximum limit is 14 semesters (Marwan, 2022).

UIN Sumatera Utara Medan is one of the State Islamic Religious Universities in Indonesia which has several faculties, one of which is the Faculty of Science and Technology (FST). The Department of Mathematics is one of the study programs at FST UIN Sumatera Utara Medan which hopes that its graduates will become consultants in the field of mathematics, research assistants who carry out data processing, practitioners, and employees both government and private who work in the fields of banking, banking, insurance. and the field of science and technology.

A person's goal in pursuing higher education is to get a job as soon as possible with a decent income to improve their quality of life. In living in society, a graduate graduate is not expected to become unemployed but must become an agent of change who advances and prospers social life. Undergraduate wait time is the time between when a student starts from being declared graduated from college to getting a job first. The waiting time for each graduate varies. Some people immediately get jobs after graduating, some even haven't graduated but have got a permanent job, but there are also those who have to wait several months to get a job. This can happen because of influencing factors. Undergraduate waiting time is the length of time a graduate takes from graduating from college to getting his first job. According to (Dito et al., 2019), the average waiting period for a graduate (S1) to get a first job is 0 to 9 months. If after 9 months you have not found a job, then it can be said that there is something wrong with the graduate, whether from external or internal factors.

Based on a field assessment in the mathematics study program on 7-8 December 2023, there must be evaluation and follow-up regarding the study period and undergraduate waiting period. This is done to ensure that the number of students who graduate on time can reach 85% and the waiting period for graduates to get their first job is less than 9 months. One form of follow-up that can be carried out is by conducting experiments (presenting practitioner lecturers) and identifying the dominant factors that cause them to not match the goals and objectives of the study program.

The decline in employment rates in this country is an external factor that has a big impact, even though the number of university graduates which increases every year is not able to keep up with the demand for the workforce. On the other hand, the length of the study period, field of specialization taken, current final assignment position, working status, grade point average (GPA), organizational participation, use of gadgets and marital status are internal characteristics that have an impact on the length of time it takes for undergraduate graduates to get a job. To find out the elements that influence the length of time it takes a graduate to get his first job, an in-depth search must be carried out to find out the most dominant factors that determine the completion of studies and the waiting time for graduates to get a job as quickly as possible.

The determinants of the study period and undergraduate waiting time are influenced by many interrelated factors so that in regression modeling, the factors that influence the determinants of the study period and undergraduate waiting time are susceptible to detection by multicollinearity problems. Prediction accuracy can sometimes be increased by reducing the regression coefficient value to zero (Altelbany, 2021). The application of data mining techniques in this research uses the neural network method, which is expected to offer deeper insight into the factors that influence students' graduation times (Ariani et al., 2024). To gain new knowledge from the tracer study dataset regarding the relationship between university contribution and alumni capability in the job market, in this study, data mining techniques are used to determine what factors influence the length of time it takes college graduates to find employment. The features are selected using chi-square. Two classification algorithms, Decision Tree and Support Vector Machine, are compared for the best model. This study also used hyperparameter tuning to improve accuracy (Miranda & Lhaksamana, 2022). Various attempts were made by universities to prepare graduates to be ready to face the world of work. One of the readiness is to predict the waiting period for first time employment for prospective graduates. With this prediction, universities can evaluate the quality of education always to be superior and better. This study aims to make a prediction model of students' waiting periods when getting their first job. The problem is solved using classification data mining techniques, namely the Naïve Bayes algorithm. The analysis results using 199 training data and 22 testing data obtained an accuracy level of 90.90%, recall of 90.48%, and 100% precision (Amalia & Wibowo, 2020).

From much of the literature above, the problem of study length and waiting time has been explained with various methods applied. Researchers are interested in solving the same problem but with different methods. In this research, the Least Absolute Shrinkage And Selection Operator (LASSO) method was chosen because this method is more complex and provides calculation accuracy in large data (Sari et al., 2022) and (Cahya et al., 2022). In this method there is a state of multicollinearity, where the state of multicollinearity is problem that often occurs in multiple regression analysis where there is a significant relationship between two or more independent variables (Altelbany, 2021). Multicollinearity results in least squares estimators having large variances (Fitriani et al., 2022) and (Nur et al., 2023). Multicollinearity will affect the accuracy of model predictions and cause errors in decision making. There are many methods that can be used to overcome this multicollinearity problem, including the ridge regression method (Enwere, 2023), binary logistic equations and the Least Absolute Shrinkage And Selection Operator (LASSO) (Herawati et al., 2018) and (Enwere et al., 2023).

Researchers use the LASSO method which is a technique for selecting variables in data with large dimensions and can reduce the regression coefficient to exactly zero. The difference between LASSO regression and ridge regression is in terms of estimating regression coefficients where the ridge regression coefficient can only be reduced to close to zero, while the LASSO regression coefficient allows it to be reduced to exactly zero (Li et al., 2019). The advantage of LASSO regression is that it can be used to select independent variables in the model, so that only influential variables are included in the model and makes it easier to interpret the regression model (Rahmawati & Suratman, 2022). The LASSO method is also increasingly popular because of its fast calculations for solving convexity optimization problems (Santi et al, 2019). To make precise calculations in the LASSO method better, use the Least Angle Regression (LAR) algorithm, which is an algorithm that can be converted into a computational algorithm in the LASSO method. This research aims to apply the LASSO, the dominant factors that influence the study period and waiting time for undergraduate mathematics study programs at FST UIN Sumatera Utara Medan until getting their first job in less than 9 months can provide accurate and optimal results and contribute to the mathematics study program for improvement in the future of accreditation.

2. Methods

2.1. Location, Time and Type of Research

This research was carried out at the department of mathematics, faculty of science and technology UIN Sumatera Utara Medan which is located at Deli Serdang Regency, North Sumatra 20353 Indonesia. The duration of this research will be carried out from December 2023 until completion. Quantitative descriptive research was used in this research, where the research was carried out to obtain a systematic description of the circumstances under study. Secondary data obtained from Googleform which was created by the Quality Control Group in department of mathematics Quality Control Group for the mathematics study program, where the data is tested for validation and reliability to ensure the data is more valid, after which the valid data will be tested again using the LASSO method with totaled 88 respondents and this data became a reference in this research.

2.2. Research Variable

The dependent variable used is study time which is symbolized (Y), namely time survive from graduation to getting a job first (in months). Meanwhile, the independent variable is symbolized (X) which contains six variables. can be seen from the table1.

Table 1. Research Variables

Variable	Description
Y	Study Time
X_1	Field of Research Interest
X_2	Final Assignment Position
X_3	Working Status
X_4	Grade Point Average (GPA)
X_5	Organizational participation
X_6	Use of gadgets
X_7	Married Status

2.3. Research procedure

The research procedure steps carried out are:
1. Start: Literature study of the research being researched
2. Identify the problem and formulate the problem
3. Analyze the problem with LASSO:

a. Collecting secondary data on active students and undergraduate graduates of mathematics study programs from google forms and filling out questionnaires..
b. Estimate the model with existing variables using the Ordinary Least Square (OLS) then carry out a significance test.
c. Test the independent variable by looking for the VIF value to find out whether there is a multicollinearity problem. If the data multicollinearity conditions are not met, the data will be tested again using the classic assumption test using the Ordinary Least Square (OLS) method in step (b).
d. Standardize the independent variable data so that it has a distribution of zero and one.
e. Test variables using LASSO analysis using the LARS algorithm.
f. Determining the best model using cross validation using the LARS algorithm.
g. Interpreting the LASSO regression model

4. Draw conclusions
5. Done

3. Result and Discussion

3.1. Initial Data

Initial research data used was data from questionnaires and respondents given to 88 students from the 2017-2020 class. This data is also synchronized with bank data in the faculty quality assurance unit as well as with the quality control group in the study program. The values listed are the result of answers to students' complaints about the questions given in the questionnaire. For more details, the initial research data can be seen in table 2 below:

Table 2. Initial Data

Data	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7
1	3.67	1	4	0	3.84	0	7	0
2	4.8	1	4	0	3.28	0	8	0
3	5.8	1	3	2	3.5	0	10	0
4	3.67	2	4	0	3.89	1	5	0
5	5	2	4	0	3.58	0	4	0
6	3.67	2	4	0	3.73	1	12	0
7	6	2	4	0	3.65	0	5	0
8	4.75	2	4	0	3.52	0	7	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
85	4.1	1	4	0	3.57	5	16	0
86	5	2	3	0	3.67	0	10	0
87	5.5	2	4	0	3.56	0	3	0
88	7	2	3	0	3.41	0	20	0

3.2. Descriptive Statistical Analysis

Descriptive analysis aims to see the characteristics and description of the number of active students who still have problems with their college studies and also collect data on the number of alumni fron department of mathematics starting from the 2017-2020 class of students where the number of respondents who filled out the questionnaire was around 88 students. Statistical test results were completed using the SPSS program.

Table 3. Statistical Analysis Data

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Y	88	3.67	7.00	5.1109	0.8933
X_1	88	1	2	1.5	0.50287
X_2	88	1	4	3.5909	0.83922
X_3	88	0	7	0.9660	1.76295
X_4	88	2.85	3.93	3.5725	0.20783
X_5	88	0	5	1	1.10381
X_6	88	1	20	6.7841	4.04699
X_7	88	0	4.25	0.1051	0.58810

Table 2 above shows the number of observations (N) of 88 observations. The minimum value for the independent variables X_3, X_5 and X_7 is the smallest minimum value among all variables, namely 0 and the highest minimum value is 2.85 for the independent variable The smallest maximum value among all variables is variable X_1 of 2 and the highest maximum value is 20 for the independent variable X_6. The average study period is 5.1109 with a standard deviation of 0.8933. The average for the independent variable X_6 is 6.7841 with a standard deviation of 4.04699 and is the variable that has the highest average and standard deviation. The average of the independent variable X_2 is 3.5909 with a standard deviation of 0.83922 which is the second variable that has a high average.

3.3. Multicollinearity Test

Multicollinearity test is used to determine whether there is a multicollinearity problem or not by looking for the Variant Inflation Factor (VIF) value. This test is carried out with the equation:

$$VIF_k = \left(1 - R_k^2\right)^{-1} \tag{1}$$

where R_k^2 is the coefficient of determination obtained from the predicator variable which is regressed on other predicator variables. The results of multicollinearity test can be seen in table 4.

Table 4. Multicollinearity Test Result

Variable	Description
X_1	2.0342
X_2	10.5032
X_3	5.1543

X_4	19.8021
X_5	2.1324
X_6	3.5546
X_7	1.6590

Based on table 4, based on the results of the multicollinearity test by looking at the VIF value for each independent variable, there are two variables were obtained that had VIF values > 10, namely variables X_4 and X_2 and other variables had VIF values < 10, namely variables variable X_1, X_3, X_5, X_6, and X_7. The results of this VIF test indicate the occurrence of multicollinearity in the model, which means there is a linear relationship between independent variables, as seen from variables X_4 and X_2 which have serious multicollinearity problems with high VIF values.

3.4. LASSO Process

Based on the VIF test and correlation test, it is proven that the data used in this research contains multicollinearity problems so that this problem can be solved using the Least Absolute Shrinkage and Selection Operator (LASSO) method. Where the work of the LASSO method uses equation (2)-(3) and assisted computationally using Rstudio software because the amount of data is too large.

$$Y^{**} = X^{**}\beta + \varepsilon^{**} \tag{2}$$

From the equation (2) above will be reduced to a coefficient estimate using the LARS algorithm and assisted by R studio software. So equation (2) becomes (Sari et al., 2022),

$$JKG = \sum_{i=1}^{n}\left(Y_i^* - \beta_0 - \sum_{j=1}^{k}\beta_j X_{ij}^*\right) \tag{3}$$

Next, the LASSO method is calculated using a numerical approach using the LARS algorithm. Before entering the LASSO method, the data must be normalized by converting the data into a standard score. In table 5, presented a table of candidate LASSO Regression coefficients at each stage of the LARS algorithm.

Table 5. Variable Coefficients Using LARS Algorithm

Stage	Independent Variables Included in The Model					
	X_1	X_2	X_3	X_4	X_5	X_6
1	0	0	0	0	0	0
2	0	0	0	-0.01032345	0	0
3	0	0	0.04349411	-0.05381759	0	0
4	0	-0.1097083	0.17022566	-0.16771097	0	0
5	0	-0.1634291	0.26511857	-0.28194397	-0.1386637	0
6	0	-0.1780510	0.28799305	-0.30184880	-0.1713286	0.03137296
7	0.01170891	-0.1842067	0.29742426	-0.31017141	-0.1806146	0.04416468
R-squared: 0.351						

Based on table 3, to obtain prospective LASSO coefficient values, it is carried out in 6 stages, where in the first stage all coefficient variables are initially set to zero. Variable X_4 is the first variable entered into the model. The coefficient X_3 is the highest coefficient among the other variables. This proves that among all the variables X_3 is the variable that has the most influence on the dependent variable. Until the stage 6, all independent variable coefficients have been obtained. From the stage starting from point 0 to stage 6 the LASSO coefficient estimator will change when variable selection at each stage is carried out. Furthermore, the value of R-squared (R^2) = 0.851 is obtained, this indicates that 85.1% of the factors that influence the dependent variable can be explained by the independent variables, and the rest is explained by other variables or other factors outside the model.

Selection of the best model in the LASSO method is done by looking for the minimum cross validation value. Based on the LASSO coefficient estimator variable selection stage obtained using the LARS algorithm, 6 stages were obtained with candidate coefficient values for each variable. After all independent variables have obtained candidate coefficient values, the next step is to determine the best model using cross-validation (cross-validation) with the help of the LARS algorithm. The selection of the best LASSO model is determined by looking at the minimum s value. The results of cross validation can be seen in the figure below.

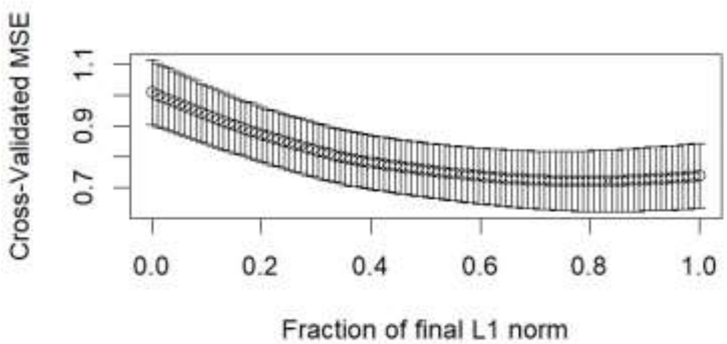

Figure 1. Cross Validation Results with Fraction Mode

Based on figure 1, it can be seen that the minimum value of s is located in the interval $0.7 < s < 0.8$. Minimum cross validation value can be different every time the function is called. The minimum value of s explains the stopping of the iteration stage to determine the coefficients of the best model for the LASSO method. The s-value at each stage is shown by the formula:

$$s = \frac{\sum \left| \hat{\beta}_j^{LASSO} \right|}{\sum \left| \hat{\beta}_j^{OLS} \right|} \tag{4}$$

Table 6. s-value of Each Stage Using the LASSO Method

Stage	$\sum\left\|\hat{\beta}_j^{LASSO}\right\|$	$s=\dfrac{\sum\left\|\hat{\beta}_j^{LASSO}\right\|}{\sum\left\|\hat{\beta}_j^{OLS}\right\|}$
1	0.010323	0.010039
2	0.097312	0.094634
3	0.447645	0.435329
4	0.849155	0.825793
5	0.970594	0.943891
6	1.028291	1

Based on calculations that have been carried out in cross validation criteria using fraction mode and with the help of R-studio software, the LASSO method produces the best model is:

$$\hat{Y}=10.10955-0.1634291X_2+0.26511857X_2-0.28194397X_4-0.1386637X_5$$

The results of the dominant variable values that greatly influence the study period and undergraduate waiting time can be seen in table 7.

Table 7. Results of LASSO Calculations For Dominant Influencing Variables

Variable	LASSO
Intercept	10.10955
X_1	0
X_2	-0.1634291
X_3	0.26511857
X_4	-0.28194397
X_5	-0.1386637
X_6	0
X_7	0

Based on the table above, it can be seen that there are 4 variables that greatly influence the study period and undergraduate waiting time. Working status (X_3) is the dominant factor that influences the most along with other variables, namely field of research interest (X_1), final assignment position (X_2), grade point average (X_4), organizational participation (X_5), use of gadgets (X_6) and married status (X_7).

After carrying out the analysis using the LASSO method and having obtained the best LASSO model, the next step is to check whether the multicollinearity problem has been resolved or not so that a multicollinearity test will be carried out again on the variables included in the model. Based on table 4, the VIF value after analysis carried out using LASSO regression decreased. This proves that LASSO regression can overcome multicollinearity problems as well as being able to act as a selection variable. So the resulting model is simpler and free from multicollinearity problems.

4. Conclusion

LASSO method used in this research is proven to be able to overcome the problem of multicollinearity even though the coefficient variance of the resulting model does not really shrink to zero. LASSO method can successfully carry out variable selection because it can shrink several variables to exactly zero. Where the resulting model will be simpler, so that model interpretation will be easier because the number of independent variables used is reduced. LASSO method regression model produced from data determining the dominant factors that influence the study period and waiting time for undergraduate mathematics study programs until getting their first job is less than 9 months with LASSO analysis using the LARS algorithm is obtained: it produces 4 variables that have a significant influence, namely final assignment position, working status, GPA and organizational participation with a classification accuracy of 85.1% such as working status, grade point average (GPA), organizational participation and final assignment position. The results of this research hope to provide benchmarks for assessment and improvement for students, study programs for field assessors and accreditation of study programs in the future.

5. Acknowledgment

This research was supported by funding by the Ministry of Religion of the Republic of Indonesia through BOPTN 2023 research in in the basic research cluster of the study program.

6. References

Altelbany, S. (2021). Evaluation of Ridge, Elastic Net and Lasso Regression Methods in Precedence of Multicollinearity Problem: A Simulation Study. *Journal of Applied Economics and Business Studies*, *5*(1), 131–142. https://doi.org/10.34260/jaebs.517.

Amalia, R., & Wibowo, A. (2020). Prediction of the Waiting Time Period for Getting a Job Using the Naive Bayes Algorithm. *International Research Journal of Advanced Engineering and Science*, *5*(2), 225–229.

Ariani, Y., Masrizal, M., & Muti'ah, R. (2024). Prediction of Student Graduation Rates using the Artificial Neural Network Backpropagation Method. *Sinkron*, *8*(2), 1169–1177. https://doi.org/10.33395/sinkron.v8i2.13659

Azzahra, F. N., & Zahra, N. (2023). *Establishing Foreign Higher Education Institutions in Indonesia (Policy Brief No. 18)*. *18*, 1–16. https://repository.cips-indonesia.org/media/publications/559380-establishing-foreign-higher-education-in-1bb14c5e.pdf.

Cahya, S. D., Sartono, B., Indahwati, I., & Purnaningrum, E. (2022). Performance of LAD-LASSO and WLAD-LASSO on High Dimensional Regression in Handling Data Containing Outliers. *JTAM (Jurnal Teori Dan Aplikasi Matematika)*, *6*(4), 844. https://doi.org/10.31764/jtam.v6i4.8968.

Digdowiseiso, K. (2020). The development of higher education in Indonesia. *International Journal of Scientific and Technology Research*, *9*(2), 1381–1385.

Dito, G. A., Safitri, A., Afendi, F. M., Anisa, R., Salim, A., & Sartono, B. (2019). Graphical user interface (GUI) for the least absolute shrinkage and selection operator (LASSO) regression. *IOP Conference Series: Earth and Environmental Science*, *299*(1). https://doi.org/10.1088/1755-1315/299/1/012031.

Enwere, K., Nduka, E., & Ogoke, U. (2023). Comparative Analysis of Ridge, Bridge and Lasso Regression Models In the Presence of Multicollinearity. *IPS Intelligentsia Multidisciplinary Journal*, *3*(1), 1–8. https://doi.org/10.54117/iimj.v3i1.5.

Fadhil, I., & Sabic-El-Rayess, A. (2021). Providing Equity of Access to Higher Education in Indonesia: A Policy Evaluation. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, *3*(1), 57–75. https://doi.org/10.23917/ijolae.v3i1.10376.

Fitriani, S. A., Astuti, Y., & Wulandari, I. R. (2022). Least Absolute Shrinkage and Selection Operator (LASSO) and k-Nearest Neighbors (k-NN) Algorithm Analysis Based on Feature Selection for Diamond Price Prediction. *2021 International Seminar on Machine Learning, Optimization, and Data Science, ISMODE 2021*, *January*, 135–139. https://doi.org/10.1109/ISMODE53584.2022.9742936.

Herawati, N., Nisa, K., & Setiawan, E. (2018). Regularized Multiple Regression Methods to Deal with Severe Multicollinearity. *International Journal of Statistics and Applications*, *8*(4), 167–172. https://doi.org/10.5923/j.statistics.20180804.02.

K.P., E., & U.P., O. (2023). A Comparative Approach on Bridge and Elastic Net Regressions. *African Journal of Mathematics and Statistics Studies*, *6*(1), 103–115. https://doi.org/10.52589/ajmss-lbjo9ucu.

Li, C., Chen, L., Feng, J., Wu, D., Wang, Z., Liu, J., & Xu, W. (2019). Prediction of length of stay on the intensive care unit based on least absolute shrinkage and selection operator. *IEEE Access*, *7*, 110710–110721. https://doi.org/10.1109/ACCESS.2019.2934166.

Marpi, Y. (2023). Harmonizing the Concept of Omnibus Law As a Regulatory Solution for Education Transformation. *Ekspose: Jurnal Penelitian Hukum Dan Pendidikan*, *22*(1), 9–18. https://doi.org/10.30863/ekspose.v22i1.1388.

Marwan, M. (2022). Process governance and administration of in-service education in the national education system. *JPPI (Jurnal Penelitian Pendidikan Indonesia)*, *8*(1), 125. https://doi.org/10.29210/020221470.

Miranda, A., & Lhaksamana, K. M. (2022). Classification Analysis of Waiting Period for Telkom University Alumni to Get Jobs Using Decision Tree and Support Vector Machine. *Building of Informatics, Technology and Science (BITS)*, *4*(2), 433–440. https://doi.org/10.47065/bits.v4i2.1963.

Nur, A. R., Jaya, A. K., & Siswanto, S. (2023). Comparative Analysis of Ridge, LASSO, and Elastic Net Regularization Approaches in Handling Multicollinearity for Infant Mortality Data in South Sulawesi. *Jurnal Matematika, Statistika Dan Komputasi*, *20*(2), 311–319. https://doi.org/10.20956/j.v20i2.31632.

Nurwahida. (2022). Globalization and It ’ S Impact Globalization and It’S Impact on Higher Education in Indonesia. *El-Idarah*, 51–59.

Rahmawati, F., & Suratman, R. Y. (2022). Performa Regresi Ridge dan Regresi Lasso pada Data dengan Multikolinearitas. *Leibniz: Jurnal Matematika*, *2*(2), 1–10. https://doi.org/10.59632/leibniz.v2i2.176.

Sari, N. I., Cipta, H., & Fathoni, M. (2022). Determining Factors Identifying Poverty Rate Due To Covid-19 Pandemic in North Sumatera Using the Least Absolute Shrinkage and Selection Operator (Lasso) Method. *Jurnal Mantik*, *6*(1), 271–277.