



Early Detection of Mathematics Learning Difficulties Using a Deep Learning Neural Network and SMOTE

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Abstract. This study follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, a structured methodology that guides data mining projects through six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The dataset used in this research consists of academic variables (grades, remedial sessions, online activities) and psychological variables (motivation, anxiety, interest) collected from SMA Muhammadiyah 16 Jakarta. The workflow involves data preprocessing, data augmentation, class balancing using SMOTE, and training a neural network model with four hidden layers using ReLU and Softmax activation functions, focal loss, and class weight balancing. The model achieved an accuracy of 98%, along with an average recall and F1-score of 0.98, indicating excellent performance across all classes. Further analysis showed that semester exam scores, number of remedial sessions, motivation levels, and self-confidence were the most influential factors in distinguishing the categories “easy,” “moderate,” and “difficult.” These findings demonstrate that the model effectively identifies patterns of learning difficulties and can support teachers in providing targeted interventions. Thus, the research objective of developing a highly accurate predictive model has been successfully achieved. Moreover, this study makes a significant contribution to the development of AI-based decision support systems in education and introduces a prototype of a web-based early warning system for schools.

Keywords: Mathematics Learning Difficulty Prediction, Deep Learning Neural Network, CRISP-DM, Educational Early Warning System, Educational Decision Support System.

1 Introduction

Mathematics learning difficulties among senior high school students in Indonesia represent a significant challenge affecting academic achievement. These difficulties are not only associated with cognitive factors such as the complexity of the material, lack of mastery of fundamental concepts, and limited teaching strategies. However, they are

also influenced by affective factors such as mathematics anxiety, low learning motivation, and insufficient support from the school or family environment [1, 2]. Several studies indicate that mathematics anxiety can disrupt concentration, reduce self-confidence, and lower students' academic performance [3, 4]. Factors such as self-efficacy, a positive classroom climate, and social support from parents or peers play an important role in mitigating the negative effects of anxiety [5]. Moreover, good time management skills and emotional support have been proven to help students maintain an academic performance even under learning pressure [6].

Self-regulated learning is considered a key element in reducing mathematics anxiety, as students with goal-setting, strategic planning, and self-evaluation skills tend to be more adaptive when facing academic challenges [7]. Furthermore, a positive attitude toward mathematics, appropriate learning styles, and effective teaching strategies have directly or indirectly influenced students' mathematics performance [8-9]. However, the identification of learning difficulties in schools still relies heavily on conventional methods such as teacher observations and written tests, which are often subjective, time-consuming, and fail to capture the root causes comprehensively [10]. This creates a risk of delayed interventions that may exacerbate students' psychological stress. Therefore, a holistic assessment system is needed, integrating academic and psychological data objectively and can be applied on a large scale, enabling more timely and targeted early detection of learning difficulties.

Previous studies have utilized Artificial Neural Networks (ANNs) in education to predict academic achievement. Detecting dropout risks, and identifying learning difficulties [11-14]. The results demonstrate that ANNs can capture complex nonlinear patterns from academic and psychological data. Nevertheless, most studies remain limited to academic data alone or rely on simple balancing methods, resulting in low predictive accuracy for minority classes. This research addresses that gap by integrating both academic and psychological factors comprehensively, while simultaneously applying advanced balancing techniques (SMOTE, data augmentation, focal loss) to ensure consistent model performance across all classes [15, 16].

2 Literature Review

2.1 Mathematics Learning Difficulties

Mathematics learning difficulties at the senior high school level are a critical issue as they directly affect students' academic achievement. The contributing factors may include limited mastery of fundamental concepts, ineffective learning strategies, and affective barriers such as mathematics anxiety [17]. Mathematics anxiety has been shown to reduce concentration and self-confidence, whereas social support, high self-efficacy, and a positive classroom climate can mitigate its negative impact [18]. In addition, self-regulated learning plays an important role, as students who can set goals, apply strategies, and conduct self-evaluations tend to be more adaptive in facing academic challenges [19]. The relevance to this study lies in the fact that the academic and psychological factors identified in previous literature serve as the basis for selecting input variables in the predictive model of learning difficulties.

2.2 Factors Influencing Learning Difficulties

The causes of learning difficulties can be classified into three main groups:

- (i) Academic Factors – including exam scores, number of remedial sessions, and academic achievement in related subjects.
- (ii) Affective Factors – including motivation, interest, self-efficacy, and levels of anxiety.
- (iii) Behavioral & Environmental Factors – including independent study habits, discipline in submitting assignments, use of online learning media, and social support.

The factors influencing mathematics learning difficulties, categorized into academic, affective, and behavioral-environmental aspects, along with their corresponding variables and impacts, are summarized in Table 1.

Table 1. Factors influencing mathematics learning difficulties.

Factor Category	Example Variables	References	Impact on Learning Difficulties
Academic	Exam scores, number of remedials	[15,17]	Low academic achievement increases the risk of learning difficulties
Affective	Motivation, mathematics anxiety, and self-efficacy	[16,18]	Influences persistence, self-confidence, and learning interest
Behavioral & Environmental	Task discipline, independent study habits, and social support	[19]	Positive support enhances independence and learning effectiveness

Relevance to this study: these factor categories are used as indicators in the dataset, allowing the ANN model to analyze learning difficulties more comprehensively compared to traditional approaches that rely solely on academic scores.

2.3 Artificial Neural Network (ANN) dalam Bidang Pendidikan

Artificial Neural Networks (ANNs) are a machine learning method that mimics the functioning of biological neural networks to process information. ANNs are effective in modeling complex nonlinear relationships, making them reliable for classification, prediction, and pattern recognition. In the field of education, ANNs have been applied to predict academic performance, detect dropout risks, and identify learning difficulties [20-21].

Limitations of previous studies: Most research has primarily focused on academic data, with only a few integrating psychological factors. Moreover, the use of simple balancing methods has often resulted in poor performance for minority classes.

Relevance to this study: This research extends the ANN approach by incorporating academic, psychological, and behavioral data, while also applying advanced balancing techniques to improve predictive performance.

2.4 Handling Data Imbalance

Class imbalance is a common challenge in predicting learning difficulties, where the distribution of students across categories is uneven. Several techniques are employed to address this issue, including:

- (i) SMOTE (Synthetic Minority Oversampling Technique): generates synthetic samples for the minority class [15].
- (ii) Data Augmentation: increases the variation of training.
- (iii) Focal Loss: assigns greater weight to the minority class.
- (iv) Relevance to this study: The combination of SMOTE, data augmentation, and focal loss is applied to enable the ANN model to produce balanced predictions across the “easy,” “moderate,” and “difficult” categories.

2.5 CRISP-DM Methodology

CRISP-DM (Cross Industry Standard Process for Data Mining) is a data analysis framework consisting of six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

Relevance to this study: CRISP-DM ensures that this research follows a systematic process, starting from the identification of educational problems to the development of a prototype early warning system ready for use in schools.

2.6 Previous Studies

Several studies have utilized Artificial Neural Networks (ANNs) to predict learning difficulties and academic achievement. These prior works provide important benchmarks and highlight gaps that this study aims to address. A summary of representative studies, including the methods used, variables considered, and key findings, is presented in Table 2.

Table 2. Previous studies on ANN applications in Education

Author & Year	Method Used	Variables Used	Key Findings
Sari et al. (2021)	ANN	Exam scores, attendance, motivation	Prediction accuracy for mathematics achievement reached 91%
Al-Saqqa et al. (2019)	ANN + Psychological Data	Academic & psychological data	Higher accuracy compared to using academic data only
Romero & Ventura (2020)	ANN + Data Mining	Academic scores, e-learning interactions	High accuracy in detecting dropout risks

Gap Analysis:

- (i) Previous studies successfully utilized ANNs, but most were limited to academic data or incorporated psychological factors only to a limited extent [20-22].
- (ii) Class imbalance issues were often overlooked, resulting in uneven predictive performance across student categories.
- (iii) Some studies did not integrate model outputs into a practical web-based system that teachers could directly use. Variable

Contributions of this study:

- (i) Integrates academic, psychological, and behavioural data to generate more comprehensive predictions.
- (ii) Addresses class imbalance through the combination of SMOTE, data augmentation, and focal loss.
- (iii) Implements the CRISP-DM framework so that the model is not only validated academically but also realized in the form of a web-based early warning system prototype applicable for teachers and schools.

3 Research Method

This study employs a machine learning approach based on Artificial Neural Networks (ANN) to predict students' levels of mathematics learning difficulties. The research stages follow the CRISP-DM framework, which consists of six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

3.1 Conceptual Framework

The conceptual methodology is illustrated in Fig. 1. The diagram presents the research flow, beginning with input data in the form of students' academic and psychological factors, followed by data preprocessing, which includes normalization, encoding, augmentation, and balancing using SMOTE. The processed data is then used to train the ANN model, which is subsequently evaluated to generate the output in the form of categorized levels of mathematics learning difficulties. This conceptual flow also maps onto the CRISP-DM phases, starting from data understanding and data preparation, progressing to modeling and evaluation, and ultimately producing outputs that can be implemented in the deployment phase.

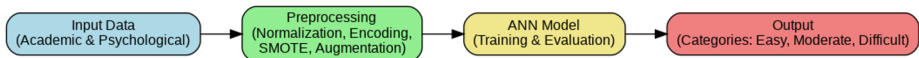


Fig. 1. Conceptual method.

3.2 Data Set

The dataset was obtained from questionnaires filled out by students of SMA Muhammadiyah 16 Jakarta, with a total of 163 entries. The output variable of this study is the

level of mathematics learning difficulty, divided into three categories: difficult, moderate, and easy, based on the average score of daily tests, semester exams, and assignments. The categorization criteria are presented in Table 3.

Table 3. Output variable.

Class	Score Range	Description
Difficult	< 60	Students experience high difficulty in understanding mathematics lessons.
Moderate	60 – 79	Students are at a moderate level of understanding of mathematics.
Easy	≥ 80	Students do not experience significant difficulty in learning mathematics.

The input variables comprise 16 indicators that cover both a academic and psychological factors of students. Academic factors include age, daily test scores, semester exam scores, assignment scores, number of remedials, and the average score of other subjects. Non-academic factors include motivation, anxiety, self-confidence, interest in learning, discipline in submitting assignments, and online learning activities. Table 4. summarizes the complete list of input variables used in this study.

Table 4. Input variable.

No	Variable
1	Age
2	Latest Mathematics Daily Test Score
3	Mathematics Semester Exam Score
4	Mathematics Assignment Score
5	Number of Mathematics Remedials Taken
6	Average Score of Other Subjects
7	I am motivated to learn mathematics
8	I feel anxious when solving mathematics problems
9	I have a high interest in mathematics
10	I am confident in solving mathematics problems
11	My parents have high expectations for my mathematics score
12	Hours per day spent learning mathematics at home
13	Number of logins to the online learning platform this week
14	Minutes per day spent accessing online mathematics material
15	The number of mathematics assignments submitted on time this week
16	I actively participate in mathematics discussions

3.3 Preprocessing and Balancing

The preprocessing stage was carried out to ensure that the data could be optimally used in the model training process. This process included class label encoding using Label

Encoder and numerical feature normalization with StandardScaler. Synthetic data augmentation was then applied to increase sample variation, for example, by adding random noise to numerical data.

$$x' = x + \epsilon, \epsilon \sim N(0, \sigma^2) \tag{1}$$

Class balancing was performed using the Synthetic Minority Oversampling Technique (SMOTE), which generates new samples through interpolation between a minority sample x_i and one of its nearest neighbours x_{nn} :

$$x_{new} = x_i + \delta \cdot (x_{nn} - x_i), \delta \in [0,1] \tag{2}$$

The output variable was then converted into one-hot encoding. The dataset was divided into three subsets: 64% for training, 16% for validation, and 20% for testing, using stratification to maintain class proportions. In addition, class weights were calculated to reduce model bias toward the majority class.

3.4 Detailed Research Method

The technical research flow is illustrated in Fig. 2. The diagram explains that the collected dataset is first processed through the preprocessing and augmentation stages. The processed data is then used to train the ANN model, including hyperparameter tuning to improve model performance. Subsequently, 30% of the data is allocated as a test set to evaluate the model. The prediction results are analyzed using accuracy, precision, recall, and F1-score metrics and are further visualized in the form of accuracy, loss, precision, recall, and F1-score graphs per epoch.

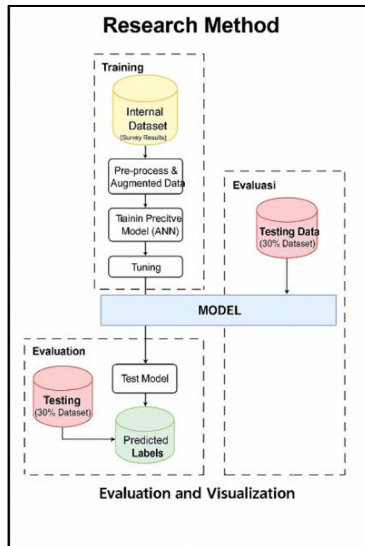


Fig. 2. Research method.

3.5 Model Architecture

The classification model was built using TensorFlow/Keras with a multi-layer perceptron architecture. The network consists of an input layer with 16 neurons corresponding to the 16 features in Table 4 (X1-X16), four hidden layers with 256, 128, 64, and 32 neurons, respectively, each equipped with Batch Normalization and Dropout for regularization, and an output layer with three neurons using the Softmax activation function.

Each hidden layer applies the ReLU activation function, formulated as a:

$$a_j = f(z_j) = \max(0, z_j), \quad z_j = \sum_{i=1}^n w_j x_i + b_j \tag{3}$$

While the output layer applies the Softmax function to produce class probabilities:

$$y_k = \frac{e^{z_k}}{\sum_j e^{z_j}}, \quad k = 1, 2, 3 \tag{4}$$

Where $y_1, y_2,$ and y_3 represent the predicted probabilities for the categories difficult, moderate, and easy in mathematics learning, respectively.

To address class imbalance, the model used Focal Loss as the loss function, defined as:

$$FL(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t) \tag{5}$$

Where p_t is the predicted probability for the true class, α_t is the class weight, and γ is the focusing parameter. The optimization was performed using the Adam algorithm.

Fig. 3 illustrates the overall architecture of the Artificial Neural Network. The input nodes (X1-X16) represent the academic and psychological indicators listed in Table 4, while the output nodes (Y1, Y2, Y3) correspond to the predicted categories of students' mathematics learning difficulties.

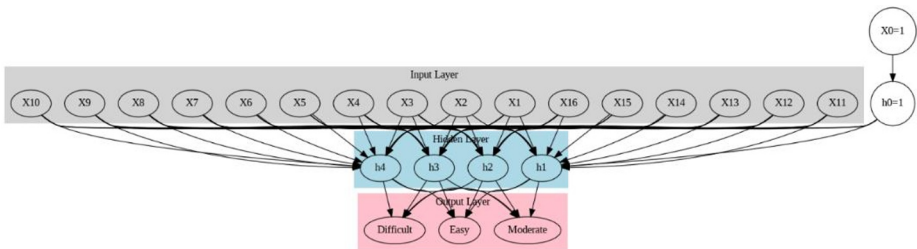


Fig. 3. Artificial neural network (ANN) architecture.

3.6 Training and Evaluation

The training process was conducted for up to 150 epochs with a batch size of eight samples per iteration. To prevent overfitting, callbacks were employed, including Early Stopping with a patience of ten epochs, ReduceLROnPlateau to adaptively reduce the learning rate, and Metrics History to monitor precision, recall, and F1-score on the validation set. Model evaluation was performed using 30% of the dataset as test data, with accuracy, precision, recall, and F1-score as the key performance metrics. The evaluation results were visualized in graphs to monitor the stability of the training process.

3.7 Mapping to CRISP-DM

The research stages were mapped onto the CRISP-DM framework as illustrated in Figure 4. The business understanding phase began with identifying the issue of low mathematics achievement and defining the research objective, namely, to design a predictive system for students' learning difficulties. The data understanding phase involved collecting and exploring student questionnaire data covering both academic and psychological factors.

Next, the data preparation phase consisted of data cleaning, augmentation, balancing with SMOTE, and splitting the dataset into training, validation, and testing sets. Once the data was ready, the modelling phase was carried out by building and tuning the Artificial Neural Network (ANN) model. At this stage, focal loss and class weights were applied to address class imbalance, accompanied by hyperparameter tuning to achieve optimal performance.

The subsequent evaluation phase measured accuracy, precision, recall, and F1-score on the test data, with results visualized in graphs to ensure training stability. Finally, the deployment phase aimed at integrating the model into a prototype web-based early warning system designed to assist teachers in identifying students at risk of experiencing learning difficulties.

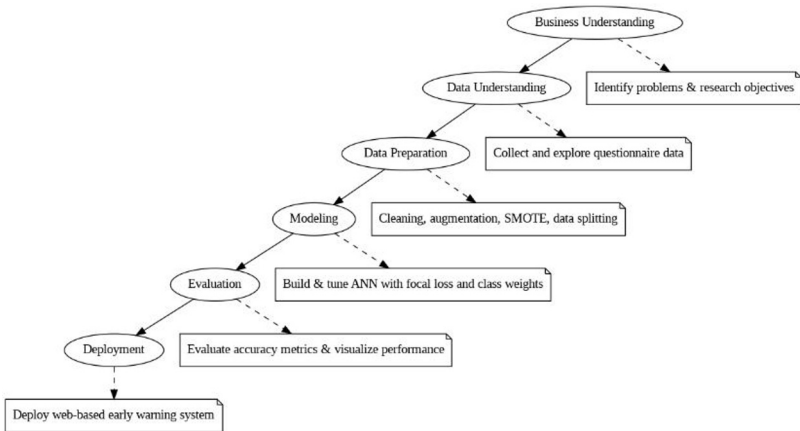


Fig. 4. Mapping research stages to CRISP-DM.

4 Results and Discussion

This study encompasses the stages of data exploration, development, and evaluation of an Artificial Neural Network (ANN) model, as well as predictive analysis for classifying students' levels of mathematics learning difficulties.

4.1 Data Set

The dataset was collected from questionnaires at SMA Muhammadiyah 16 Jakarta, consisting of 163 entries (113 original and 50 augmented). It includes both academic (age, daily and semester test scores, remedials) and psychological (motivation, anxiety, self-confidence, online learning activities) factors.

Class distribution (before balancing): Easy 33 (20.2%), Moderate 53 (32.5%), Difficult 27 (16.6%). After augmentation and balancing with SMOTE, each class contained 83 samples, ensuring equal representation.

To provide a clearer overview, Table 5 summarizes the descriptive statistics of key numerical variables from the original dataset ($n = 113$).

Table 5. Summary Statistics of Key Numerical Variables (Original Data, $n = 113$)

Variable	Mean	Min	Max
Age	16.2	15	18
Daily Test Score	68.4	40	95
Semester Exam Score	66.7	35	92
Number of Remedials	3.1	0	7

Missing data: Less than 2%, mainly in non-academic variables. Missing values were handled using mean imputation (numerical) and mode imputation (categorical). The dataset was then pre-processed through normalization, target label encoding (easy, moderate, difficult), augmentation, and class balancing using SMOTE before being split into training, validation, and testing sets.

4.2 Data Exploration

The data exploration results indicate that the majority of students fall into the moderate category (mathematics scores 60–79). Semester exam scores and the number of remedial sessions is strongly correlated with learning difficulty levels; students with low scores and a high number of remedials tend to fall into the difficult category. Affective variables, such as motivation and anxiety, showed high variability among respondents, providing enriched information for the model.

4.3 Modelling

The classification model was built using an Artificial Neural Network (ANN) with a multilayer perceptron architecture consisting of four hidden layers (256–128–64–32

neurons). Each layer employed ReLU activation, batch normalization to stabilize activation distributions, and dropout to prevent overfitting. The output layer used Softmax for multi-class classification. The optimizer applied was Adam, with focal loss as the loss function to give higher sensitivity to minority classes.

The model was trained for up to 150 epochs, exploring several hyperparameter combinations. Tuning results indicated that a learning rate of 0.001 and a batch size of 8 provided the best validation performance, which was therefore selected as the final configuration.

The data distribution before and after augmentation and SMOTE is shown in Table 6. After balancing, each class contained an equal number of samples (83 per class), eliminating bias toward the majority class (moderate).

Table 6. Class distribution before and after augmentation.

Category	Before Augmentation	After Augmentation	After SMOTE
Easy	33	43	83
Moderate	53	83	83
Difficult	27	37	83
Total	113	163	249

Training results showed a significant performance improvement. Without balancing the model accuracy reached only 68.33% due to predictions being dominated by the moderate class. After augmentation and SMOTE, along with the application of focal loss, accuracy increased to 98%. This improvement occurred because the more balanced data distribution allowed the model to better recognize patterns in the minority classes (easy and difficult).

The detailed comparison of model performance before and after balancing is presented in Table 7.

Table 7. Comparison of model accuracy.

Method	Accuracy
ANN (without SMOTE)	68.33%
ANN + Augmentation + SMOTE	98.00%

The training process visualization is presented in Fig. 5 and 6. The accuracy graph shows stable improvement for both training and validation data, reaching >0.9 , while the loss consistently decreased, converging around the 15th epoch.

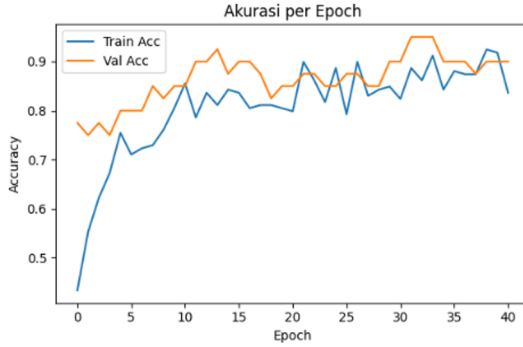


Fig. 5. Accuracy per epoch.



Fig. 6. Loss per epoch.

This visualization confirms that there is no indication of overfitting; the validation accuracy is consistently equal to or even higher than the training accuracy. Thus, the model can generalize well to new data patterns.

Furthermore, the comparison of per-class metrics shows that after balancing, the easy and difficult categories, which previously had F1-scores around 0.48–0.51, increased to 0.97–1.00. This indicates that the improvement in accuracy is not only aggregate but also evident for each class.

4.4 Model Performance and Evaluation

The increase in accuracy can be empirically explained: augmentation and SMOTE created a balanced data distribution, preventing the model from being biased toward the moderate class. Focal loss assigned higher weights to errors in minority classes, enhancing prediction sensitivity.

To provide a more detailed perspective, Table 8 presents the precision, recall, and F1-score for each category before and after the application of balancing techniques.

Table 8. Per-Class metrics before and after balancing.

Category	Precision (without)	Recall (without)	F1 (with-out)	Precision (with)	Recall (with)	F1 (with)
Easy	0.55	0.48	0.51	1.00	1.00	1.00
Moderate	0.72	0.85	0.78	0.94	1.00	0.97
Difficult	0.59	0.41	0.48	1.00	0.94	0.97
Macro						
Avg	0.62	0.58	0.59	0.98	0.98	0.98

Overall, the model achieved a macro and weighted average accuracy of 98%. Validation graphs of precision, recall, and F1-score in Figures 5 and 6 demonstrate stable performance throughout training without any significant signs of overfitting.

The confusion matrix illustrating the model’s classification performance is presented in Fig. 7. Additionally, the validation graph of precision, recall, and F1-score per epoch is shown in Fig. 8.

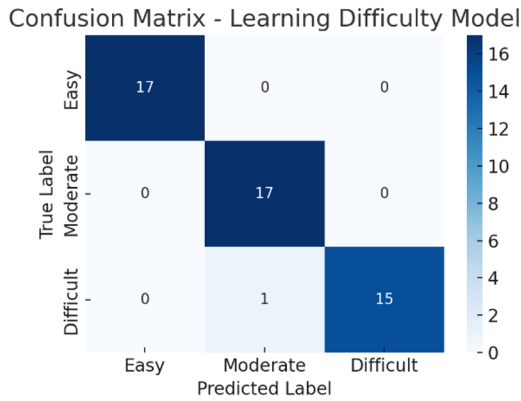


Fig. 7. Confusion matrix.

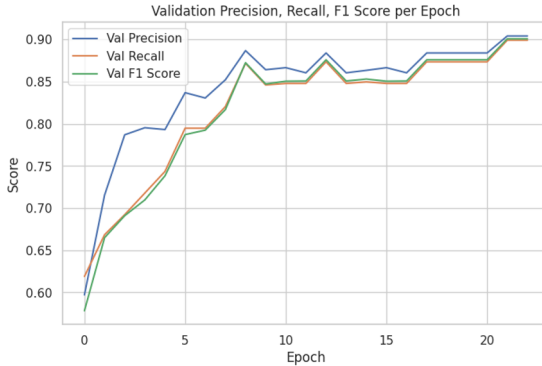


Fig. 8. Validation graph of precision, recall, and f1-score per epoch.

Based on Fig. 7, the model exhibits excellent performance in predicting students' mathematics learning difficulty levels using a multi-class classification approach. Overall accuracy reached 98%, with average precision, recall, and F1-score of 0.98, indicating that the model can consistently distinguish the three categories (easy, moderate, difficult).

In detail, the “easy” and “difficult” classes achieved perfect or near-perfect precision and recall (1.00 and 0.94–1.00), while the “moderate” class achieved precision of 0.94, recall of 1.00, and an F1-score of 0.97. The balanced class distribution (17 easy, 17 moderate, 16 difficult) ensured the model was free from bias.

Overall, the model proved effective in identifying levels of learning difficulty based on the available data. Despite the high performance, further testing with new data is necessary to ensure consistent performance under real-world conditions.

4.5 Comparative Analysis with Prior Work

Compared this study, which reported an accuracy of 91% using exam scores, attendance, and mathematics anxiety as variables, demonstrates a significant improvement of up to 98% due to the application of data balancing and focal loss [22]. Furthermore, these results align with the findings [21]. This emphasizes the importance of integrating academic and psychological data to enhance ANN accuracy. In addition, this study is consistent with [20], who used ANN to detect dropout risk based on academic and behavioral data; the key difference is that the present study extends the scope to detailed multi-class classification of learning difficulties.

4.6 Interpretation and Feature Importance

Feature importance analysis was conducted using Permutation Importance on the ANN model. The features with the highest contributions were semester mathematics exam scores (0.24), number of remedials (0.19), self-confidence (0.15), learning motivation (0.14), and timely submission of assignments (0.12).

These findings indicate that the model relies not only on academic performance but also incorporates psychological and behavioral factors.

4.7 Limitations

Despite the model's high performance, this study has several limitations. First, the sample size is relatively small, consisting of 163 entries, all from a single school (SMA Muhammadiyah 16 Jakarta), limiting the generalizability of the results to other student populations. Second, data were collected via self-report questionnaires, which may introduce respondent bias. Third, although feature importance analysis was applied, the ANN model remains a black-box system, limiting the interpretability of its internal mechanisms.

4.8 Research Implications

Theoretically, this study reinforces evidence that ANN can effectively predict learning difficulties by integrating academic and psychological data. Practically, the model has the potential to assist schools in early detection and targeted intervention, while reducing reliance on manual assessments prone to bias. Moreover, the model can be utilized by educational authorities to map students requiring special attention, provided that ethical, privacy, and transparency considerations are addressed to avoid stigmatization.

4.9 Strengths of the Study

In addition to its limitations, this study presents several significant strengths. First, the data used are authentic and directly collected from students through questionnaires encompassing academic, psychological, and behavioral aspects, providing a comprehensive picture of the factors influencing learning difficulties. Second, the preprocessing process was conducted systematically, including normalization, data augmentation, and SMOTE balancing, as well as class weight application, all of which help reduce bias toward the majority class. Third, the implemented ANN architecture is sufficiently deep, incorporating batch normalization, dropout, and focal loss, achieving high accuracy while maintaining training stability. Finally, the feature importance analysis demonstrates the relative contribution of both academic and non-academic factors, making the model not only accurate but also practically insightful for schools to perform early detection and intervention of learning difficulties.

5 Conclusion

This study developed a predictive model for mathematics learning difficulties based on Artificial Neural Networks (ANN) within the CRISP-DM framework, following systematic stages from preprocessing, data augmentation, and class balancing with SMOTE, to training a multi-layer architecture model with focal loss and dropout. The evaluation results showed that the model achieved an accuracy, precision, recall, and F1-score of 0.98, outperforming several previous studies that reported accuracies in the range of 85–91% [21-22]. The main contribution of this research lies in the combination of methods (ANN, SMOTE, augmentation, and focal loss), which are rarely applied

together in the educational context, as well as the explicit mapping to the CRISP-DM phases that ensures a structured workflow and facilitates replication. The feature importance analysis revealed that semester exam scores, number of remedial sessions, motivation, and self-confidence were dominant predictors, underscoring the importance of integrating both academic and psychological data in early detection systems. Practically, this model can be implemented as a web-based early warning system to assist teachers and educational authorities in identifying at-risk students, designing targeted interventions, and reducing reliance on manual assessments that are often subjective. Despite the promising results, this study still has limitations, particularly regarding the relatively small sample size and the limited scope of schools involved. Therefore, further testing with larger and more diverse datasets is required to ensure the generalizability of the findings.

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References

1. Salma, E., El-Mutaz, A.M., Ghariani, F.A.: Mathematics Anxiety Among High School Students: Causes, Consequences, and Coping Mechanisms. *International Journal of Mathematics and Science Education*, **1**(1), 55-61 (2024)
2. Alhadoor, Z.A.N., Aldbyani, A., Alshammari, K.K.: A meta-analysis on the effectiveness of strategies and programs used to address the mathematics learning difficulties. *Eurasia Journal of Mathematics, Science and Technology Education*. **19**, em2337 (2023). <https://doi.org/10.29333/ejmste/13607>.
3. Magnate, F., June Rey, S.: Mathematics Performance as Influenced by Mathematics Anxiety and Self-Efficacy: A Modeling Study. *Journal for Educators, Teachers and Trainers*. **14**(5), (2023). <https://doi.org/10.47750/jett.2023.14.05.028>.
4. Fadli, M.R.: The Effect of Mathematics Anxiety on Students' Learning Achievement: An Ex Post Facto Study. In *Proceeding of the International Conference on Mathematical Sciences, Natural Sciences, and Computing*, vol. 1, pp. 01-14 2024
5. Su, Z., Woodman, R., Smyth, J., Elliott, M.: The relationship between aggressive driving and driver performance: A systematic review with meta-analysis. *Accident Analysis & Prevention*. **183**(2), 106972 (2023). <https://doi.org/10.1016/j.aap.2023.106972>.
6. Silitonga, J., Nabila, T., Sihombing, D., Luthfi, M., Rahmayanti, N., Arnita, V.: Analysis of the Effect of Emotional Intelligence, Time Management, and Academic Stress on the Learning Behavior of Accounting Students. *Journal of Advances in Accounting, Economics, and Management*. **2**(3), 14 (2025). <https://doi.org/10.47134/aaem.v2i3.573>.
7. Andayani, S., Ekwan, D.: Exploring the Impact of Self-Regulated Learning on Reducing Students' Mathematics Anxiety. *Hipotenusa: Journal of Mathematical Society*, **6**(2), 199-215 (2024)

8. Nurhayati, I., Akbar, M.F.R., Putra, H.D., Fitriani, N.: Does Math Anxiety Influence Students' Self-Regulated Learning? A Predictive Relationship Study at Two Vocational Schools at Bandung Regency. (JIML) JOURNAL OF INNOVATIVE MATHEMATICS LEARNING. **7**(3), 330–336 (2024). <https://doi.org/10.22460/jiml.v7i3.21547>.
9. Ahmad, A., Mohamed, Z., Setyaningsih, E., Sugihandardji, C.: ONLINE LEARNING INTERACTION OF MATHEMATICS TEACHER IN JUNIOR HIGH SCHOOL: A SURVEY IN THE COVID-19 PANDEMIC. *Infinity Journal*. **10**(2), 271 (2021). <https://doi.org/10.22460/infinity.v10i2.p271-284>.
10. Dawkins, P.C., Karunakaran, S.S.: Why research on proof-oriented mathematical behavior should attend to the role of particular mathematical content. *The Journal of Mathematical Behavior*, **44**(1), 65–75 (2016)
11. Van Heerden, B., Aldrich, C., Du Plessis, A.: Predicting student performance using artificial neural network analysis. *Medical Education*. **42**(5), 516–517 (2008). <https://doi.org/10.1111/j.1365-2923.2008.03052.x>.
12. Chen, M., Liu, Z.: Predicting performance of students by optimizing tree components of random forest using genetic algorithm. *Heliyon*. **10**(12), e32570 (2024). <https://doi.org/10.1016/j.heliyon.2024.e32570>.
13. Roda-Segarra, J., De-la-Peña, C., Mengual-Andrés, S.: Effectiveness of Artificial Intelligence Models for Predicting School Dropout: A Meta-Analysis. *Multidisciplinary Journal of Educational Research*. **14**(3), 1–24 (2024). <https://doi.org/10.17583/remie.13342>.
14. Alnasyan, B., Basher, M., Alassafi, M.: The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review. *Computers and Education: Artificial Intelligence*. **6**(1), 100231 (2024). <https://doi.org/10.1016/j.caeai.2024.100231>.
15. Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P.: SMOTE: Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*. **16**(1), 321–357 (2002). <https://doi.org/10.1613/jair.953>.
16. Wanti Siahaan, S.: Implementation of Artificial Neural Networks in Predicting Students' English Understanding Level Using the Backpropagation Method. *Journal of Computer Science, Information Technologi and Telecommunication Engineering*. **1**(2), (2020). <https://doi.org/10.30596/jcositte.v1i2.5072>.
17. Klorina, M.J., Juandi, D.: Kesulitan Belajar Matematika Siswa di Indonesia Ditinjau dari Self-Efficacy: Systematic Literature Review (SLR). *Symmetry: Pasundan Journal of Research in Mathematics Learning and Education*. **7**(2), 181–192 (2022). <https://doi.org/10.23969/symmetry.v7i2.6435>.
18. Quratul Ain, S.: Analysis of Students' Learning Difficulties in Learning Mathematics at Elementary Schools. *AL-ISHLAH: Jurnal Pendidikan*. **13**(2), 892–899 (2021). <https://doi.org/10.35445/alishlah.v13i2.745>.
19. Baldock, R., Maennel, H., Neyshabur, B.: Deep learning through the lens of example difficulty. *Advances in Neural Information Processing Systems*, **34**, 10876–10889 (2021)
20. Romero, C., Ventura, S.: Educational data mining and learning analytics: An updated survey. *WIREs Data Mining and Knowledge Discovery*. **10**(3), (2020). <https://doi.org/10.1002/widm.1355>.
21. Al-Saqqa, S., Awajan, A.: The Use of Word2vec Model in Sentiment Analysis. In: *Proceedings of the 2019 International Conference on Artificial Intelligence, Robotics and Control*. pp. 39–43. ACM, New York, NY, USA (2019)
22. Sari, D.P., Rahmat, T., Aprison, W., Fitri, H.: Pengaruh kecemasan matematika (math anxiety) terhadap hasil belajar siswa kelas VIII MTsN 6 Agam tahun pelajaran 2020/2021. *INNOVATIVE: Journal Of Social Science Research*, **3**(2), 2514–2526 (2023)

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