

Towards Explainable Multidimensional Digital Divide Classification in Online Learning Using Artificial Neural Networks and SHAP

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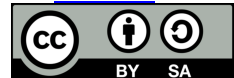
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ABSTRACT

The transformation of online learning increases access to education, but also increases the risk of digital divide influenced by various technological and educational factors. This study aims to develop a framework Towards Explainable Multidimensional Digital Divide Classification in Online Learning Using Artificial Neural Networks and SHAP to classify cluster-derived digital divide categories transparently. Data were obtained from 324 students through a questionnaire covering Primary Device, Internet Stability, Equity Score, and Accessibility Score. The target Digital Divide categories were analytically derived using K-Means clustering based on respondents' multidimensional characteristics and subsequently used as labels for supervised classification. The data were processed through one-hot encoding, Min-Max normalization, and splitting the training and test data before training the model. The performance of ANN was compared with Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM). The results showed that ANN achieved 90.77% accuracy, with competitive performance against the comparison models. Furthermore, SHapley Additive exPlanations (SHAP) was used to interpret the model's decisions at both global and local levels. The analysis shows that Primary Device is the most influential factor, followed by Accessibility Score, Equity Score, and Internet Stability. The main contribution of this research is the presentation of an Explainable AI framework that combines the predictive capabilities of ANN with the interpretability of SHAP to support a more transparent multidimensional digital divide classification and can serve as a basis for developing data-driven digital inclusion policies.

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1. INTRODUCTION

Digital Digital transformation has driven the widespread adoption of online learning in higher education. While it offers flexibility, access to learning resources, and efficiency in the learning process, its implementation has also created a digital divide, namely the gap in students' ability to access and utilize digital technology [1]. Various studies have shown that differences in device ownership, internet connection quality, and digital readiness lead to inequalities in student participation and learning experiences [2]. The impact of this gap not only affects access to learning but also academic engagement and overall educational success [3], [4], [5].

Research developments indicate that the digital divide is no longer understood solely as a first-level digital divide focused on device and internet access, but has evolved into a multidimensional phenomenon encompassing connectivity quality, equity, accessibility, institutional support, and student digital readiness [6], [7], [1], emphasize that digital

unpreparedness between students and institutions is a major cause of inequality in online learning. These findings are reinforced by [8], who used machine learning to analyze learning access from a social justice perspective, and [9], who demonstrated the persistence of a digital access gap between public and private university students. Other studies also reveal that limited devices, unstable internet connections, and limited access to digital learning resources hinder the effectiveness of online learning [10], [11]. These findings indicate that digital divide classification requires an approach that is capable of representing various dimensions comprehensively.

In line with this, the development of Artificial Intelligence in Education (AIED) has opened new opportunities in educational data analysis. Artificial Intelligence is widely used for classification, academic performance prediction, learning personalization, and data-driven decision-making [12], [13]. Bibliometric studies show that AI research continues to grow in the fields of Educational Data Mining and Learning Analytics [14], [15], [16], [17], and is expected to increase further with the adoption of AI in the education sector [18], [19]. In the context of the digital divide, [8], [20] show that AI is capable of identifying patterns of digital inequality and supporting data-driven decision-making. However, most research still focuses on improving model accuracy without explaining how classification decisions are generated.

The development of Explainable Artificial Intelligence (XAI) offers a solution to these limitations by increasing model transparency and interpretability. [21] explains that XAI is able to reveal the contribution of each variable to the prediction results. In the field of education, [22], shows that Explainable Machine Learning improves the transparency of academic decision-making, while [23], [24] emphasize the importance of Explainable Learning Analytics in building trustworthy models. Research by [25], [26], [27] also proves that SHapley Additive exPlanations (SHAP) effectively explains model decisions without reducing predictive performance. However, the application of XAI to Artificial Neural Network (ANN) based digital divide classification is still very limited.

Based on this review, three main research gaps exist. First, most digital divide research still focuses on the technology access dimension, thus failing to integrate equity and accessibility into a single classification model [28], [29]. Second, AI-based research on the digital divide is still dominated by black-box models that lack interpretation [30], [31]. Third, the application of explainable AI to digital divide classification is still far less common than its application to educational data mining and learning analytics [22], [23], [24], [25], [26], [27].

Based on these gaps, this study proposes Towards Explainable Multidimensional Digital Divide Classification in Online Learning by integrating Artificial Neural Network (ANN) and SHAP. The model was developed using four variables: Primary Device, Internet Stability, Equity Score, and Accessibility Score, which represent the dimensions of technology access, connectivity quality, equitable access, and accessibility of digital learning. The novelty of this study lies in the integration of multidimensional digital divide classification with an explainable AI approach, resulting in a model that not only has high predictive performance but is also able to transparently explain the contribution of each variable to the classification results. The contribution of this study is to provide a more comprehensive, interpretative, and data-driven digital divide classification framework to support the development of digital inclusion policies in higher education.

2. RESEARCH METHOD

This study proposes an Explainable Artificial Intelligence (XAI) framework to classify the level of digital divide in online learning for students using Artificial Neural Network (ANN) and SHapley Additive Explanations (SHAP). The research flow, as shown in Figure 1, consists of the stages of Questionnaire Data, Data Cleaning, Validity and Reliability Test, Target Label Construction (K-Means Clustering), Feature Encoding (One-Hot Encoding), Feature Scaling (Min-Max Normalization), Train-Test Split, ANN Training, Baseline Model Comparison, Comparative Performance Evaluation, and SHAP Explainability. This series of stages is designed to produce an accurate and transparent classification model through the interpretation of the contribution of each feature to the model's decision, thereby supporting data-driven decision-making in the field of education [21], [22], [23].

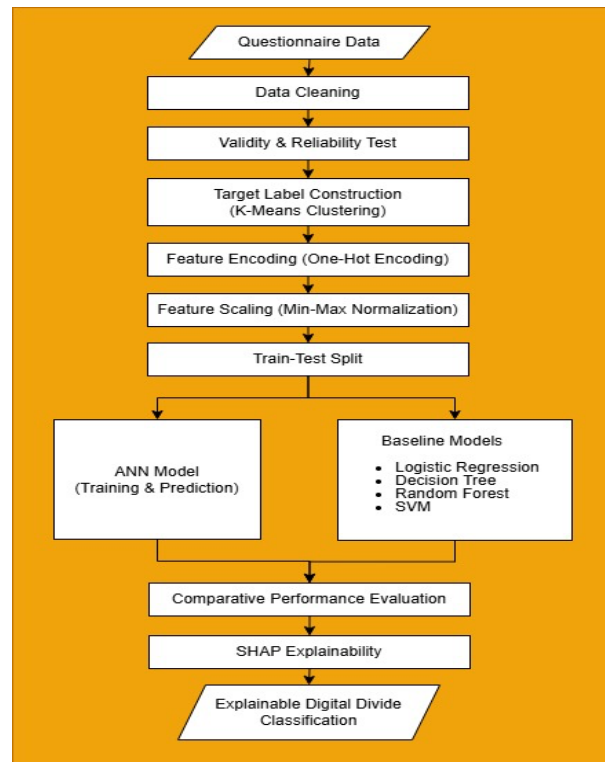


Figure 1. System Design of The Research Framework

2.1. Data Collection

The study used primary data obtained through the distribution of questionnaires distributed via Google Form in December 2025 to 324 students participating in online learning. The sampling technique used in this study was Simple Random Sampling which is included in the Probability Sampling Technique. Furthermore, to determine the sample size quantitatively, this study used the Slavin formula with a set error rate (e) to ensure the accuracy of the questionnaire results [32]. This study used four independent variables, namely Primary Device, Internet Stability, Equity Score, Accessibility Score and one dependent variable, namely Digital Divide Level which consists of three classes, namely Low, Medium, and High Digital Divide. The selection of these four variables is based on previous research showing that the digital divide is a multidimensional phenomenon influenced by device quality, internet connectivity, equal access to education, and ease of accessing digital services [1], [8], [11], [28].

2.2. Data Cleaning

This process includes checking for missing values, removing duplicate data, identifying inconsistent data, and detecting outliers, if necessary. This stage is crucial for improving data quality so that the model doesn't learn noisy patterns [8], [20].

2.3. Validity and Reliability

Validity and reliability tests were conducted to ensure that each question accurately and consistently measures the construct being studied. These validity and reliability evaluation procedures refer to the guidelines for quality testing of quantitative research instruments as described by [33].

2.4. Target Label Construction

In this study, the target variable, Digital Divide Level, was neither subjectively determined nor directly derived from the four predictor variables used in the classification model. The target label was obtained through an unsupervised learning process conducted before the classification stage using the K-Means Clustering algorithm on 24 indicators representing various dimensions of the digital divide in online learning. These indicators include characteristics of technology and

digital access, equity indicators, accessibility indicators, and perceptions of the online learning experience. This approach was used to produce a more comprehensive representation of the digital divide than using only the technology access indicator [2], [28], [34]. Indicators Used for K-Means Clustering are presented in Table 1.

Table 1. Indicators Used for K-Means Clustering

Indicator	Number of Items	Description
Technology and Digital Access	5	Device ownership, internet connectivity, digital access
Equity Indicators	7	Equal opportunity and learning support
Accessibility Indicators	7	Ease of accessing online learning resources
Perceptions of Online Learning Experiences	5	Student perceptions and learning experiences
Total	24	Indicators used to construct Digital Divide Level

Before the clustering process was carried out, all data underwent a data preprocessing stage, which included checking for missing values, removing duplicate data, transforming questionnaire scores into numerical form, and normalizing numerical variables [35]. Next, the clustering process was carried out using the K-Means Clustering algorithm, which aims to partition the data into several groups based on similar characteristics between respondents [36]. Based on the clustering evaluation results, three groups of students were obtained with different digital divide characteristics. Interpretation of each cluster was carried out through centroid analysis, so that each group was labeled Low Digital Divide, Medium Digital Divide, and High Digital Divide. Cluster labels were assigned by comparing centroid values across Technology Access, Equity, Accessibility, and Perception dimensions.

The labeling process was intended for interpretation purposes and was not externally validated. The labels resulting from the clustering are then used as Cluster-derived Digital Divide labels in this research to build a classification model based on Artificial Neural Network (ANN). In contrast to the clustering process which utilizes 24 indicators, the ANN model only uses four representative variables, namely Primary Device, Internet Stability, Equity Score, and Accessibility Score, as input variables. This approach aims to produce a simpler and more efficient classification model without having to use all indicators during prediction. Thus, this research does not reshape the target labels using the same predictor variables, but instead utilizes labels that have been generated through an unsupervised learning process based on multidimensional indicators. The Digital Divide Level used in this study is not an independently observed Cluster-derived Digital Divide labels but an analytical label derived through K-Means clustering based on multidimensional indicators. Therefore, the proposed ANN model is interpreted as learning a clustering structure, not as predicting externally validated outcomes.

2.5. Data Preparation

Since most of the research attributes are categorical variables, One-Hot Encoding was used to facilitate processing by an Artificial Neural Network. This approach was chosen because it allows each category to be represented independently without assuming any numerical relationship between categories, making it more suitable for neural network-based machine learning modeling [8], [12], [37]. Numerical variables such as Equity Score and Accessibility Score were normalized using the Min-Max Scaling method so that all features are within the same range as equation 1.

$$x'_{i,d} = \frac{x_{i,d} - x_{d,\min}}{x_{d,\max} - x_{d,\min}} \quad (1)$$

Normalization is carried out to make the optimization process in the neural network more stable and accelerate convergence [12].

2.6. Train-Test Split

The dataset was divided into 80% training data and 20% testing data for model training and evaluation. The data was divided using a stratified split to maintain a proportional distribution of output classes in the training and testing data, allowing for a more representative model evaluation process [8], [20]. The dataset consisting of 324 observations was first divided into 80% training

data (259 samples) and 20% testing data (65 samples) using a hold-out strategy. During ANN training, 20% of the training subset was further reserved as the validation set through the `validation_split=0.2` parameter in Keras. Consequently, approximately 207 samples were used for weight optimization, 52 samples were used for validation during training, and 65 samples were retained as an independent testing set for final model evaluation.

2.7. ANN Training & Prediction

An Artificial Neural Network model was used to classify the digital divide into three classes: low, medium, and high. The ANN was selected based on its ability to learn nonlinear relationships between educational variables [12], [13], [20].

The classification model is built using a Multilayer Perceptron (MLP). The architecture consists of an Input Layer, a Hidden Layer, and an Output Layer. Neuron activation is calculated using Equation 2.

$$z_j = \sum_{i=1}^n w_{ij} x_i + b_j \quad (2)$$

Then the ReLU activation function is used with equation 3.

$$\text{ReLU}(z) = \max(0, z) \quad (3)$$

Meanwhile, the output layer uses Softmax with equation 4 to produce multi-class classification probabilities.

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (4)$$

The model is optimized using Adam Optimizer with Categorical Cross Entropy loss function with equation 5.

$$L = - \sum_{i=1}^N \sum_{k=1}^K y_{ik} \log(\hat{y}_{ik}) \quad (5)$$

The selection of ANN was based on its ability to learn nonlinear relationships between educational variables [12], [13], [20]. The ANN architecture is presented in Table 2 and ANN The Training Configuration is presented in Table 3.

Table 2. ANN Architecture

Layer	Neurons	Activation
Input	8	-
Hidden Layer 1	64	ReLU
Hidden Layer 2	32	ReLU
Hidden Layer 3	16	ReLU
Output Layer	3	Softmax

As shown in Table 2, the proposed ANN consists of 8 input features obtained after one-hot encoding and feature scaling, followed by three hidden layers containing 64, 32, and 16 neurons, respectively. The ReLU activation function is employed in the hidden layers to capture nonlinear relationships among input variables, while two Dropout layers with rates of 0.30 and 0.20 are incorporated to reduce overfitting by randomly deactivating neurons during training. The output layer contains three neurons with the Softmax activation function corresponding to the Low, Medium, and High Digital Divide classes.

Table 3. ANN Training Configuration

Parameter	Value
Input Features	8
Hidden Layers	64-32-16
Activation Function	ReLU
Dropout Rate	0.30, 0.20

Output Neurons	3 (Softmax)
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	8
Maximum Epochs	300
Validation Split	0.20
Early Stopping	Monitor = Validation Loss
Patience	20 epochs
Restore Best Weights	True

Prior to model training, the dataset was divided into 80% training data (259 samples) and 20% testing data (65 samples) using a stratified hold out strategy. During training, 20% of the training subset was further allocated as validation data (`validation_split = 0.2`), resulting in approximately 207 training samples, 52 validation samples, and 65 testing samples. The validation data were not used to update the network weights. Instead, they were employed to monitor the learning process and activate the Early Stopping mechanism, which monitored the validation loss with a patience of 20 epochs and restored the model weights corresponding to the lowest validation loss. This strategy helps reduce overfitting while preserving the model with the best generalization performance. The ANN model was optimized using the Adam optimizer and the categorical cross-entropy loss function. The model was trained for a maximum of 300 epochs with a batch size of 8. After the training process, the optimized model was used to predict the Digital Divide Level of unseen testing samples, where the final class label was determined from the highest Softmax probability.

2.8. Baseline Models and Comparative Evaluation

To demonstrate the effectiveness of the proposed model, this study not only evaluates the Artificial Neural Network (ANN), but also compares it with several commonly used classification algorithms as baseline models, namely Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM). The selection of these models is based on their widespread use in various classification studies in the fields of Educational Data Mining and Artificial Intelligence in Education as a comparison to deep learning-based models [12], [13], [17].

All models were developed using the same dataset, with 80% training and 20% testing, so each algorithm was evaluated under identical conditions. The input variables used in all models were Primary Device, Internet Stability, Equity Score, and Accessibility Score, while the Digital Divide Level was used as the target variable. This approach aimed to ensure that any performance differences stemmed from the characteristics of the algorithms, rather than differences in the training data or variables used. The performance of each model was evaluated using Accuracy, Precision, Recall, and F1-score based on the prediction results on the test data. The evaluation results of all models were then compared to determine the performance position of the ANN model against other classification algorithms. In addition to comparing prediction performance, this study also assessed the model's interpretability through the integration of SHapley Additive Explanations (SHAP) into the proposed ANN model.

2.9. SHAP Explainability

Although classification metric evaluation can indicate the level of model accuracy, these metrics are not able to explain how each variable influences the decisions generated by the model. In the educational context, model transparency is an important aspect because the prediction results will be used as a basis for decision-making and education policy formulation [22], [23], [24]. Therefore, this study integrates SHapley Additive Explanations (SHAP) to provide interpretation of the proposed ANN model. SHAP calculates the contribution of each feature to the prediction based on the Shapley Value concept from cooperative game theory, thus being able to explain the influence of each variable at both the global and local levels [21], [25], [27]. The SHAP value is calculated using equation 8.

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (8)$$

In this study, SHAP analysis was performed after the ANN model was trained using the training data. DeepExplainer was used to interpret the neural network-based model because it is able to efficiently calculate the contribution of each feature to the model output by utilizing the internal structure of the network (deep neural network) [25], [26]. Part of the training data was used as a background dataset to calculate the model's expected value, then the SHAP value was calculated for each observation in the test data to obtain the contribution of each feature to the classification results [23], [27]. Since the proposed ANN performs multiclass classification (Low, Medium, and High Digital Divide), SHAP values were computed separately for each output class. The global explanations reported in this study were obtained by averaging the absolute SHAP values across all classes to identify the overall contribution of each feature to the model. In contrast, the local explanations were generated for the predicted class of an individual observation, allowing the contribution of each feature to a specific prediction to be interpreted.

Interpretation of SHAP results was conducted through both global and local analyses. For the multiclass ANN model, the global interpretation summarizes feature contributions across all output classes, whereas the local interpretation explains the prediction for a specific output class of an individual student. At the global level, the SHAP Summary Plot presents the mean absolute SHAP values aggregated across the three Digital Divide classes, enabling the identification of features that consistently influence the multiclass ANN model [21], [27]. Furthermore, the SHAP Dependence Plot is used to analyze the relationship between a feature's value and its contribution to the prediction and identify possible interactions between features [25]. The dependence plots presented in this study correspond to the SHAP values of the analyzed output class. At the local level, the SHAP Waterfall Plot explains the contribution of each feature to the predicted class of an individual student rather than to the overall model output [22], [26]. Through the combination of global and local analysis, this study not only produces a high-performance classification model, but also provides a transparent interpretation of the factors influencing the level of digital divide among students, thereby increasing confidence in the prediction results and supporting data-based decision-making in the field of education [23], [24].

3. RESULTS AND DISCUSSION

This chapter presents the implementation results of the proposed method for classifying the level of digital divide in online learning using an Artificial Neural Network (ANN) approach combined with SHAP (SHapley Additive exPlanations) as a model interpretation method. The research results are presented in stages, including dataset characteristics, data preparation results, the ANN model training process, classification performance, and interpretability analysis using SHAP. All results are then discussed to evaluate the model's ability to identify factors influencing the level of digital divide while providing explanations for the resulting prediction decisions.

3.1. Dataset Characteristics

The initial stage of the analysis was carried out by identifying the characteristics of the dataset used in the study. A description of the dataset is necessary to provide an overview of the research variables and the data types used as the basis for the digital divide classification process. A summary of the dataset characteristics is presented in Table 4.

Table 4. Dataset Description

Variable	Type	Category
Primary Device	Categorical	Smartphone, Laptop, Combination
Internet Stability	Categorical	Very Smooth, Fairly Smooth, Not Smooth
Equity Score	Numerical	Likert Score
Accessibility Score	Numerical	Likert Score
Digital Divide Level	Target	Low, Medium, High

Based on Table 4, the research dataset consists of four independent variables and one dependent variable. The Primary Device and Internet Stability variables are categorical data representing aspects of technology access, while the Equity Score and Accessibility Score are numeric data based on a Likert scale that describe the dimensions of equity and ease of access in online learning. Meanwhile, the Digital Divide Level is used as the target variable, classified into three categories: Low, Medium, and High Digital Divide. The combination of these four

independent variables is expected to provide a multidimensional representation of the digital divide in online learning.

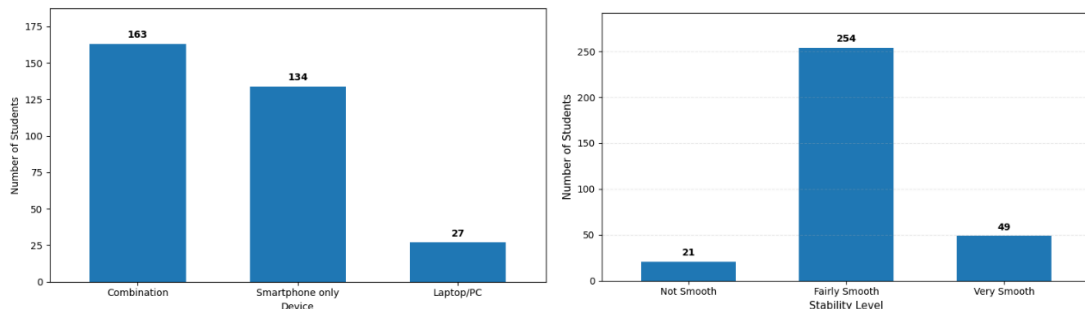


Figure 2. Primary Device & Internet Stability Distribution

Respondent characteristics in Figure 2 are divided into two main distributions. In the Primary Device Distribution graph, combined device use dominates with 163 students, followed by smartphone use alone (134 students), and laptop/PC use alone (27 students). Meanwhile, in the Internet Stability Distribution graph, the majority of students are in the Fairly Smooth category (253 students), far exceeding the Very Smooth (49 students) and Not Smooth (21 students) categories.

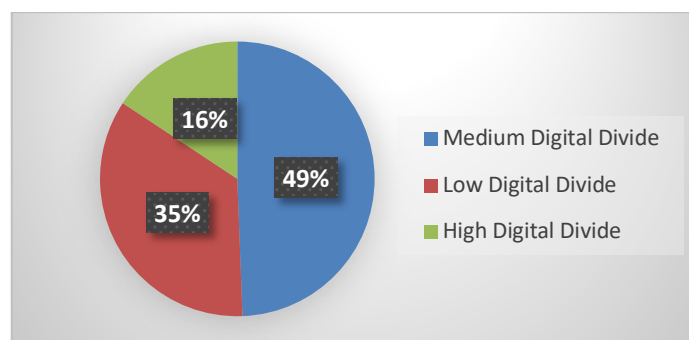


Figure 3. Digital Divide Class Distribution

Figure 3 shows that the Medium Digital Divide category dominates the data distribution with a percentage of 49%, followed by Low Digital Divide (35%) and High Digital Divide (16%). This distribution shows that the majority of respondents are not yet completely free from the digital divide, so efforts are needed to increase access and support for digital learning to reduce the level of the digital divide.

Figure 4 shows the distribution of Equity Scores and Accessibility Scores across all respondents. Most students scored in the mid-to-high range for both variables, with the highest concentration at 26 for the Equity Score (83 respondents) and 21 for the Accessibility Score (63 respondents). Furthermore, the distribution of both variables tended to be concentrated in the 20–30 range, with only a few respondents having very low scores. These findings indicate that the majority of students have relatively good levels of equity and accessibility to online learning. However, the presence of a number of respondents with low scores indicates the persistence of a digital access gap that has the potential to impact the online learning experience and is an important factor in the digital divide classification process.

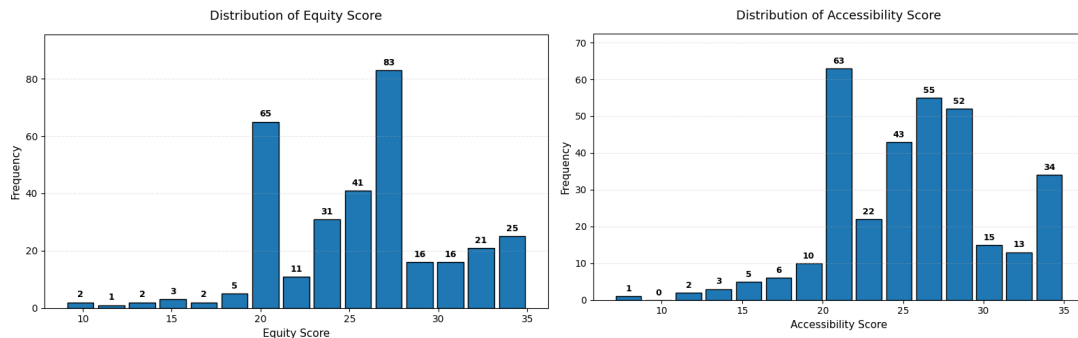


Figure 4. Distribution of Equity Score & Accessibility Score

3.2. Questionnaire Validity and Reliability

Before the modeling process was carried out, the research instrument was tested to ensure its validity and reliability. Validity was measured using Pearson Product Moment Correlation, while reliability was measured using Cronbach's Alpha. The test results are presented in Tables 5 and 6. Access to technology and digital, equity indicators, accessibility indicators, and perceptions of the online learning experience.

Table 5. Summary of Validity Test

Indicator	Number of Items	Range of Pearson Correlation	Sig.	Result
Technology and Digital Access	5	0.476-0.737	< 0.001	Valid
Equity Indicators	7	0.589-0.763	< 0.001	Valid
Accessibility Indicators	7	0.634-0.824	< 0.001	Valid
Perceptions of Online Learning Experiences	5	0.581-0.748	< 0.001	Valid

Table 6. Reliability Statistics

Cronbach's Alpha	N of Items
.947	24

Based on the validity test results in Table 5, all items have a positive correlation value with a range of 0.476-0.824 and are significant at the $p < 0.001$ level. All correlation values are above the recommended minimum limit ($r > 0.30$), so all items are declared valid and able to represent the construct being measured. Furthermore, the reliability test results in Table 6 show a Cronbach's Alpha value of 0.947, which far exceeds the minimum limit of 0.70. This value indicates that the research instrument has very high internal consistency and is suitable for use in the label formation, model training, and classification evaluation stages.

3.3. Target Label Construction

Before the classification process was carried out, this study first developed a target label for the Digital Divide Level using an unsupervised learning approach through the K-Means Clustering algorithm. The clustering process was carried out on 24 indicators consisting of 5 indicators of Technology and Digital Access, 7 indicators of Equity, 7 indicators of Accessibility, and 5 indicators of Perceptions of Online Learning Experiences. All of these indicators were chosen because they represent the concept of the digital divide multidimensionally, so that the formation of the label is not only based on technology access, but also considers aspects of equal access, ease of use, and student experience in online learning.

The number of clusters was set at three to represent the Low Digital Divide, Medium Digital Divide, and High Digital Divide levels. The selection of the number of clusters was considered using the Elbow Method and Silhouette Score. The Elbow Method and Silhouette Score plots are presented in Figure 5.

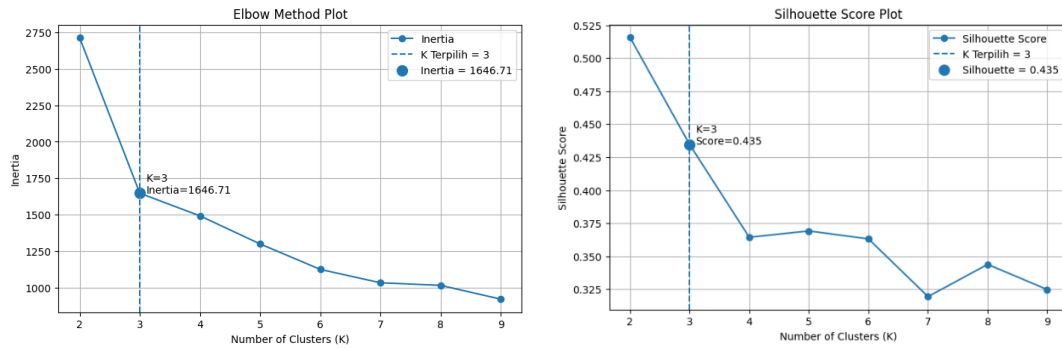


Figure 5. Elbow Method dan Silhouette Score Plot

Figure 5 shows that the inertia value experiences a very sharp decrease from $K=2$ to $K=3$, then tends to stabilize in the next Cluster, so that $K=3$ can be identified as the optimal elbow point. In terms of Cluster quality, the highest silhouette score is indeed obtained at $K=2$ (0.516), but $K=3$ still shows a fairly good value (0.435), which indicates that the Cluster separation remains in the acceptable category. Although the highest silhouette score was obtained at $k=2$, three clusters were selected because the objective of this study was to distinguish Low, Medium, and High Digital Divide categories that are more meaningful from an educational intervention perspective. Similar approaches have been adopted in educational data mining where interpretability and practical usefulness are considered alongside clustering validity.

K-Means Clustering produces three clusters, namely Cluster 0, Cluster 1, and Cluster 2. Table 7 presents the distribution of the number of students in each cluster resulting from the K-Means algorithm. Of the total research population, Cluster 0 is the group with the largest members, namely 160 students, followed by Cluster 2 with 113 students, and Cluster 1 as the smallest group with 51 students.

Table 7. Digital Divide Class Distribution

Cluster	Number of Students	Percentage (%)
Cluster 0	160	49.38
Cluster 1	51	15.74
Cluster 2	113	34.88

After the convergence process, the characteristics of each cluster are analyzed based on the centroid value to obtain an interpretation of the digital divide level of each cluster. The labels generated from the clustering process are then used as target classes in the classification stage using an Artificial Neural Network (ANN). Since the target labels are generated using unsupervised clustering of the same multidimensional indicators, the proposed model is interpreted as a reproduction of analytically derived digital divide categories, rather than as a prediction of independently observed truth labels.

Table 8. Characteristics of K-Means Clusters and Assigned Labels

Cluster	Technology & Digital Access	Equity	Accessibility	Perceptions	Label
Cluster 0	Low	High	High	Low	Medium Digital Divide
Cluster 1	Low	Low	High	High	High Digital Divide
Cluster 2	High	Low	Low	High	Low Digital Divide

Table 8 presents the characteristics of each cluster generated by the K-Means algorithm along with the Digital Divide label given based on the combination of Technology & Digital Access, Equity, Accessibility, and Perceptions levels. Cluster 0 is characterized by low levels of technology access, but has high equity and accessibility scores with relatively low perceptions, thus categorized as Medium Digital Divide. Cluster 1 has low levels of technology access and equity, although supported by high accessibility and perceptions, thus representing a group with High Digital Divide. Conversely, Cluster 2 shows high technology access, but has lower equity and accessibility scores with high perceptions, thus classified as Low Digital Divide. These characteristics indicate that the level of digital divide is not determined by a single factor, but rather

the result of a multidimensional interaction between technology access, equity of access, ease of access, and student perceptions of online learning. Consequently, the assigned labels should be interpreted as analytical categories rather than universally established digital divide classes.

3.4. Feature Encoding

The use of one-hot encoding shows improved model performance compared to ordinal encoding because it is able to eliminate numerical bias in categorical variables. Generated Features after One-Hot Encoding are presented in Table 9.

Table 9. Generated Features after One-Hot Encoding

Original Variable	Generated Feature
Primary Device	Primary Device_Combination
Primary Device	Primary Device_Laptop/PC
Primary Device	Primary Device_Smartphone only
Internet Stability	Internet Stability_Very Smooth
Internet Stability	Internet Stability_Fairly Smooth
Internet Stability	Internet Stability_Not Smooth

Table 9 shows the results of the One-Hot Encoding process for the categorical variables used in the study. This technique converts each category in the Primary Device and Internet Stability variables into binary features (dummy variables), so that each category is represented by a single column with a value of 1 if the respondent holds that category and 0 otherwise. This approach avoids the assumption of ordinal relationships in categorical data and allows the Artificial Neural Network (ANN) model to independently learn the contribution of each category during the classification process.

3.5. Feature Encoding

Before the data is used as input to an Artificial Neural Network (ANN) model, all numerical features are first normalized using the Min-Max Normalization method. This stage aims to equalize the value range of each feature into the interval $[0,1]$, so that differences in scale between variables do not affect the model learning process and accelerate convergence during training. To ensure that the normalization process runs smoothly without changing the characteristics of the data distribution, a comparison of the feature distribution before and after the feature scaling process is carried out, as shown in Figure 6.

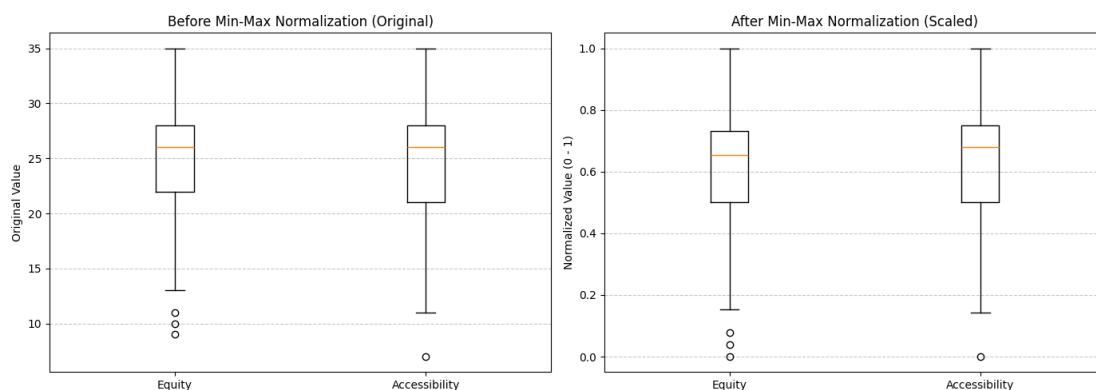


Figure 6. Feature Distribution before and after Min-Max Normalization

Figure 6 shows the distribution of the Equity Score and Accessibility Score before and after the Min-Max Normalization process. Before normalization, both variables had different value ranges, whereas after normalization, all values were successfully mapped into the 0-1 range without significantly changing the distribution pattern, median, or data spread. This indicates that the feature scaling process successfully standardized the scale of both numeric features while maintaining the characteristics of the original data, making the data more suitable for use as input in an Artificial Neural Network (ANN) model.

3.3. ANN Training & Prediction

The performance of the ANN model was analyzed first through a training process before being evaluated on the test data. During the training process, accuracy and loss values for both training and validation data were recorded at each epoch to generate learning curves. These curves were used as indicators of model convergence, optimization process stability, and the model's ability to avoid overfitting and underfitting. The visualization of the learning curves is presented in Figure 7.

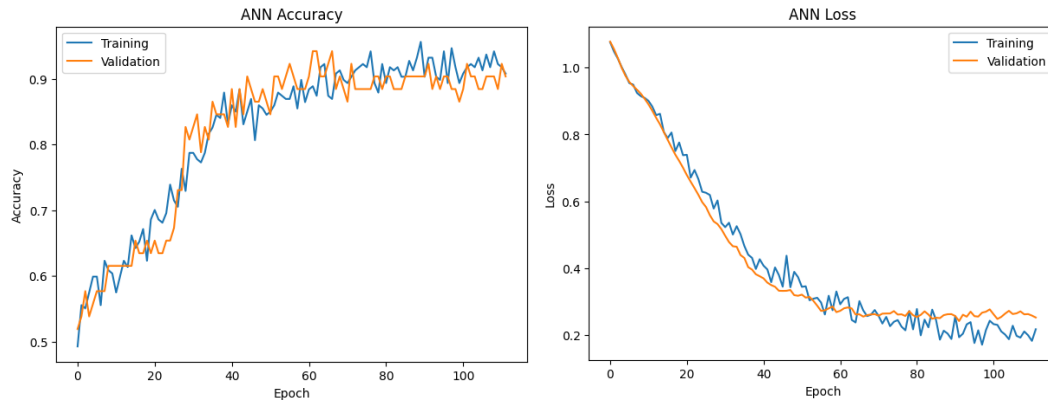


Figure 7. Training vs Validation Accuracy & Loss

Figure 7 shows the development of accuracy and loss values during the ANN model training process. The training accuracy and validation accuracy curves increase gradually until they reach values above 90%, with a relatively close pattern throughout the training process. At the same time, the training loss and validation loss experience a consistent decrease and then tend to stabilize in the final epoch. The closeness between the training and validation curves and the absence of significant differences indicate that the model is able to effectively learn data patterns without significant indications of overfitting, thus having good generalization ability to data not used during the training process. The validation accuracy and validation loss were computed from the validation subset (52 samples), which was automatically separated from the training data using `validation_split=0.2`.

Table 10. Classification Report

	Precision	Recall	F1-Score	Support
Low Digital Divide	0.90	0.83	0.86	23
Medium Digital Divide	0.86	0.94	0.90	32
High Digital Divide	1.00	1.00	1.00	10
accuracy			0.91	65
macro avg	0.93	0.92	0.92	65
weighted avg	0.91	0.91	0.91	65

Table 10 presents the results of the ANN model evaluation on the test data. The model achieved an accuracy of 91%, with a weighted precision, weighted recall, and weighted F1-score of 0.91 each, indicating good overall classification performance. At the class level, High Digital Divide performed best with a precision, recall, and F1-score of 1.00 each, while Medium Digital Divide achieved an F1-score of 0.90 and Low Digital Divide of 0.86. The differences in values between classes indicate that the model was able to effectively identify all digital divide categories, although the Low Digital Divide class still had some misclassifications compared to the other classes. Overall, these results indicate that the ANN model was able to provide stable and balanced classification performance across all three digital divide categories.

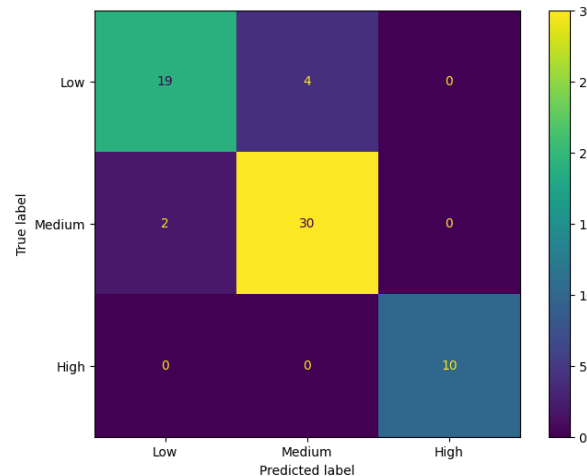


Figure 8. Confusion Matrix

Figure 8 presents the confusion matrix resulting from the ANN model classification on the test data. Most samples were correctly classified: 19 out of 23 data points in the Low Digital Divide class, 30 out of 32 data points in the Medium Digital Divide class, and all 10 data points in the High Digital Divide class. Misclassification errors occurred only between the Low Digital Divide and Medium Digital Divide classes, with four Low Digital Divide samples predicted as Medium Digital Divide, and two Medium Digital Divide samples predicted as Low Digital Divide. There were no misclassification errors involving the High Digital Divide class, indicating that the model was able to distinguish groups with high levels of digital divide very accurately. These results indicate that the ANN model has good discrimination capabilities, especially in identifying the High Digital Divide category, while a small amount of overlap still occurs between the Low and Medium Digital Divide categories due to the relatively close characteristics of the two classes.

3.7. Baseline Model Comparison

To evaluate the effectiveness of the proposed model, the performance of an Artificial Neural Network (ANN) was compared with four commonly used classification algorithms: Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM). The evaluation was conducted using accuracy, precision, recall, and F1-score metrics to provide an objective comparison of each model's ability to classify the digital divide. The Performance Comparison of Classification Models is presented in Table 11.

Table 11. Performance Comparison of Classification Models

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.830769	0.874061	0.830769	0.818709
Decision Tree	0.876923	0.882802	0.876923	0.876484
Random Forest	0.907692	0.908963	0.907692	0.907388
SVM	0.861538	0.873161	0.861538	0.860385
ANN (Proposed)	0.907692	0.908382	0.907692	0.906993

Table 11 and Figure 9 show that all models produced good classification performance with accuracy levels above 83%. Logistic Regression provided the lowest performance with an accuracy of 83.08%, while Decision Tree and SVM achieved accuracies of 87.69% and 86.15%, respectively. Random Forest and the proposed ANN achieved the same classification accuracy (90.77%), indicating that both models provided comparable predictive performance. Random Forest showed marginally higher precision (0.9090) and F1-score (0.9074) than ANN; however, the differences were negligible (<0.001), indicating that both models exhibited comparable predictive capability.

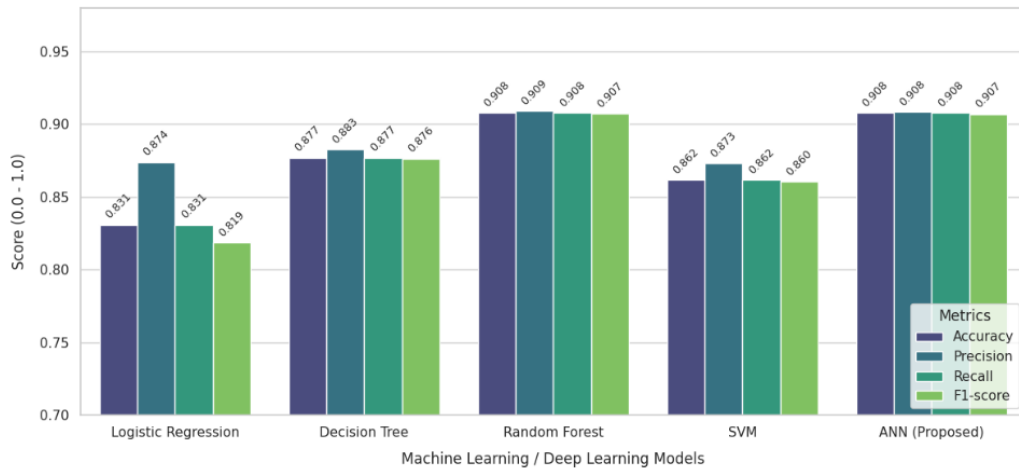


Figure 9. Model Performance Comparison

Since ANN and Random Forest demonstrated comparable predictive performance, ANN was selected as the primary model because it can be effectively integrated with SHAP (SHapley Additive exPlanations) to provide transparent global and local explanations of the classification results. Accordingly, this study emphasizes not only competitive predictive performance but also model interpretability, enabling the analytically derived digital divide classifications to be understood transparently and supporting evidence informed educational decision making.

3.8. SHAP Explainability Analysis

To improve the transparency of the proposed multiclass ANN model, this study integrates SHapley Additive exPlanations (SHAP) to interpret the contribution of each feature to the model predictions. Because the ANN classifies students into three categories (Low, Medium, and High Digital Divide), SHAP values were computed separately for each output class. Global explanations were obtained by aggregating the mean absolute SHAP values across all classes, whereas local explanations were generated for the predicted class of an individual observation. The SHAP Summary Plot is presented in Figure 10.

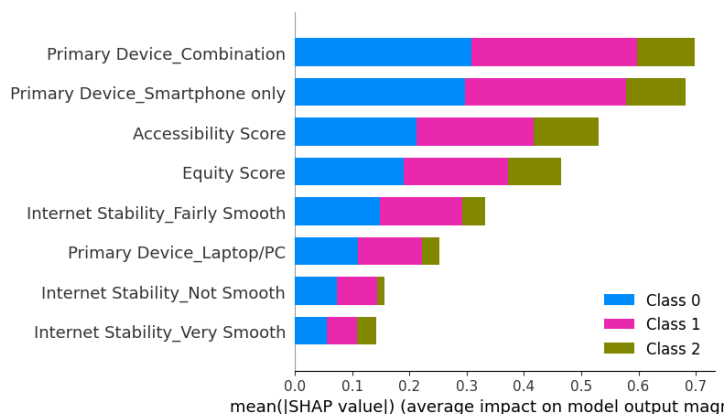


Figure 10. SHAP Summary Plot

Figure 10 presents the SHAP Summary Plot, which summarizes the mean absolute SHAP values aggregated across the three output classes (Low, Medium, and High Digital Divide). Therefore, the feature importance reflects the overall contribution of each predictor to the multiclass ANN model rather than to a single Digital Divide category. Based on the aggregated mean absolute SHAP values across the three output classes, Primary Device_Combination and Primary Device_Smartphone only are the most influential predictors in the multiclass ANN model. In contrast, the Internet Stability variables contribute relatively less to the overall model predictions. These findings indicate that students' device characteristics, together with accessibility

and equity dimensions, are the dominant factors influencing the multidimensional digital divide classification.

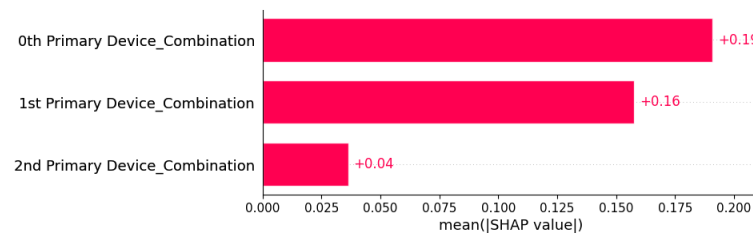


Figure 11. SHAP Feature Importance

Figure 11 illustrates the class-specific SHAP Feature Importance for Primary Device_Combination. The feature contributes differently across the three output classes, with the largest average absolute SHAP value observed for Class 0, followed by Class 1 and Class 2. This result demonstrates that the contribution of a feature varies depending on the predicted Digital Divide category rather than remaining constant across all classes.

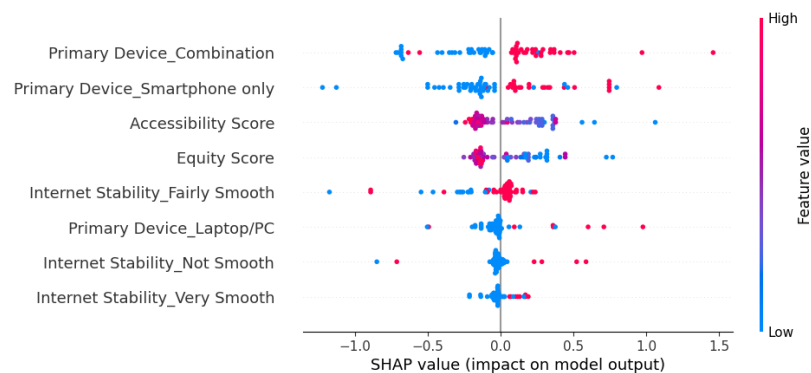


Figure 12. SHAP Beeswarm

Figure 12 presents the SHAP Beeswarm Plot summarizing the distribution of SHAP values across all observations and output classes. Each point represents the SHAP value of one observation for the corresponding class, while the horizontal position indicates the magnitude and direction of the feature contribution. Features with wider SHAP distributions contribute more substantially to the multiclass prediction. Primary Device_Combination and Primary Device_Smartphone only show the broadest distributions, followed by Accessibility Score and Equity Score, whereas Internet Stability contributes relatively less.

Figure 13 presents the SHAP Dependence Plot for the High Digital Divide class. The plot illustrates how Internet Stability and Accessibility Score influence the SHAP values associated with the predicted High Digital Divide category. Meanwhile, the Accessibility Score shows a tendency that the higher the accessibility value, the smaller the SHAP contribution to increasing the risk of digital divide, indicating a negative relationship between ease of access to digital learning and the level of digital divide. Furthermore, the color variations in both plots indicate interactions with other features, namely Primary Device_Combination and Internet Stability_Fairly Smooth, so that the influence of each variable is not independent. These findings demonstrate that the ANN model is able to capture complex and nonlinear relationships between variables, while also providing interpretation of how changes in feature values affect classification results at the individual level.

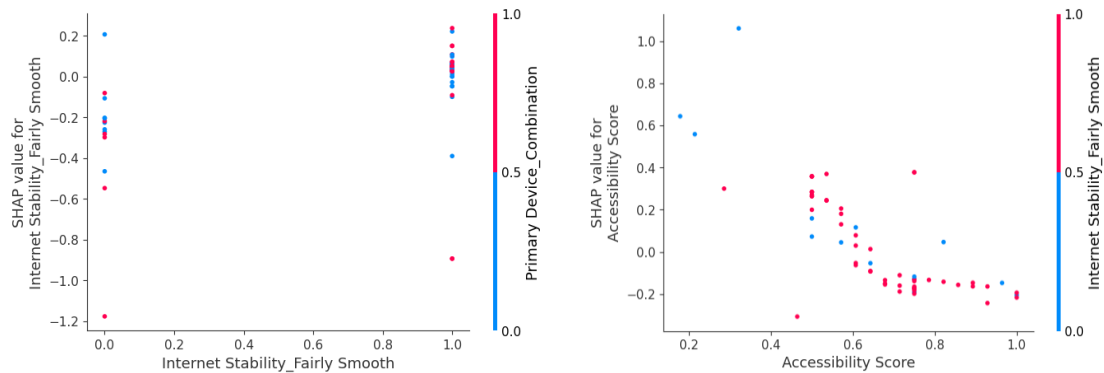


Figure 13. SHAP Dependence Plot for the High Digital Divide Class

3.9. Local Explanation

After explaining the global influence of features through the SHAP Summary Plot, Feature Importance, Beeswarm Plot, and Dependence Plot, the next step is to analyze the contribution of each feature at the individual level (local explanation). This analysis aims to explain how the combination of feature values in a particular sample influences the classification decision generated by the ANN model. To obtain this interpretation, this study uses the SHAP Waterfall Plot, which shows the positive and negative contributions of each feature to the final predicted value. This visualization provides a more transparent explanation of the model's reasoning in producing a digital divide classification decision for each observation.

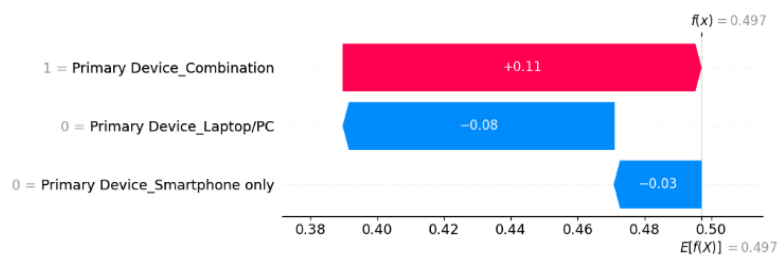


Figure 14. SHAP Waterfall Plot for an instance predicted as High Digital Divide

Figure 14 explains the contribution of each feature to the prediction of one student classified as High Digital Divide. This plot shows how each feature contributes positively and negatively to the final predicted value of 0.497. In this sample, the Primary Device_Combination feature makes the largest positive contribution (+0.11) to the model's predictions, while Primary Device_Laptop/PC (-0.08) and Primary Device_Smartphone only (-0.03) make negative contributions. These results indicate that the model's decision is not determined by a single variable, but rather by the accumulated contributions of all the features considered. Thus, the SHAP Waterfall Plot provides a transparent interpretation of the reasoning behind each individual prediction, increasing the explainability and confidence in the classification results produced by the ANN model.

The results showed that the Artificial Neural Network (ANN) model produced good classification performance with an accuracy of 90.77%, a precision of 90.84%, a recall of 90.77%, and an F1-score of 90.70%. This performance is comparable to Random Forest, which achieved the same accuracy. Although ANN achieved predictive performance comparable to Random Forest, it was selected as the primary model because this study aims to investigate the interpretability of neural network based classification through SHAP. These findings indicate that in digital divide classification problems involving nonlinear relationships between variables, the learning curves suggest that the model converged consistently during training and validation without obvious signs of severe overfitting. These results are consistent with the studies of [12], [13], [20], who reported that ANN is effective in handling complex and multidimensional characteristics of educational data.

It is important to note that the Digital Divide Level used in this study represents cluster-derived analytical categories generated through K-Means clustering rather than independently observed ground-truth labels. Consequently, the ANN should be interpreted as learning multidimensional clustering patterns instead of predicting externally validated outcomes. Although the highest silhouette score was obtained at $k=2$, three clusters were retained because they provide a more meaningful educational interpretation by distinguishing low, medium, and high levels of digital divide.

The SHAP analysis showed that Primary Device was the variable that contributed the most to the model's decision, followed by Accessibility Score, Equity Score, and Internet Stability. These results support the research of [1], [9], stated that device access is an important indicator of the first-level digital divide. However, this study also shows that the Accessibility Score and Equity Score have a relatively large influence on the classification results, indicating that the digital divide is not only influenced by device ownership or internet connection, but also by equal opportunities and ease of access for students to digital learning services. These findings align with research by [10], [11], [28], [29], which emphasize that the digital divide is a multidimensional phenomenon. The primary contribution of this study is demonstrating how SHAP can be integrated with an ANN-based digital divide classification framework to improve model interpretability while maintaining competitive predictive performance. Unlike most previous studies that focus on improving prediction accuracy, this study shows how each variable contributes to the classification results both at the global level through the reported global SHAP importance was obtained by aggregating the absolute SHAP values across the three output classes, whereas the SHAP Waterfall Plot illustrates the explanation for an individual prediction belonging to a specific class. This approach increases model transparency, making classification results easier to understand and potentially supporting data-driven decision-making in educational settings. These findings extend the application of XAI to digital divide classification, as recommended [21], [22], [23], [25], [27].

Despite these results, several limitations should be acknowledged. The model evaluation was conducted using a single 80:20 hold-out split, resulting in 65 testing samples. Although this evaluation strategy is widely used in machine learning studies, the reported performance may vary under different data partitions. In addition, the High Digital Divide class contained only 10 testing observations. Therefore, the perfect classification performance obtained for this class should be interpreted with caution and should not be considered conclusive evidence of strong generalization. Future research should employ repeated stratified k-fold cross-validation or external validation datasets to further evaluate the robustness and generalizability of the proposed model. Furthermore, since ANN achieved performance comparable to Random Forest rather than outperforming it, future studies should investigate the proposed explainable framework using larger datasets and additional validation schemes to better assess its comparative advantages.

4. CONCLUSION

This study proposes an explainable framework for multidimensional digital divide classification in online learning by integrating Artificial Neural Networks (ANN) and SHapley Additive exPlanations (SHAP). The framework learns cluster derived digital divide categories constructed from four dimensions: Primary Device, Internet Stability, Equity Score, and Accessibility Score. The ANN model achieved competitive classification performance with an accuracy of 90.77%, while SHAP provided both global and local explanations of model decisions. The results indicate that Primary Device is the most influential factor, followed by Accessibility Score, Equity Score, and Internet Stability, supporting the view that the digital divide is a multidimensional phenomenon extending beyond technology access alone. Methodologically, this study demonstrates how Explainable AI can improve the transparency of ANN based educational data mining models. However, because the target labels were analytically derived using K-Means clustering and the evaluation employed a single hold out split, the findings should be interpreted within these limitations. Future research should validate the proposed framework using larger and more diverse datasets, independently observed labels, repeated cross validation, and comparisons with other explainable machine learning models.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to ethical considerations and the protection of participants' privacy.

AUTHOR CONTRIBUTIONS

Imalatul Hidayah: Conceptualization; Data Curation; Data Labeling; Methodology; Writing-Original Draft; Visualization; Writing-Review & Editing. **Ririen Kusumawati:** Conceptualization; Data Labelling; Methodology; Supervision. **Mochamad Imamudin:** Methodology; Supervision; Funding Acquisition.

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