Journal of Business, Social and Technology
Volume 7, Issue 4, 1850-1863
e_ISSN: 2807-6362
https://bustechno.polteksci.ac.id/index.php/jbt/index
DOI: doi.org/10.59261/bustechno.v7i4.770

Prediction of New Student Registration Trends at Religious Higher Education Institutions Using Machine Learning and Deep Learning Approaches with SHAP Interpretation

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Article Info:
Article history:
Received: July 08, 2026
Revised: August 20, 2026
Accepted: September 05, 2026
Available Online: September 12, 2026

Keywords:
CNN-LSTM; Feature Engineering; Multivariate Time Series Forecasting; New Student Registration; SHAP.

Abstract

Background: Reliable forecasts of new student registration are essential for religious higher education institutions because admission volumes affect capacity planning, resource allocation, promotional strategies, and program sustainability. Historical admission data are often used descriptively rather than to generate forward-looking and interpretable estimates.
Objective: This study developed an explainable multivariate time-series framework for forecasting new student registration by integrating domain-based feature engineering, comparative machine-learning and deep-learning models, CNN-LSTM forecasting, and SHAP interpretation.
Methods: Historical admission records from 40 study programs at UIN Ar-Raniry for 2017–2025 were analyzed, comprising 360 program-year observations. The workflow included data validation and preprocessing, construction of share, pressure, and lag features, two-year sequence construction, temporal train-validation-test splitting, train-only scaling, comparative model evaluation, 2026 forecasting, and SHAP-based global and local interpretation.
Results: CNN-LSTM achieved the best average performance across five iterations, with an MAE of 6.0394, an RMSE of 8.6185, a MAPE of 27.7548%, and an R^2 of 0.9167. Its advantage is consistent with the structure of the data: convolutional layers extract local relationships among multivariate admission features, while LSTM captures temporal dependencies. SHAP showed that recent historical registration variables, especially reg_span_lag1, reg_um_lag1, and total_reg_lag1, together with capacity-related features such as jml_dt, were major contributors to the forecasts.
Conclusion: The study demonstrates that combining domain-informed feature engineering, CNN-LSTM, and SHAP provides both accurate and interpretable registration forecasts. The framework contributes an explainable decision-support approach for admission planning, quota setting, resource allocation, and targeted recruitment in religious higher education.

To cite this article: Kurniawan, A. F., Yuhana, U. L., & Amaliah, B. (2026). Prediction of New Student Registration Trends at Religious Higher Education Institutions Using Machine Learning and Deep Learning Approaches with SHAP Interpretation. *Journal of Business, Social and Technology*, *7*(4), 1850-xx. https://doi.org/10.59261/bustechno.v7i4.770

INTRODUCTION

New student admissions are one of the important processes in the management of religious higher education institutions. The number of applicants and students who register not only affects admissions outcomes but also directly relates to capacity planning, resource provision, promotional strategies, class distribution, and study program sustainability (Liu et al., 2025). In the context of religious higher education, the ability to estimate the number of new students in the following period is an important need because prediction results can be used as a basis for more targeted decision-making. Predicting the number of new students at religious higher education institutions is an urgent need because it plays a role in strategic decision-making, program accreditation, and institutional resource optimization (Bousnguar et al., 2022). Therefore, predicting new student registration trends is not only a technical issue but also part of religious higher education institutions' efforts to improve the quality of academic and managerial planning.

The scale of higher education strengthens the need for more reliable planning tools. UNESCO reports approximately 264 million students enrolled in universities worldwide, while the global tertiary enrollment ratio is about 43%. OECD data further show that 48% of young adults across OECD countries now hold a tertiary qualification, illustrating both the scale and continuing expansion of tertiary participation (OECD, 2025; UNESCO, 2026). The World Bank also tracks tertiary enrollment through the UNESCO Institute for Statistics indicator SE.TER.ENRR, underscoring the importance of comparable enrollment data for planning and policy (Bank, 2026).

In practice, analysis of new student admission data is still often conducted descriptively. Historical data are typically used to examine the number of applicants, the number of students who passed the selection, the number of registrations, and increasing or decreasing trends from year to year. Such analysis can indeed provide a picture of past conditions, but it is not sufficient to address predictive needs, namely, estimating the likelihood of student registrations in the following year. In fact, in decision-making, religious higher education institutions not only need information about what has already happened but also need a picture of what might happen. Forecasting in higher education is used to provide accurate prediction values with minimum error rates, thus supporting data-based decision-making processes (Bousnguar et al., 2022). Based on this, a predictive approach capable of utilizing historical new student admission data to estimate registration trends in future periods is needed.

At UIN Ar-Raniry, the available admission dataset covers 40 study programs, three admission pathways, and nine annual cohorts from 2017 to 2025, producing 360 program-year observations. The multiyear and multipathway structure indicates that institutional planning must accommodate heterogeneous registration patterns across programs and pathways rather than rely only on aggregate historical reporting. This empirical setting provides the basis for testing whether recent admission history, capacity, applicant pressure, and pathway composition can jointly improve forecasting.

New student admission data have complex characteristics because they are multivariate and temporal. The number of student registrations is not only influenced by the number of registrations in the previous year but also by capacity, the number of applicants, admission pathways, competitive pressure, and historical patterns across years. Thus, admission data cannot be viewed as a single time series but rather as a multivariate time series that captures relationships among variables and across time. Multivariate time series data exhibit temporal correlations and complex relationships among variables, making multivariate prediction more challenging than univariate prediction because the model needs to capture relationships among features and temporal patterns simultaneously (Chen et al., 2025). This condition aligns with the characteristics of the admission data used in this research, namely, data consisting of several admission pathways, capacity, applicants, and registrations for each study program from year to year.

To handle the temporal characteristics of the data, a time-series forecasting approach becomes relevant. Time-series forecasting aims to utilize historical information to predict values in the next period. In this research, prediction is conducted by forming a t+1 forecasting target, i.e., using historical data patterns to predict student registrations in the following year. Time-series forecasting essentially uses data from previous periods to predict future information, and this approach is widely used in various fields to support data-based decision-making (Wen & Li, 2023). With this approach, new student admission data can be processed not only as historical reports but also as a basis for building a student registration trend prediction model.

Before the data are used in the prediction model, feature engineering is necessary to make the data more representative. Raw admission data generally contain values for capacity, applicants, students who passed the selection, and registrations. However, these values do not fully explain the dynamics of competition and distribution among admission pathways. Therefore, this research forms several derived features, namely, share features, pressure features, lag features, and t+1 forecasting targets. Share features are used to represent the proportion of capacity and applicants accounted for by each admission pathway. Pressure features are used to describe the competitive pressure between the number of applicants and capacity. Lag features are used to capture historical registration patterns from the previous year, while the t+1 target is used to define the prediction target for the following year. Feature selection and formation have a direct influence on the effectiveness of time-series prediction models, especially because time-series data have characteristics such as temporal relationships, sequential patterns, and the possibility of noise (Huang et al., 2024; Kabir et al., 2025). Thus, feature engineering in this research is not performed randomly but is directed toward representing the characteristics of the admission domain.

After the features are formed, the prediction model needs to be selected according to the characteristics of the data. Simple statistical or machine learning models can be used as baselines, but admission data that exhibit temporal and multivariate relationships require models capable of capturing more complex patterns. Deep learning is one approach widely used in time-series forecasting because it can learn nonlinear patterns and temporal dependencies. LSTM is known for its ability to learn sequential patterns and short- and long-term dependencies, while CNN can be used to extract local patterns from data. Research by Livieris et al. (2020) shows that the combination of CNN and LSTM can improve forecasting performance because the convolutional layer can extract important representations from time-series data, while LSTM can capture temporal dependencies from historical data (Kabir et al., 2025; Livieris et al., 2020). This serves as the basis for using CNN-LSTM in this research because admission data require a model that can capture local patterns among features as well as historical patterns across years.

New student admissions are one of the main processes in the management of religious higher education institutions because they are directly related to academic intentions, capacity management, resource needs, and study program planning. In the context of religious higher education, new student admissions are not only understood as an administrative process for accepting students but also as a strategic information source that can be used to examine the development of prospective student interest, the effectiveness of selection pathways, and registration tendencies from year to year. Therefore, new student admission data are an important source of information that can be utilized to support institutional planning and decision-making (James & Weese, 2022; Wahyuni, 2025). Accordingly, admission data in the present study are treated as strategic institutional data whose value depends on their ability to support forward-looking decisions rather than retrospective reporting alone.

Forecasting is the process of estimating future values or conditions based on available historical data patterns. In the context of higher education, forecasting is used to help institutions obtain a predictive picture of conditions that may occur in the following period. This approach is important because higher education institutions not only need information about past data but also need future estimates as a basis for academic and managerial planning. In new student admissions, forecasting can be used to estimate the number of students likely to register in the following year. This information can help higher education institutions, including religious higher education institutions, prepare policies related to capacity, resource needs, study program management, and student admissions strategies. This perspective positions forecasting accuracy as a managerial requirement because forecast errors can translate into mismatches between expected registrations and institutional capacity.

After new student admission data are represented as a multivariate time series, the next stage is to perform feature engineering. This stage is conducted so that the data used as model inputs are not only raw data but also contain additional information that is more closely aligned with the characteristics of the admission domain. Raw data such as capacity, number of applicants, and number of registrations are indeed important but do not fully explain the relationships between admission pathways, competition levels, and historical registration patterns from year to year (Saravana et al., 2026; Shih et al., 2019). Therefore, derived features are needed that can help the model understand the data more informatively. In the present study, feature engineering therefore serves a domain-representation function: it translates raw admission counts into variables that express pathway share, competitive pressure, and temporal persistence.

In this research, feature engineering is conducted by forming four main feature groups, namely, share features, pressure features, lag features, and t+1 forecasting targets. Share features are used to describe the proportion of capacity and applicants accounted for by each admission pathway. Pressure features are used to describe the level of pressure or competition between the number of applicants and capacity. Lag features are used to capture historical registration patterns from the previous year, while the t+1 forecasting target is used to define the prediction target for student registrations in the following year.

After the feature engineering process is completed, the next stage is to arrange the data into sequence form. Sequence building is the process of forming historical data into input sequences based on specific time periods so that they can be used by prediction models (Farisi et al., 2024; Kong et al., 2025). In time-series data, the temporal order cannot be ignored because values in one period may be related to previous periods. Therefore, data are not only treated as a collection of ordinary rows but are arranged into historical sequences that can be learned by the model.

In this research, sequence building is conducted so that the model can use historical new student admission information before predicting registrations in the following year. The admission data used span the years 2017 to 2025. Because the number of observation years is relatively limited, this research uses a lookback window of 2 years. This means that the model uses information from the two previous years as a basis for predicting the target in the following year. The selection of a 2-year lookback window is also consistent with the historical features that have been previously formed, namely, lag1 and lag2.

After the data are formed into sequences, the next stage is scaling or normalization of feature values. Scaling is the process of transforming feature values to a common numerical scale so that differences in magnitude among features do not disproportionately influence model training (Pranolo et al., 2024). This stage is important because admission data contain features with different value ranges. For example, the number of applicants can have values far larger than share or pressure features (Harahap & Alfadri, 2021; Wahyudin et al., 2025). If this scale difference is left unaddressed, the model may be more strongly influenced by features with large numerical values (Lima & Souza, 2023), even though features with smaller values may also contain important information.

SHAP (SHapley Additive exPlanations) is one of the methods used in Explainable AI to explain the contribution of each feature to a model's prediction results. SHAP is developed based on the Shapley value concept from game theory, a concept used to calculate how much each player contributes to the final outcome of a game. In the context of machine learning, these "players" are represented by features, while the "final outcome" is represented by the model's prediction output (Neubauer et al., 2025; Parisineni & Pal, 2024).

Simply put, SHAP answers the questions: Which features most influence the prediction results, and do those features drive the predictions higher or lower? This is important because deep-learning models such as CNN-LSTM can produce good predictions, but the internal processes of such models are not easily understood directly. With SHAP, prediction results are not only presented as numerical outputs but can also be explained based on the contribution of each input feature (Agustina et al., 2022; Puspanagara, 2025; Saputra & Pratama, 2025). The literature consequently suggests that an effective admission-forecasting framework should combine predictive performance with feature-level explanations, which motivates the integration of CNN-LSTM and SHAP in this study.

Previous studies demonstrate several relevant directions but leave an identifiable gap. James and Weese (2022) applied neural-network-based enrollment forecasting, Bousnguar et al. (2022) compared forecasting approaches in higher education, Liu et al. (2025) used machine learning to inform admission decisions, and Livieris et al. (2020) demonstrated the forecasting potential of CNN-LSTM in a different time-series domain (Kabir et al., 2025; Livieris et al., 2020).

Kabir et al. (2025) further demonstrated a hybrid LSTM-Transformer architecture, while van Zyl et al. (2024) highlighted the role of SHAP in interpreting time-series models. Taken together, these studies support predictive modeling, hybrid architectures, and explainability, but they do not integrate domain-based admission feature engineering, CNN-LSTM, multivariate t+1 forecasting, and SHAP within a single framework for religious higher education admissions.

Based on the multivariate and temporal characteristics of admission data, this research proposes the use of CNN-LSTM as the main prediction model. CNN is chosen for its ability to extract local patterns among multivariate features, while LSTM is chosen for its ability to capture temporal dependencies from historical data. Additionally, SHAP is used to explain the contribution of each feature to the prediction results, so that the model not only produces predictions but can also be interpreted by institutional stakeholders.

The research gap is therefore both methodological and contextual. Prior studies commonly emphasize a single forecasting model or predictive accuracy, while interpretability is often treated separately. Moreover, limited attention has been given to the simultaneous interaction of admission pathways, capacity, applicant pressure, and recent registration history in religious higher education. Without an explainability layer, an accurate deep-learning forecast remains difficult for institutional decision-makers to interrogate and translate into policy.

This study addresses these gaps by integrating multivariate time-series representation, domain-informed feature engineering, CNN-LSTM, comparative model evaluation, and SHAP-based global and local interpretation. The novelty lies in treating admission forecasting as an explainable multivariate decision-support problem rather than as a purely predictive task. The study aims to identify the best-performing forecasting model, estimate 2026 registrations by pathway and total enrollment, and explain the features driving those predictions. The results are expected to support admission quota setting, promotional prioritization, lecturer and classroom planning, and evidence-based program management.

METHOD

This study employed a quantitative predictive design using a multivariate time-series forecasting approach. The research was conducted using historical new student admission data from UIN Ar-Raniry, Banda Aceh, Indonesia. The analytical workflow was designed to compare baseline machine-learning, deep-learning, and hybrid models and subsequently interpret the best-performing model using SHAP.

The data source was the institutional new student admission dataset for 2017–2025. Data collection was conducted through documentary analysis and covered annual admission records for each study program and admission pathway. Before modeling, the records were validated for duplicate observations, missing or inconsistent values, pathway labels, and nonnegative numeric counts. The cleaned records were then ordered by study program and year to preserve the temporal structure of the data.

The dataset covered 40 study programs and three admission pathways (SPAN-PTKIN, UMPTKIN, and Mandiri) over nine years, yielding 360 program-year observations. The raw data contained six core fields: year, study program, admission pathway, capacity, number of applicants, and number of registrations. These fields were transformed into multivariate input features comprising share, pressure, lag1, and lag2 variables, while four t+1 target variables were predicted: SPAN-PTKIN registrations, UMPTKIN registrations, Mandiri registrations, and total registrations. A two-year lookback window was used to construct the forecasting sequences.

The computational analysis was implemented in Python. TensorFlow/Keras was used for deep-learning architectures, scikit-learn for baseline models, preprocessing, and evaluation, and the SHAP library for model interpretability. The data were split temporally into training, validation, and test sets to prevent future information from entering earlier periods, and scaling parameters were fitted only to the training data to reduce data leakage. Model performance was evaluated using MAE, RMSE, MAPE, and R^2: MAE provides an intuitive measure of the average error in student counts, RMSE assigns greater weight to larger forecasting errors, MAPE expresses error as a relative percentage, and R^2 indicates the proportion of variance in the observed data explained by the model. The best-performing model was selected based on its average performance across five iterations and was subsequently used for 2026 forecasting and SHAP interpretation.

RESULTS AND DISCUSSION

Analysis of the Best Model

Based on the evaluation results of all models in the previous section, CNN-LSTM was selected as the best model in this research. This model achieved an MAE of 6.0394, an RMSE of 8.6185, a MAPE of 27.7548%, and an R^2 of 0.9167. These values indicate that CNN-LSTM has the lowest prediction error among the tested models while also demonstrating the strongest ability to capture variations in the actual data.

The selection of CNN-LSTM as the best model was based on a performance comparison with all tested models. This model not only performed better than baseline machine learning models such as Linear Regression, Random Forest, and XGBoost but also outperformed several other deep learning models, including LSTM, Transformer, LSTM-Attention, BiLSTM, BiLSTM-Attention, and Hybrid LSTM-Transformer-MLP. Thus, CNN-LSTM was considered the most suitable model for forecasting new student registrations for 2026.

CNN-LSTM is well suited to the structure of the admissions dataset because its two components perform complementary representation-learning tasks. The convolutional stage can extract short-range patterns and interactions among multivariate inputs such as capacity, applicants, share, pressure, and lag features, whereas the LSTM stage retains sequential information across the two-year lookback window. This architecture reduces the burden on the recurrent layer to learn all cross-feature interactions directly and provides a compact representation before temporal dependencies are modeled.

The results also indicate that architectural complexity alone does not guarantee superior performance. Although the Hybrid LSTM-Transformer-MLP contains more modeling components, it performed below CNN-LSTM on this dataset. A plausible explanation is the relatively limited sample size—40 study programs observed across 2017–2025—which favors an architecture with sufficient nonlinear capacity but fewer degrees of freedom than a more complex hybrid architecture. This interpretation is consistent with the principle that model complexity should be proportional to data volume and signal structure rather than maximized independently of the dataset.

When compared with LSTM and BiLSTM models, CNN-LSTM also demonstrated better performance. This indicates that using CNN before LSTM helps the model obtain better feature representations before learning temporal patterns. In other words, CNN helps extract patterns from relationships among features, while LSTM continues this process by learning relationships according to temporal order. This combination makes CNN-LSTM more effective for learning from admissions data that are both multivariate and temporal. The finding is consistent with Livieris et al. (2020), who reported that CNN-LSTM can benefit time-series forecasting by combining local feature extraction with recurrent temporal learning (Ji et al., 2026). In contrast, Kabir et al. (2025) found value in a more complex LSTM-Transformer-MLP architecture for financial data; the different outcome here is likely related to the smaller educational dataset and its program-year structure, highlighting the importance of domain- and sample-sensitive model selection.

Practically, the MAE of 6.0394 indicates that the average prediction error of CNN-LSTM is approximately six students. The RMSE of 8.6185 shows that the model also has relatively small large errors compared with the other models. The R^2 of 0.9167 indicates that the model can explain most of the variation in the actual data. Based on these results, CNN-LSTM can be considered sufficiently stable and feasible for use as the final model in this research.

Based on this analysis, CNN-LSTM was used in the next stage to forecast new student registrations for 2026. The forecasting results from this model were then interpreted using SHAP to determine the features that contributed most to the predictions, both for total registrations and for each admission pathway, namely SPAN-PTKIN, UMPTKIN, and Mandiri.

2026 Registration Forecasting Results

After CNN-LSTM was established as the best model, the next stage was to forecast new student registrations for 2026. This forecasting was conducted using the latest historical data that had undergone feature engineering, time-series sequence formation, and scaling. The prediction results at this stage were used to estimate the number of new student registrations in 2026 for each study program.

The model output consists of four prediction targets, namely SPAN-PTKIN pathway registrations, UMPTKIN pathway registrations, Mandiri pathway registrations, and total new student registrations. Thus, the forecasting results not only provide an overall picture of total registrations but also show registration estimates for each admission pathway.

The 2026 forecasting results are presented as prediction values for each study program. The prediction values generated by the model are in decimal form and are then rounded for easier interpretation in the context of student numbers. This rounding is performed because the number of student registrations is a discrete, integer-valued quantity.

Table 1

Predicted 2026 New Student Registrations by Admission Pathway and Total Output

Prediction Component	Total Prediction
SPAN-PTKIN registration prediction 2026	894
UMPTKIN registration prediction 2026	1,228
Mandiri registration prediction 2026	950
Total registration prediction 2026 based on model output	3,025
Total registration prediction 2026 based on pathway	3,072

The forecasting results show a direct total registration prediction of 3,025 students for 2026, whereas the sum of the three pathway-specific predictions is 3,072 students. The 47-student difference arises because total registration was modeled as an independent target rather than as a deterministic sum of the three pathway-specific outputs. Consequently, the four outputs should be interpreted as simultaneous model estimates, and the direct total forecast should be used when reporting the model's total-registration target.

By admission pathway, the highest registration prediction is for the UMPTKIN pathway, with a total of 1,228 students, followed by the Mandiri pathway with 950 students and the SPAN-PTKIN pathway with 894 students. These results indicate that the model estimates the UMPTKIN pathway to have the largest contribution to registrations in 2026.

Based on the study program data, the highest total registration prediction is for Islamic Economic Law, with 246 students, followed by Islamic Economics with 244 students, English Language Education with 210 students, Islamic Religious Education with 207 students, and Islamic Banking with 203 students. These study programs are predicted to have higher registration numbers than the other study programs in 2026.

Meanwhile, several study programs have relatively low registration predictions, such as Chemistry, Biology, Chemistry Education, Religious Studies, and Physics Education. These results indicate variation in predictions across study programs. Such variation is expected because each study program has different historical patterns, capacities, numbers of applicants, and registration levels in previous years.

Additionally, for several study programs, the forecasting results show zero prediction values for certain pathways. These values do not necessarily indicate that the model failed to produce a prediction; rather, they may reflect historical data patterns in which the study program had no capacity, applicants, or registrations for that particular admission pathway. Thus, zero prediction results need to be interpreted in the context of the availability of admission pathways for each study program. Conversely, prediction results for other pathways can still be positive if the study program has a historical admission pattern for those pathways.

These forecasting results should be understood as estimates based on historical patterns learned by the CNN-LSTM model. The 2026 prediction values cannot yet be compared with actual data because actual registration data for 2026 were not available at the time the research was conducted. Therefore, these results serve as an initial projection that can help institutions understand the possible pattern of new student registrations in the following year.

Global SHAP Interpretation

Global SHAP interpretation was conducted to determine the features that most influence the overall prediction results of the CNN-LSTM model. At this stage, SHAP was used to explain the new student registration forecasts for 2026, both for total registration predictions and for predictions based on admission pathways. This global interpretation does not focus on a specific study program but instead examines the pattern of feature contributions across all prediction data.

In this research, global interpretation is presented through two visualization forms, namely the global feature importance plot and the summary plot. The global feature importance plot is used to rank features based on their mean absolute SHAP values. The larger the absolute SHAP value of a feature, the greater its overall influence on the model's prediction results. Meanwhile, the summary plot is used to examine the direction of feature influence and whether certain feature values tend to increase or decrease predictions.

In general, the SHAP results show that historical registration features are the most dominant group of features in shaping the prediction model. Additionally, capacity features, the number of applicants, and engineered features such as share and pressure also appear as contributing factors. This indicates that the CNN-LSTM model not only utilizes past registration data but also considers admission capacity conditions and prospective-student interest.

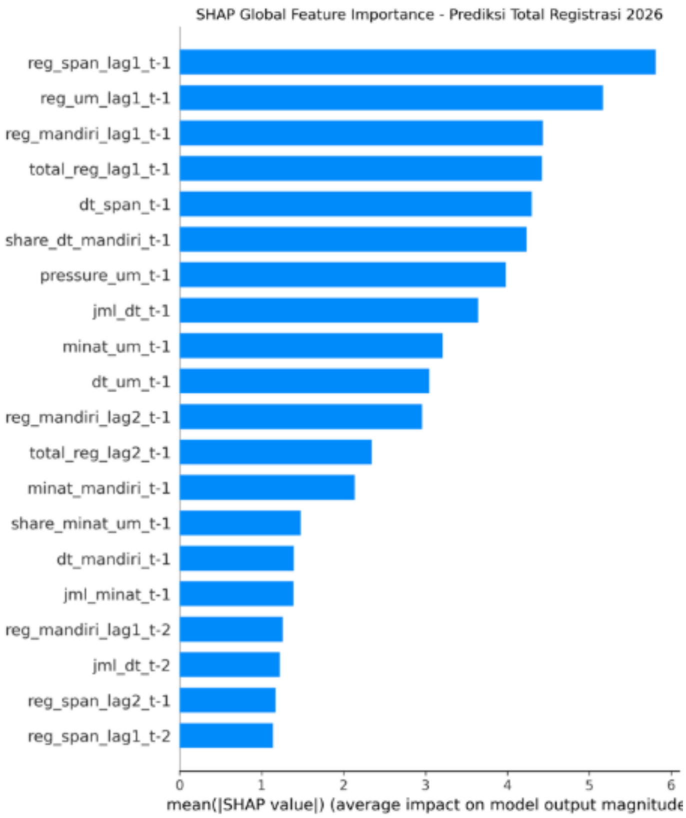

Figure 1. Global Feature Importance for Total Registration Prediction in 2026

Based on the figure above, it can be understood that the CNN-LSTM model places considerable importance on registration patterns from the previous year when forming the total registration prediction for 2026. This is consistent with the characteristics of time-series data because values from the previous period often provide important information for describing values in the following period. In the context of admissions, study programs that had high registration levels in the previous year tend to provide strong signals for the following year's registration predictions.

In addition to historical registration features, several other features also make substantial contributions, such as dt_span_t-1, share_dt_mandiri_t-1, pressure_um_t-1, jml_dt_t-1, minat_um_t-1, and dt_um_t-1. The emergence of capacity, applicant, share, and pressure features shows that total registration predictions are influenced not only by registration history but also by admission capacity and interest levels in specific admission pathways. This is important because admissions data are inherently both temporal and multivariate.

Based on the summary plot, features such as reg_span_lag1_t-1, reg_um_lag1_t-1, total_reg_lag1_t-1, and dt_span_t-1 appear to make substantial contributions to the model output. High feature values for several historical features tend to appear on the right side of the plot, indicating that high registration levels in the previous period tend to drive total registration predictions upward. Conversely, low feature values tend to appear on the left side and can lower predictions.

These results show that the CNN-LSTM model uses a combination of historical registration patterns and capacity features to predict total registrations for 2026. In other words, total registration predictions are not determined by a single feature but by the interaction of several complementary features. Historical features provide information about past patterns, while capacity, applicant, share, and pressure features provide context regarding admission conditions.

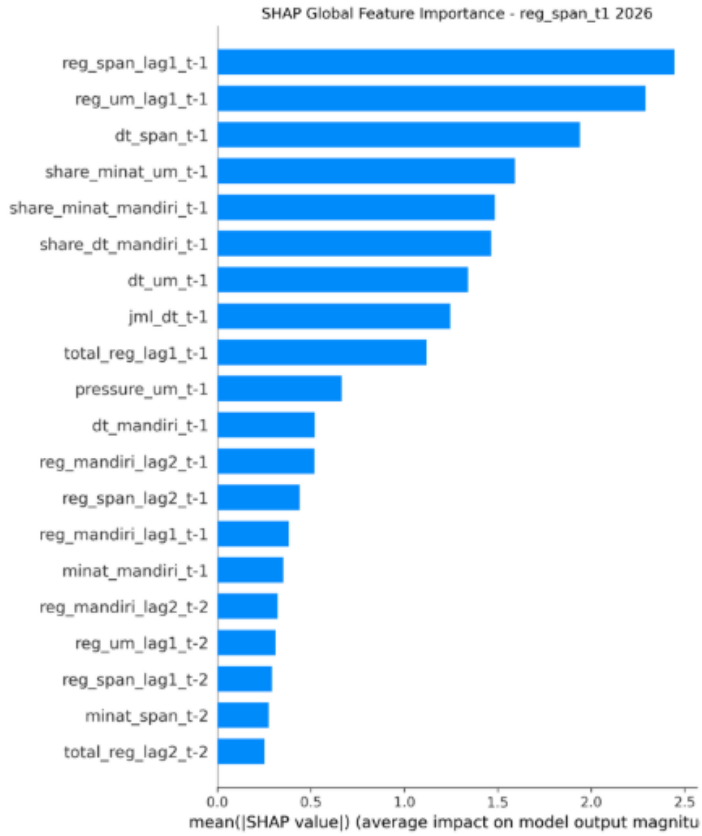

Figure 2. Global Feature Importance for SPAN-PTKIN Registration Prediction in 2026

These results indicate that SPAN registration predictions are primarily influenced by SPAN registration history from the previous year. The emergence of dt_span_t-1 also shows that capacity in the SPAN pathway is an important factor in the prediction. In addition, the features share_minat_um_t-1 and share_minat_mandiri_t-1 show that interest patterns in other pathways also provide information to the model. This is plausible because, in admissions, changes in interest in one pathway can be related to dynamics in other pathways.

Based on the SPAN summary plot, historical features such as reg_span_lag1_t-1 and reg_um_lag1_t-1 have clear contribution distributions across the predictions. High feature values tend to provide positive contributions for some observations, whereas low values can lower predictions. This indicates that the model utilizes historical information and SPAN pathway capacity to form SPAN registration predictions for 2026.

These results show that UMPTKIN predictions are influenced not only by UMPTKIN registration history but also by SPAN registration history and capacity in both the SPAN and UMPTKIN pathways. The emergence of dt_um_t-1, minat_um_t-1, share_minat_um_t-1, and pressure_um_t-1 shows that features directly related to the UMPTKIN pathway still play a role in forming predictions. Thus, the model represents the UMPTKIN pathway as part of an admissions system interconnected with other pathways.

In the UMPTKIN summary plot, features such as reg_span_lag1_t-1, reg_um_lag1_t-1, dt_span_t-1, and dt_um_t-1 have clearly visible SHAP value distributions. High feature values for some of these variables tend to drive predictions upward. This indicates that UMPTKIN predictions are formed through a combination of registration history and admission capacity, particularly from the SPAN and UMPTKIN pathways.

For the Mandiri registration prediction, the global feature importance results show a more specific pattern for the Mandiri pathway. The most influential feature is reg_mandiri_lag1_t-1, followed by pressure_um_t-1, share_minat_mandiri_t-1, minat_mandiri_t-1, and dt_mandiri_t-1.

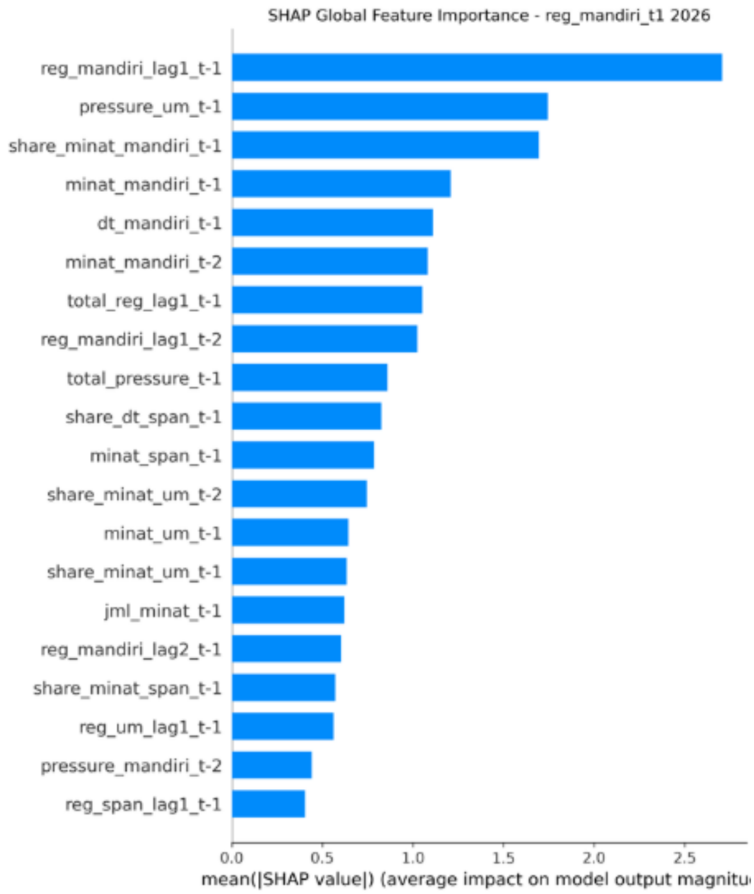

Figure 3. Global Feature Importance for Mandiri Registration Prediction in 2026

These results indicate that Mandiri registration predictions are highly influenced by Mandiri registration history from one year prior. In addition, the features share_minat_mandiri_t-1, minat_mandiri_t-1, and dt_mandiri_t-1 show that interest and capacity in the Mandiri pathway are also important factors. Interestingly, pressure_um_t-1 also appears as an important feature, showing that pressure on the UMPTKIN pathway can provide additional information about Mandiri registration patterns. This can be understood because admission pathways do not operate independently but are interconnected through prospective students' pathway choices.

Local SHAP Interpretation

Local SHAP interpretation is used to explain the contribution of features to the prediction results for each study program. Unlike global interpretation, which shows overall patterns of feature contributions, local interpretation focuses on a specific prediction case. In this research, local interpretation was conducted for 40 study programs across four prediction targets, namely SPAN-PTKIN registrations, UMPTKIN registrations, *Mandiri* registrations, and total registrations for 2026.

The visualization used for local interpretation is the force plot. In a force plot, the model's prediction value is explained as the result of the model's base value being influenced by the contributions of individual features. Features that provide positive contributions drive the prediction value upward, whereas features that provide negative contributions lower the prediction value.

The local interpretation results in this research produced force plots for each combination of study program and prediction target. Overall, there are 160 force plots originating from 40 study programs and four prediction targets. If all force plots were displayed in the main discussion, the discussion would become too long and difficult to read. Therefore, the local SHAP interpretation results are also summarized in table form so that feature contributions for each study program can be presented more concisely.

The local SHAP interpretation summary contains information on the study program, prediction target, 2026 prediction value, features that increase the prediction, and features that decrease the prediction. Each study program has a different pattern of feature contributions to its prediction results. These differences arise because each study program has different historical registration conditions, capacity, number of applicants, and admission pathway characteristics. Thus, prediction results for each study program are not determined by a single feature but are formed from a combination of several interrelated features.

In the Architecture study program, predictions for the SPAN-PTKIN and UMPTKIN pathways are low. This is evident from the absence of features that increase predictions for either target, while features that decrease predictions are dominated by share features, historical registration features, and certain admission pathway features. However, for the *Mandiri* pathway, the Architecture study program still has a positive prediction value. This condition shows that low predictions for one pathway do not necessarily imply low total registrations for that study program because other pathways can still contribute to the total prediction.

In the Islamic Economics and Islamic Economic Law study programs, several historical registration features, such as reg_span_lag1_t-1, reg_um_lag1_t-1, and total_reg_lag1_t-1, appear to provide positive contributions to predictions. This indicates that registration patterns in the previous period remain important information for the model when forming 2026 predictions. In addition, features such as jml_dt_t-1, dt_mandiri_t-2, pressure_um_t-1, and minat_um_t-1 also influence predictions, indicating that the model not only uses registration history but also considers capacity and interest across admission pathways.

In the Family Law study program, feature contributions appear more varied. Some features, such as share_minat_um_t-1, total_reg_lag1_t-1, and dt_um_t-1, drive predictions for certain pathways, whereas other targets contain features that lower predictions. This shows that each prediction target has different feature-contribution characteristics, even when the targets originate from the same study program.

In general, the local SHAP interpretation summary shows that features from period t-1 appear more frequently as influential features than those from period t-2. This means that the CNN-LSTM model utilizes historical information closest to the prediction year more heavily. This finding is consistent with the characteristics of admissions data because registration conditions, capacity, and interest in the most recent year tend to be more relevant for estimating registrations in the following year.

In addition, the emergence of share and pressure features in the local interpretation results shows that the feature engineering process provides additional information to the model. These features help the model capture the proportion of capacity, the proportion of applicants, and applicant pressure relative to admission capacity. Thus, the local interpretation results not only show which features are influential but also demonstrate that domain-based engineered features play a role in forming predictions.

Based on the four force plots for the Architecture study program, each prediction target appears to have a different feature-contribution pattern. Predictions for the SPAN-PTKIN and UMPTKIN pathways tend to be low because features that lower predictions are more dominant, and there are no sufficiently strong features to drive predictions upward. Conversely, for the *Mandiri* pathway, several features provide positive contributions, resulting in higher *Mandiri* predictions than those for the other pathways. This shows that the CNN-LSTM model represents the Architecture study program as being more strongly influenced by the *Mandiri* pathway when forming 2026 registration predictions. Thus, local SHAP interpretation can explain why prediction results differ across pathways, as each target is influenced by a different combination of features.

Discussion

The findings show that predictive performance in this admissions context depends on combining domain representation, temporal learning, and interpretability. Rather than treating feature engineering, model selection, and SHAP as independent technical steps, the results indicate that these components form a coherent forecasting pipeline: engineered features encode admission conditions, CNN-LSTM learns cross-feature and temporal patterns, and SHAP translates the learned relationships into explanations that institutional users can examine.

The role of feature engineering is supported by the SHAP results, in which lag, capacity, share, and pressure variables repeatedly contributed to predictions. This extends the general feature-selection argument of Huang et al. (2024) by showing that domain-derived features can be substantively meaningful in higher-education forecasting. The stronger contribution of t-1 variables relative to t-2 variables also supports the time-series assumption that recent observations contain more immediately relevant information for the next forecasting period (Kong et al., 2025; Wen & Li, 2023).

CNN-LSTM outperformed the baseline, recurrent, attention-based, Transformer, and hybrid alternatives because it provides a balanced representation of multivariate and temporal structures. The result is consistent with Livieris et al. (2020), who demonstrated the complementary value of convolutional feature extraction and LSTM sequence learning (Ji et al., 2026). It differs from Kabir et al. (2025), in which a more complex LSTM-Transformer-MLP architecture was effective for financial time series; the difference suggests that architecture performance is sensitive to sample size, domain volatility, feature structure, and available historical depth.

From an Explainable AI perspective, the dominance of recent registration features and the contribution of capacity and applicant-pressure variables demonstrate that high predictive accuracy can be accompanied by interpretable feature attribution. This finding aligns with van Zyl et al. (2024) and Neubauer et al. (2025), who showed that SHAP-based interpretation can clarify the drivers of time-series forecasts. In the present context, global SHAP explains institution-wide patterns, whereas local force plots reveal why individual study-program forecasts move upward or downward.

The pathway-specific forecasts add practical value because aggregate registration totals alone cannot reveal where demand is expected to enter the institution. Higher UMPTKIN estimates and variation across study programs indicate that capacity and recruitment decisions should be differentiated by pathway and program. Low or zero pathway predictions should be interpreted against each program's historical pathway availability rather than automatically being treated as model failure.

These findings have direct managerial implications. The institution can use the forecasts to review admission quotas, prioritize promotional resources for programs with weaker expected demand, align lecturer allocation and classroom capacity with projected registrations, and document evidence-based planning for accreditation and program sustainability. SHAP explanations further allow managers to distinguish whether a forecast is driven mainly by recent registrations, capacity, applicant interest, or competitive pressure, making the model more actionable than an unexplained numerical forecast.

With local SHAP interpretation, 2026 prediction results can be explained not only at the global level but also at the study-program level. This is one of the important findings of this research because institutions can obtain information about generally influential features while also identifying the factors that drive or lower predictions for specific study programs. Thus, SHAP helps make forecasting results easier to understand and more supportive of data-driven decision-making. Academically, this study contributes an integrated explainable forecasting framework for religious higher education admissions by linking multivariate time-series theory, domain-informed feature engineering, CNN-LSTM representation learning, and SHAP-based interpretation. This combination addresses the research gap between accurate forecasting and decision-oriented explainability.

CONCLUSION

This study achieved its objectives by developing and evaluating an explainable multivariate forecasting framework for new student registration at a religious higher education institution. CNN-LSTM provided the strongest predictive performance among the compared models and was therefore used to estimate 2026 registrations across SPAN-PTKIN, UMPTKIN, *Mandiri*, and total registration. SHAP analysis showed that recent registration history was the dominant predictive signal, while capacity, applicant, share, and pressure features also contributed to model decisions, confirming that admission forecasting is both temporal and multivariate.

The principal contribution is the integration of domain-based feature engineering, CNN-LSTM, and global and local SHAP interpretation into a single admission decision-support framework. Practically, the approach can inform quota setting, recruitment strategy, lecturer and classroom allocation, and program-level planning while allowing stakeholders to examine the factors behind each forecast. Future studies should validate the framework across multiple religious higher education institutions, use longer historical series and external socioeconomic or demographic variables, and evaluate forecast accuracy and calibration against realized 2026 registration data to test generalizability and temporal robustness.

ACKNOWLEDGEMENT

The authors acknowledge UIN Ar-Raniry, Banda Aceh, Indonesia, as the source of the historical new student admission data used in this study. The authors also express their appreciation to Institut Teknologi Sepuluh Nopember, Indonesia, for the academic environment and scholarly support that contributed to the completion of this research. The authors are grateful to all parties who provided valuable support during the preparation, analysis, and completion of this study.

AUTHOR CONTRIBUTION STATEMENT

Alit Fajar Kurniawan, Umi Laili Yuhana, and Bilqis Amaliah contributed to the conceptualization and development of the study, methodological design, interpretation of the findings, and critical review of the manuscript. The authors collectively contributed to improving the intellectual content of the manuscript, reviewed the final version, and approved the manuscript for publication. All authors agree to be accountable for the accuracy and integrity of the work.

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