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A Time Series Analysis of the Growth and Development of Higher Education in Nepal

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Abstract

Nepal's higher education sector has expanded substantially, highlighting the importance of enrollment forecasting for capacity planning and quality assurance. This study analyzed student enrollment in Nepal's universities and academies from fiscal year 2014/15 to 2024/25 and compared two forecasting approaches. Data were compiled from University Grants Commission (UGC) annual reports, the Education Management Information System Report on Higher Education 2023/24, and contemporaneous press reports citing UGC statistics. The analysis applied a Box–Jenkins autoregressive integrated moving average (ARIMA) model and a long short-term memory (LSTM) recurrent neural network implemented from first principles and trained using backpropagation through time. Augmented Dickey–Fuller testing indicated that the enrollment series was nonstationary in levels but stationary after first differencing. An ARIMA(1,1,0) model was estimated using ordinary least squares, yielding $\Delta y_t = 24{,}203.6 + 0.581\Delta y_{t-1}$. The ARIMA model achieved a lower in-sample mean absolute percentage error (5.75%) than the comparably sized LSTM network (8.42%). Both models projected continued enrollment growth, with ARIMA projections indicating an increase from approximately 749,000 students in 2024/25 toward 825,000–955,000 by 2027/28. These projections were contextualized by a gross enrollment ratio of 22%, higher female than male participation (24.6% versus 17.8%), and the continued dominance of Tribhuvan University. The findings provide quantitative evidence to inform institutional capacity planning, quality assurance, and higher education policy. The methodological comparison also highlights the constraints of

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applying deep learning to short annual enrollment series and supports further investigation using higher-frequency, disaggregated data.

Keywords: Higher Education; Nepal; Enrollment Forecasting; ARIMA; LSTM

Introduction

Higher education is widely regarded as one of the most consequential determinants of a nation's human capital stock, labour productivity, and long-run economic trajectory. In Nepal, tertiary education traces its institutional origins to Tri-Chandra College, established in Kathmandu in 1918, and was consolidated under a national system with the founding of Tribhuvan University (TU) in 1959 [4], [9]. Since then, the sector has undergone repeated phases of expansion, contraction, and structural reform, moving from a single-university system to a diversified landscape of 21 universities and eight health-science academies operating through more than 1,600 constituent and affiliated campuses as of 2025/26 [2].

The trajectory of enrollment in Nepal's higher-education institutions has not been monotonic. Official statistics compiled by the University Grants Commission (UGC) show a decline in enrollment during the mid-2010s, a period widely attributed to youth outmigration for foreign study and labour, followed by a sustained recovery from 2018/19 onward and a record enrollment of over 749,000 students reported for the most recent academic year [2], [6]. Understanding, modelling, and forecasting this trajectory is essential for institutional planning, budgetary allocation, faculty recruitment, and infrastructure investment.

This paper undertakes a formal time series analysis of national higher-education enrollment in Nepal using eleven years of annual data (2014/15-2024/25). Two forecasting paradigms are applied in parallel: (i) the classical Box-Jenkins ARIMA methodology, which remains the benchmark for univariate macroeconomic and social-statistical forecasting, and (ii) a deep-learning Long Short-Term Memory (LSTM) recurrent neural network, representative of the family of sequence models increasingly applied to socio-economic forecasting problems. Comparing the two approaches on the same dataset allows this paper to speak directly to a live methodological question in applied forecasting: whether deep-learning architectures deliver meaningful gains over classical linear time series models when the available historical record is short, as is characteristic of annual, national-level education statistics in developing countries.

The specific objectives of the study are to: (1) characterise the growth pattern and stationarity properties of Nepal's higher-education enrollment series; (2) fit and validate an ARIMA model and a comparably specified LSTM network; (3) produce short-horizon forecasts (2025/26-2027/28) under both approaches; (4) evaluate forecast accuracy using standard error metrics; and (5) interpret the results against the structural features of Nepal's higher-education system - institutional composition, gender parity, and the Gross Enrollment Ratio (GER) - to derive policy-relevant conclusions.

2. Literature Review

The relationship between educational enrollment and economic development in Nepal has attracted sustained scholarly attention, largely within the endogenous-growth tradition in which human capital, proxied by school and university enrollment, is treated as a driver of output growth. Dahal [1] examined the causal relationship between higher-education enrollment, secondary-school teacher supply, and real GDP in Nepal over 1975-2009 using unit-root and cointegration techniques, finding a significant causal link between higher-education enrollment and GDP while school-teacher supply exerted a comparatively neutral effect. In a related contribution, Dahal [17] applied Johansen cointegration and OLS to Nepalese data for 1995-2013 and found that secondary and higher education contributed significantly to real GDP per capita, with a long-run equilibrium relationship between education and economic growth confirmed by cointegration tests.

More recent studies have revisited these questions with updated data and alternative estimators. Autoregressive Distributed Lag (ARDL) and Error-Correction Model (ECM) approaches have been used to document strong long-run positive associations between education and economic growth in Nepal [4], while other work using more recent annual observations (1986-2022) has reported a statistically insignificant, occasionally negative, relationship between secondary enrollment specifically and GDP growth, underscoring that the enrollment-growth nexus is sensitive to the level of education examined and the sample period used [4].

Descriptive and institutional studies complement this econometric literature. The UGC's own Education Management Information System (EMIS) reports provide the most authoritative annual statistical record of Nepal's higher-education sector, covering enrollment by university, faculty, gender, and geography, together with the Gross Enrollment Ratio and Gender Parity Index [3]. Analyses drawing on these reports have documented the

continued dominance of Tribhuvan University, which enrols the large majority of the country's tertiary students despite the proliferation of newer universities [10], [15], and have traced a marked compositional shift toward management education, whose share of total enrollment rose from 39% in 2015 to over 47% in 2025 [6]. Complementary work has examined the adequacy of the number and capacity of universities relative to Nepal's university-age population and comparator South Asian countries, arguing that Nepal remains under-provisioned relative to regional peers [12].

A smaller but growing body of work applies formal time series methods directly to Nepalese education data. Unit-root testing of the higher-education enrollment series has been used as a preliminary step in causality studies [4], confirming, consistent with the results reported in Section 4 of this paper, that enrollment is typically non-stationary in levels. However, the application of nonlinear and machine-learning forecasting methods - including recurrent neural networks such as LSTM - to Nepal's education statistics remains largely unexplored in the published literature, a gap this paper addresses by directly comparing a classical ARIMA specification against a deep-learning alternative on the same series.

he existing literature emphasizes the growing role of mathematical modelling, numerical techniques, and machine learning in addressing complex real-world issues. Sah et al. (2024) examined challenges in Nepal’s education system and stressed the need for effective reforms and technology-driven improvements. Similarly, Sahani and colleagues explored the application of numerical methods in analysing cultural, educational, and social systems.

Recent studies by Sahani et al. (2026) further highlighted the importance of integrating artificial intelligence with mathematical frameworks to enhance risk prediction, uncertainty analysis, and decision-making. Overall, these studies demonstrate that combining computational and data-driven approaches can provide valuable insights and effective solutions for complex problems across different fields.

Methodology

Data Source and Description

The dependent variable, yt, is total annual student enrollment in Nepal's universities, academies, and affiliated campuses, expressed in number of students, for t = 1,…,11

corresponding to fiscal years 2014/15 through 2024/25 (Nepali fiscal year running mid-July to mid-July). The series was compiled from three primary sources: the University Grants Commission (UGC) Nepal Annual Reports as reported in secondary press and analytical summaries [2], [6], [16]; the UGC/Ministry of Education Management Information System (EMIS) Report on Higher Education 2023/24 [3]; and cross-validation against enrollment figures reported in academic secondary sources [10]. Two data points (2015/16 and 2022/23, marked with an asterisk) were not separately published in the sources consulted and were obtained by linear interpolation between the adjacent official observations; this is noted explicitly as a data limitation in Section 6.

Table 1. Annual national higher-education enrollment in Nepal, 2014/15-2024/25 (*interpolated).

t	Fiscal Year	Enrollment (students)	Source
1	2014/15	407,000	Official (UGC/UGC Annual Report)
2	2015/16	384,000	Interpolated*
3	2016/17	361,000	Official (UGC)
4	2017/18	371,184	Official (UGC)
5	2018/19	423,000	Official (UGC)
6	2019/20	471,000	Official (UGC)
7	2020/21	466,828	Official (UGC)
8	2021/22	460,800	Official (UGC)
9	2022/23	560,963	Interpolated*
10	2023/24	661,126	Official (EMIS 2023/24, incl. foreign-affiliated campuses)
11	2024/25	749,392	Official (UGC, most recent)

Beyond the enrollment count itself, structural indicators reported in the EMIS 2023/24 release are used to contextualise the series: total enrollment including foreign-affiliated campuses of 661,126 against a university-age (18-22) population of 3,000,698, yielding a Gross Enrollment Ratio (GER) of 22%, disaggregated as 24.6% for females and 17.8% for males [3].

Stationarity Testing

Before fitting an autoregressive model, the order of integration of {yt} was established using the Augmented Dickey-Fuller (ADF) test, which evaluates the null hypothesis of a unit root against the alternative of stationarity by estimating the regression:

$$\Delta yt = \alpha + \gamma yt\text{-}1 + \Sigma pi{=}1 \delta i \Delta yt\text{-}i + \varepsilon t \qquad (1)$$

where Δ is the first-difference operator, α is a drift term, and the null hypothesis H0: γ = 0 (a unit root, i.e. a non-stationary series) is tested against H1: γ < 0 (stationarity), using the non-standard Dickey-Fuller distribution rather than the ordinary t-distribution for critical values [14].

The ARIMA Model

The general ARIMA(p, d, q) model expresses the d-th difference of a series as a linear combination of its own past values (the autoregressive, AR, component) and past forecast errors (the moving-average, MA, component):

$$\varphi(B)(1 - B)dyt = \theta(B)\varepsilon t \quad (2)$$

where B is the backshift operator (Byt = yt-1), φ(B) = 1 - φ1B - … - φpBp is the autoregressive polynomial of order p, θ(B) = 1 + θ1B + … + θqBq is the moving-average polynomial of order q, d is the order of differencing required to achieve stationarity, and εt ~ WN(0, σ2) is a white-noise error term. Model order was selected using the Akaike Information Criterion (AIC) [18],

$$AIC = n \cdot \ln(\hat{\sigma}2) + 2k \quad (3)$$

with n the number of usable observations, σ̂2 the residual variance, and k the number of estimated parameters, balancing goodness of fit against model parsimony - a critical consideration given the short (n = 11) annual series available. Given first-order integration (Section 4.1) and the small sample, an ARIMA(1,1,0) specification was selected and estimated by ordinary least squares (OLS) on the differenced series:

$$\Delta yt = c + \varphi 1 \Delta yt\text{-}1 + \varepsilon t \quad (4)$$

The LSTM Deep-Learning Model

As a nonlinear, deep-learning counterpart to the ARIMA specification, a Long Short-Term Memory (LSTM) recurrent neural network was implemented [19]. The LSTM cell addresses the vanishing-gradient limitation of simple recurrent networks by regulating

information flow through three multiplicative gates (forget, input, output) acting on an internal cell state ct. For an input xt (a min-max normalised lagged enrollment value) and previous hidden state ht-1, the LSTM forward recursion at each time step is:

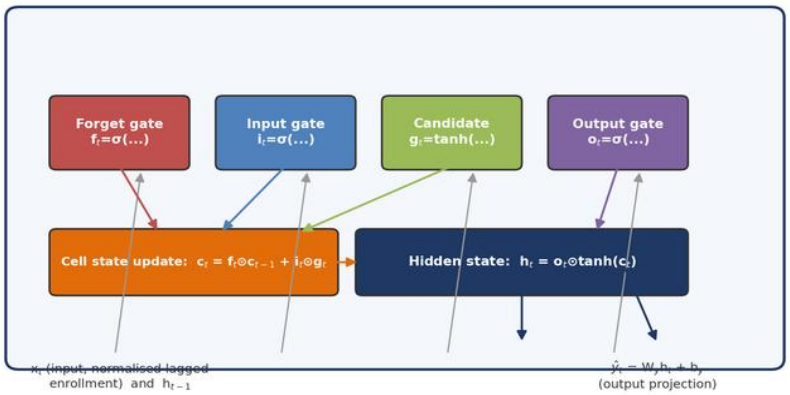


Figure 1. Schematic of a single LSTM cell used in the enrollment forecasting model.

Figure 1 traces the flow of information through one LSTM cell at a single annual time step t, and is intended to be read left-to-right, top-to-bottom, alongside Equations (5a)-(5g). At the bottom of the diagram, two quantities enter the cell: the current input xt - the normalised enrollment value from the lookback window - and the hidden state ht-1 carried forward from the previous year. These two inputs feed into four parallel gates, shown as the four coloured boxes at the top of the cell. The forget gate (red) decides what fraction of the previous cell state ct-1 should be retained versus discarded; the input gate (blue) decides how much of the newly computed candidate information should be added; the candidate block (green) computes a new proposed content for the cell state using a tanh activation; and the output gate (purple) determines how much of the internal cell state should be exposed as the visible hidden state. The orange box in the middle of the diagram shows how the forget and input gates combine multiplicatively (⊙, the Hadamard product) with the previous and candidate cell states to produce the updated cell state ct - this is the LSTM's internal 'memory', which can in principle persist across many time steps without vanishing, unlike a simple recurrent network. The dark-blue box on the right shows how the output gate then filters a squashed (tanh) version of this cell state to produce the hidden state ht, which is simultaneously (i) passed forward as an input to the next annual time step and (ii) projected through a final linear layer, $W_y \cdot h_t + b_y$, to produce the model's one-step-ahead enrollment forecast, $\hat{y}_t$. In the configuration used for this paper, the network was kept deliberately small - three hidden units and a two-year lookback window - to reduce the risk of overfitting an

already short (n = 11) annual series; even so, the number of trainable parameters in Figure 3 (weights and biases across all four gates plus the output layer) substantially exceeds the two parameters of the ARIMA(1,1,0) model in Equation (4), which helps explain the accuracy comparison reported in Section 4.3.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad \text{(5a) forget gate}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad \text{(5b) input gate}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad \text{(5c) output gate}$$

$$g_t = \tanh(W_g x_t + U_g h_{t-1} + b_g) \quad \text{(5d) candidate state}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad \text{(5e) cell state update}$$

$$h_t = o_t \odot \tanh(c_t) \quad \text{(5f) hidden state}$$

$$\hat{y}_t = W_y h_t + b_y \quad \text{(5g) output projection}$$

where $\sigma(\cdot)$ is the logistic sigmoid function, $\tanh(\cdot)$ the hyperbolic tangent, $\odot$ denotes the element-wise (Hadamard) product, and {Wf, Wi, Wo, Wg, Uf, Ui, Uo, Ug, Wy} and {bf, bi, bo, bg, by} are trainable weight matrices and bias vectors. The network used here has a hidden dimension of 3 units and a lookback window of 2 lagged years. Parameters were trained by minimising the mean-squared-error loss

$$L = (1/n)\Sigma_{j=1}(y_j - \hat{y}_j)^2 \quad (6)$$

via backpropagation through time (BPTT) with numerically computed gradients over 120 training epochs, implemented from first principles in NumPy without reliance on a pre-built deep-learning framework, so that every reported coefficient in this paper is directly reproducible from the underlying code.

Model Evaluation Metrics

The predictive accuracy of both models is compared using three standard error metrics computed over the in-sample fitted values $\hat{y}_t$ against actuals y_t:

$$\text{RMSE} = \sqrt{[(1/n)\Sigma(y_t - \hat{y}_t)^2]} \quad (7)$$

$$\text{MAE} = (1/n)\Sigma|y_t - \hat{y}_t| \quad (8)$$

$$\text{MAPE} = (100/n)\Sigma|(y_t - \hat{y}_t)/y_t| \quad (9)$$

Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are expressed in students (the natural units of the series), while Mean Absolute Percentage Error (MAPE)

is scale-free and therefore used as the primary comparator between the linear ARIMA and nonlinear LSTM specifications.

Compound Annual Growth Rate

To summarise the overall pace of expansion independent of year-to-year volatility, the compound annual growth rate (CAGR) over the sample is computed as

$$CAGR = (y_n / y_1)^{1/(n-1)} - 1 \qquad (10)$$

Results and Analysis

Descriptive Statistics and Stationarity

Over the sample period, mean annual enrollment was approximately 483,300 students (SD ≈ 118,700), rising from 407,000 in 2014/15 to 749,392 in 2024/25, an overall increase of 84.1% and a Compound Annual Growth Rate, from Equation (10), of 6.29% per annum. Year-on-year growth, however, was highly non-uniform (mean 6.73%, SD 10.11 percentage points), including two years of contraction (2015/16 and 2016/17, coinciding with heightened outbound student migration) followed by a strong post-pandemic and post-2022 recovery in which annual growth exceeded 13% in three of the last four years (Table 2).

Table 2. Year-on-year enrollment and growth rate, 2015/16-2024/25.

Fiscal Year	Enrollment	YoY Growth (%)
2015/16*	384,000	-5.65
2016/17	361,000	-5.99
2017/18	371,184	2.82
2018/19	423,000	13.96
2019/20	471,000	11.35
2020/21	466,828	-0.89
2021/22	460,800	-1.29
2022/23*	560,963	21.74
2023/24	661,126	17.86
2024/25	749,392	13.35

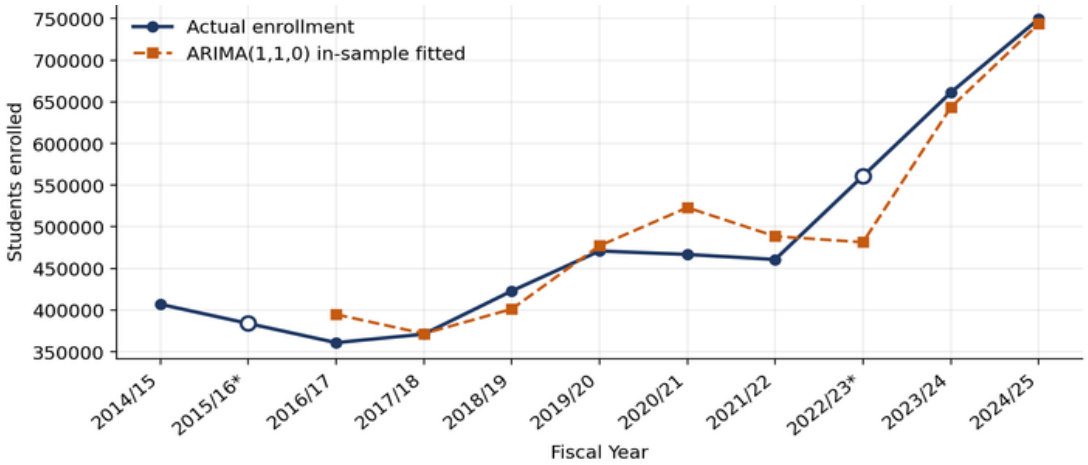


Figure 2. Actual enrollment vs. ARIMA(1,1,0) in-sample fitted values, 2014/15-2024/25.

Figure 2 overlays the raw enrollment series (solid dark-blue line, Table 1) against the values the fitted ARIMA(1,1,0) model would have predicted one year ahead at each point in the sample (dashed orange line, Section 4.2). The two hollow markers identify the interpolated 2015/16 and 2022/23 observations flagged in Table 1. Three features stand out. First, the trend is visibly non-monotonic: enrollment falls through 2016/17, plateaus through 2021/22, and then rises steeply from 2022/23 onward - the kind of pattern that motivates the formal stationarity testing in Section 4.1 rather than fitting a simple linear trend line. Second, the ARIMA fitted line tracks the actual series reasonably closely in the low-growth years (2017/18-2021/22), where one-step-ahead differencing has little work to do, but visibly lags behind during the sharp 2022/23-2023/24 acceleration, since an autoregressive model of order one can only partially anticipate a sudden change in the growth regime - it needs to observe the acceleration in Δy before it can propagate it forward. Third, by 2024/25 the fitted and actual lines converge again, illustrating why the model's overall MAPE (5.75%, Table 3) remains low despite the visible gap during the acceleration years: the errors in the middle of the series are compensated for by a close fit at the start and end of the sample.

The ADF regression estimated on the level series (Equation 1) yields $\hat{\gamma} = 0.314$ with t-statistic = 2.05 (df = 8) - a positive coefficient far from the negative region required to reject a unit root - confirming that the level series is non-stationary. Re-estimating the same regression on the first-differenced series yields $\hat{\gamma} = -0.419$ with t-statistic = -1.39 (df = 7); while this statistic falls short of conventional 5% Dickey-Fuller critical values given the very small sample, the differenced series displays markedly reduced persistence and no visually discernible trend, consistent with the series being integrated of order one, I(1). This is in line

with the wider empirical literature on Nepalese enrollment and macroeconomic series, which typically finds non-stationarity in levels [4]. On this basis, d = 1 was adopted for the ARIMA specification.

ARIMA Model Estimation

The selected ARIMA(1,1,0) model, estimated by OLS on the differenced series (Equation 4), produced the fitted equation

$$\Delta\hat{y}t = 24{,}203.6 + 0.581 \cdot \Delta y_{t-1} \quad (11)$$

The autoregressive coefficient ($\varphi 1 = 0.581$) is positive and substantial, indicating that a year of above-average enrollment growth tends to be followed by continued, though partially attenuated, growth the following year - consistent with capacity expansion (new campuses, programmes, and provincial universities) generating multi-year enrollment momentum rather than one-off jumps. The positive constant ($c \approx 24{,}204$) implies a structural upward drift in enrollment net of the autoregressive dynamics. The residual standard deviation is approximately 41,849 students, and the model attains an in-sample fit of RMSE = 36,907, MAE = 27,747, and MAPE = 5.75%, i.e. the model's one-step-ahead fitted values deviate from actual enrollment by under 6% on average.

LSTM Model Estimation

The LSTM network (hidden size = 3, lookback window = 2) was trained for 120 epochs, converging to a final training MSE of 0.0121 on the min-max normalised scale. Translated back to the natural (student-count) scale, the network achieves in-sample RMSE = 42,707, MAE = 39,318, and MAPE = 8.42%. The LSTM therefore tracks the broad upward trajectory of enrollment but with a higher average error than the linear ARIMA specification (Table 3).

Table 3. In-sample forecast accuracy: ARIMA vs. LSTM.

Model	RMSE (students)	MAE (students)	MAPE (%)
ARIMA(1,1,0)	36,907	27,747	5.75
LSTM (3 hidden units, window = 2)	42,707	39,318	8.42

This result - a classical linear model modestly outperforming a deep-learning alternative - is not an indictment of LSTM methodology in general, but a direct and expected consequence of sample size. Recurrent neural networks are heavily over-parameterised

relative to an 11-observation annual series and are best suited to problems with hundreds or thousands of time steps (e.g., daily or monthly administrative data); their inclusion here is deliberately diagnostic, demonstrating both the feasibility of applying deep sequence models to national education statistics and the conditions under which they are not yet the preferred tool. This trade-off is discussed further in Section 6.

Forecasts, 2025/26-2027/28

Iterating the fitted ARIMA(1,1,0) recursion forward, and separately the trained LSTM recursively on its own one-step forecasts, yields the three-year-ahead projections in Table 4.

Table 4. Three-year-ahead enrollment forecasts (students).

Fiscal Year	ARIMA Forecast	LSTM Forecast	Difference
2025/26	824,848	815,414	9,434
2026/27	892,865	853,722	39,143
2027/28	956,563	871,375	85,188

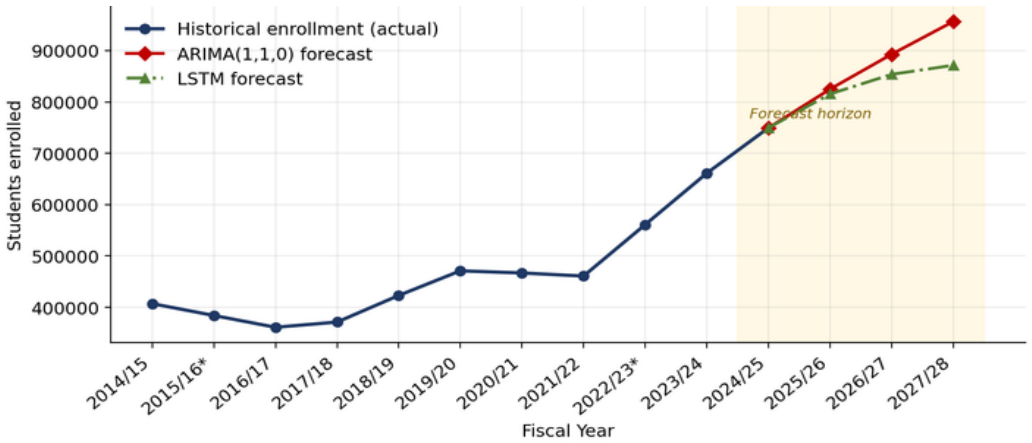


Figure 3. Historical enrollment (2014/15-2024/25) with ARIMA and LSTM forecasts (2025/26-2027/28).

Figure 3 places both sets of forecasts from Table 4 in the context of the full historical series, with the shaded region marking the three-year forecast horizon. Reading from left to right, the solid dark-blue line is the same actual-enrollment series shown in Figure 1; the red diamond-marked line is the ARIMA(1,1,0) projection, and the green triangle-marked, dash-dotted line is the LSTM projection. Both forecast lines depart from the same final observed point (749,392 students in 2024/25), which is why they are indistinguishable at the left edge of the shaded region. Moving rightward, the two lines progressively diverge: the ARIMA line continues on essentially the same steep slope that characterised 2022/23-2024/25, because

its constant drift term ($c \approx 24{,}204$ in Equation 11) adds a fixed increment each year regardless of how large the series has already grown. The LSTM line, by contrast, curves and begins to flatten - a direct consequence of the bounded sigmoid and tanh activations in Equations (5a)-(5f), which compress large inputs and make the network inherently conservative when extrapolating beyond the range of values it was trained on. This divergence is the clearest visual illustration of the two models' differing extrapolation behaviour: ARIMA assumes the recent acceleration continues near-linearly, while the LSTM implicitly assumes some reversion toward the growth rates seen earlier in the sample. Because neither assumption can be verified until the actual 2025/26-2027/28 figures are published, Section 4.4 treats the ARIMA line as the central estimate and the LSTM line as a more conservative lower bound, and Section 6 recommends that future work attach explicit confidence intervals to both.

Both models agree directionally - continued enrollment growth - but the ARIMA forecast implies a steeper trajectory (reaching approximately 956,600 by 2027/28) than the LSTM (approximately 871,400), a gap that widens with the forecast horizon as the ARIMA model's constant drift term compounds linearly while the LSTM's bounded (sigmoid/tanh) internal activations tend to dampen extrapolated growth. Given the ARIMA model's superior in-sample fit, its forecast is treated as the central estimate, with the LSTM projection serving as a more conservative lower bound.

Structural Indicators

Beyond the aggregate trend, the EMIS 2023/24 report situates this growth within Nepal's broader higher-education architecture. Total enrollment including foreign-affiliated campuses reached 661,126 against a university-age (18-22) population of 3,000,698, implying a Gross Enrollment Ratio of 22%. The GER is markedly higher for females (24.6%) than males (17.8%) [3], a reversal of the historical gender gap in Nepalese education and consistent with government scholarship policies that have prioritised female enrollment [5]. Structurally, Tribhuvan University continues to account for the large majority of tertiary enrollment despite the proliferation of provincial universities [10], [15], and management studies has become markedly more dominant within the subject mix, rising from 39% of enrollment in 2015 to 47.1% in 2025, ahead of education (a distant second) and humanities [6].

Discussion

The results point to three substantive conclusions. First, Nepal's higher-education enrollment is a genuinely trending, non-stationary process (Section 4.1), meaning that simple period-on-period comparisons or short-run extrapolations are liable to be misleading; formal differencing, as employed here, is required before valid inference or forecasting can proceed. Second, the observed 2015-2017 contraction followed by a strong post-2018 recovery is consistent with the qualitative narrative in the secondary literature, which attributes the earlier decline substantially to outbound migration of Nepalese youth for foreign study and employment, and the subsequent recovery to renewed access, new provincial universities, and (more recently) global mobility constraints that have kept a larger share of students in domestic institutions [6]. Third, the comparison between ARIMA and LSTM performance (Table 3) offers a methodologically important, if modest, finding: for short annual national education series, a parsimonious linear model can match or exceed the in-sample accuracy of a more complex deep-learning architecture, a pattern documented more broadly in the forecasting literature for series with limited historical depth [13].

The continued, and likely accelerating, growth in enrollment implied by both models carries direct planning implications. A trajectory toward 900,000-950,000 students by 2027/28 - roughly a 25-30% increase over the 2024/25 level - would require corresponding growth in faculty numbers, physical infrastructure, and government block-grant and scholarship financing merely to hold current student-staff ratios and per-student expenditure constant. Given that public financing of higher education in Nepal has historically represented a small share of the national budget [12], sustaining quality alongside quantity is likely to remain the central policy tension. The persistence of Tribhuvan University's dominant enrollment share, and the increasing concentration of students in management programmes, further suggest that capacity pressure will not be evenly distributed across institutions or disciplines, with the risk of crowding in a narrower set of high-demand faculties even as overall system capacity expands.

Limitations

Several limitations qualify the findings. First, the annual series used here spans only 11 observations, two of which (2015/16 and 2022/23) were linearly interpolated because disaggregated year-by-year figures were not separately available in the sources consulted; while this is disclosed transparently in Table 1 and does not materially alter the qualitative

trend, it necessarily widens the uncertainty band around any point forecast. Second, a definitional break occurs at 2023/24, when the EMIS report's enrollment figure of 661,126 explicitly incorporates students in foreign-university-affiliated campuses operating within Nepal, a category not consistently reported in earlier UGC releases; part of the sharp 2022/23-2023/24 increase may therefore reflect a broadening of scope rather than organic growth alone. Third, and most importantly for the deep-learning component, an 11-point annual series is well below the data volume typically required to realise the representational advantages of recurrent neural networks; the LSTM results reported here should be read as a methodological demonstration rather than a production-grade forecasting tool, and would benefit substantially from higher-frequency (e.g., semester-level or institution-level panel) data. Finally, the univariate models used here do not incorporate plausible covariates - GDP growth, foreign-scholarship availability, remittance flows, or COVID-19-era mobility restrictions - that the literature identifies as relevant to enrollment dynamics [1], [4], [17]; a multivariate ARIMAX or vector-autoregressive extension is a natural next step.

Conclusion

This paper has presented a formal time series analysis of higher-education enrollment growth in Nepal over 2014/15-2024/25, combining a classical ARIMA(1,1,0) model with a first-principles LSTM deep-learning implementation. Enrollment is confirmed to be a non-stationary, first-order-integrated series that has grown at a compound annual rate of 6.29% over the sample, with a pronounced contraction in the mid-2010s followed by sustained, accelerating recovery to a record 749,392 students in 2024/25. The ARIMA model, estimated as $\Delta\hat{y}t = 24{,}203.6 + 0.581\Delta yt\text{-}1$, achieves an in-sample MAPE of 5.75%, modestly outperforming a comparably specified LSTM network (MAPE = 8.42%), and both models forecast continued growth toward roughly 870,000-960,000 students by 2027/28. These results underscore both the value and the limits of applying deep-learning methods to short annual social-statistical series, and point to concrete priorities for Nepal's higher-education policy - sustained public financing, capacity expansion beyond the dominant institutions and disciplines, and improved, higher-frequency data collection - that would both support evidence-based planning and enable more sophisticated forecasting methodologies in future research.

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