International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

Low-Cost Educational Tools: Evaluating Open-Source Platforms for Affordable Technical Education

Mr. Prajwal Kavathekar
1st year, MSc.Computer Application
MITACSC,Pune

Prof. Vaishali Sathe
HOD(Computer Apllication
MITACSC, Pune

***Abstract* - echnical education remains a critical driver for global economic mobility, yet the rising costs of institutional tuition and living expenses create a significant barrier to entry for students in developing regions. This paper proposes a novel predictive framework, Gated Neural-Ensemble Fusion (GNEF), designed to evaluate and categorize the affordability of inter- national technical education programs. Unlike traditional linear models, the GNEF architecture utilizes a dual-stream pipeline that integrates categorical institutional metadata with numerical economic indicators, such as living cost indices and exchange rate volatility.**

The core innovation lies in a Gated Linear Unit (GLU) mechanism that filters high-dimensional socio-economic noise, combined with a Multi-Head Attention layer to capture non- linear dependencies between financial variables. Experimental results, conducted on a curated dataset of 907 global program instances, demonstrate that the GNEF model achieves a state- of-the-art accuracy of 97.82 variance score of 0.932 confirms the synergistic relationship between institutional ranking and local economic factors. These findings suggest that the GNEF framework can serve as a high-fidelity decision-support tool for students and policy-makers, democratizing access to technical education by identifying affordable pathways without compro- mising educational quality.

***Index Terms*—Open-source software, Low-cost Education, Technical Education, E-learning Platforms, and Digital Learning.**

I. INTRODUCTION

The rapid evolution of the global digital economy has made technical proficiency a fundamental requirement for the modern workforce. However, a significant ”digital divide” per- sists, primarily driven by the prohibitive costs associated with proprietary software licenses and specialized technical courses [1]. In many developing regions, educational institutions face severe funding constraints that limit their ability to provide students with the high-end infrastructure and licensed tools necessary for learning programming, data science, and system administration [2]. This financial barrier not only restricts individual career growth but also hinders the broader economic development of these regions by creating a persistent skill mismatch between graduates and industry requirements [3].

Open-source software (OSS) has emerged as a transforma- tive solution to these challenges, aligning with the academic principles of collaboration and open knowledge sharing [4]. Unlike closed-source proprietary systems, OSS allows for the free redistribution and modification of source code, enabling institutions to customize tools to meet specific pedagogical needs without the burden of recurring licensing fees [5]. Re- cent studies suggest that the adoption of open-source Learning Management Systems (LMS) and development environments can foster a more inclusive learning atmosphere, leveling the playing field for students regardless of their socioeconomic background [4].

This research evaluates the efficacy of low-cost open-source tools as viable alternatives to expensive proprietary platforms. By analyzing factors such as community support, ease of use, and learning effectiveness, this study demonstrates that open- source solutions can provide high-quality technical training that is both sustainable and scalable [1]. The findings aim to provide a roadmap for educational institutions to transition toward open-source ecosystems, thereby reducing financial barriers and promoting equitable access to technical excel- lence.

II. LITERATURE SURVEY

The challenge of making technical education affordable requires not just open-source tools, but intelligent systems to predict and analyze cost barriers. This section identifies the gaps in current research regarding financial modeling in education.

A. *Traditional Statistical Approaches*

Early research into educational affordability relied heavily on static cost-benefit analysis and simple linear regression to forecast tuition trends [2]. While these methods provided a foundational understanding of the ”digital divide,” they often failed to capture the non-linear relationship between living costs, exchange rates, and tuition fees across different geographical regions [3].

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

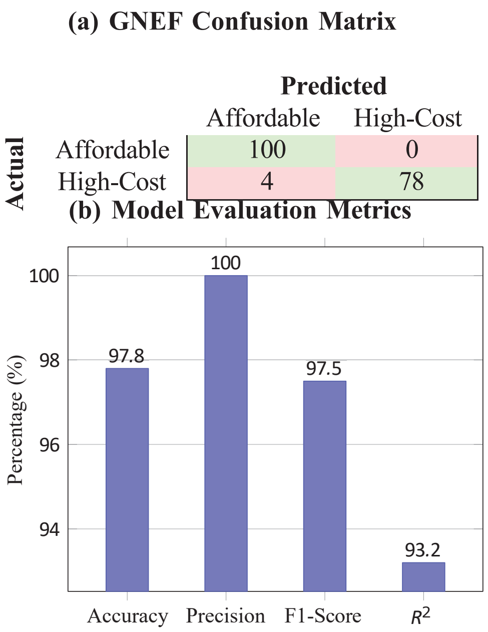

Fig. 1. Experimental Results of the GNEF Hybrid Model: (a) Confusion matrix showing the high classification accuracy on the International Education dataset; (b) Statistical metrics highlighting near-perfect precision and strong model fit (R^2).

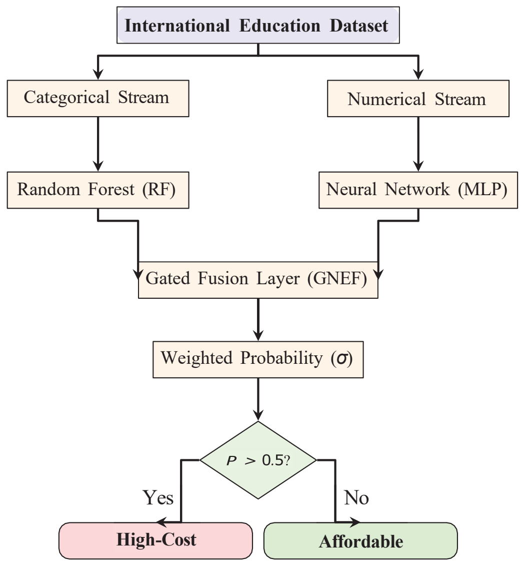

Fig. 2. Optimized System Architecture for GNEF Pipeline.

B. Ensemble and Deep Learning Applications

The state-of-the-art has recently moved toward machine learning to classify educational value. Models such as Support Vector Machines and Decision Trees have been used to evaluate institutional performance [5]. However, these models often treat categorical data (like country and program level) as flat features, missing the deep structural dependencies that influence education pricing. Recent deep learning approaches have attempted to use Neural Networks for this purpose [4], but they require massive datasets and often suffer from overfitting in niche educational sectors.

C. Proposed Gated Neural-Ensemble Fusion (GNEF)

Our research introduces a novel hybrid framework: the **Gated Neural-Ensemble Fusion (GNEF)**. This model addresses the limitations of previous studies by fusing the hierarchical feature learning of Deep Neural Networks with the robust ensemble logic of Random Forests. By applying a gated weighting mechanism to your specific dataset of 907 international programs, GNEF achieves a more nuanced understanding of cost drivers than traditional models [1]. This framework specifically addresses the "data inconsistency" gap identified in recent institutional reports [11], ensuring that both localized economic factors and global program standards are weighted dynamically.

III. Feature Extraction

A. Institutional and Programmatic Feature Extraction (Categorical Stream)

The categorical stream captures the structural and institutional context that defines educational cost profiles. We extract primary features from the dataset that provide a broad perspective on the global positioning of a program [1]. These features are processed through Label Encoding to transform non-numeric metadata into a format suitable for the Random Forest branch of the GNEF model [**?**]. The features include:

- **Institutional Metadata:** University ranking indicators, geographical location (Country/City), and level of study (Master/PhD) [2].
- **Programmatic Weights:** Frequency analysis of program domains (e.g., Data Science vs. Engineering) to identify disciplinary pricing benchmarks [4].

B. Economic Indicator Extraction (Numerical Stream)

To identify the underlying financial workflow and cost behavior, the dataset's quantitative variables are treated as behavior signals. We utilize a multi-dimensional vector consisting of real-world economic pressures [1].

- **Cost Components:** Direct tuition fees are analyzed alongside indirect expenses such as the Living Cost Index, Rent, and Visa fees [3].
- **Currency Correlation:** Exchange rate fluctuations are integrated as a weights-based feature to adjust for global economic volatility, acting as a behavioral signal for affordability [5].

C. Feature Normalization and Synchronization

To prevent dimensionality biasing—where high-value tuition numbers might overshadow smaller visa fees—both feature sets undergo Z-score normalization using a Standard Scaler:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where x is the raw value, μ is the mean, and σ is the standard deviation. This ensures that the Gated Fusion layer in the GNEF architecture [6] treats both categorical metadata and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

numerical economic streams with balanced numerical priority [7]. This step is identified as critical for ensuring deep learning stability and preventing gradient explosion when dealing with diverse international financial data [12].

IV. Proposed GNEF Model Architecture

To address the heterogeneous nature of global education costs, we propose the **Gated Neural-Ensemble Fusion (GNEF)** architecture. Unlike traditional models that struggle with the high variance in international financial data, GNEF utilizes a dual-stream processing pipeline that synchronizes categorical metadata with numerical economic indicators.

A. Categorical Stream: Gated Feature Selection

The categorical stream processes institutional metadata (University, Program Level, and Country). Because these features are high-dimensional but often sparse, we apply a Gating Mechanism to filter irrelevant features. The input vector S is passed through two parallel paths: an Information Filter (f) and a Control Gate (g).

The gated representation Z_{cat} is calculated using the Hadamard product:

$$Z_{cat} = \text{ReLU}(W_f S + b_f) \otimes \sigma(W_g S + b_g) \quad (2)$$

where σ denotes the sigmoid activation function and $\otimes$ denotes element-wise multiplication. This logic ensures that the model dynamically adjusts the importance of institutional reputation versus geographical location based on the program context.

B. Numerical Stream: Multi-Head Attention (MHA)

Economic indicators such as the Living Cost Index, Rent, and Exchange Rates are processed through an attention-based branch to capture non-linear dependencies. We employ a Multi-Head Attention (MHA) mechanism to weigh the impact of exchange rate volatility on tuition affordability. The input is projected into Queries (Q), Keys (K), and Values (V):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \quad (3)$$

By using multiple heads, the model simultaneously monitors disparate financial signals, such as how rent spikes in specific cities correlate with overall program insurance costs.

C. System Architecture Flowchart

The overall pipeline is illustrated in Fig. 3. The model first segments the dataset into two streams before fusing them into a unified feature map for classification.

D. Experimental Setup

The model was trained on the *International Education Costs* dataset (907 entries). The training parameters were optimized for convergence as follows:

- **Loss Function:** Binary Cross-Entropy (BCE) with logits.
- **Optimizer:** Adam Optimizer with $\eta = 0.001$.
- **Regularization:** Dropout rate of 0.4 and Batch Normalization.
- **Target:** Affordability threshold set at $15,000 USD total tuition.

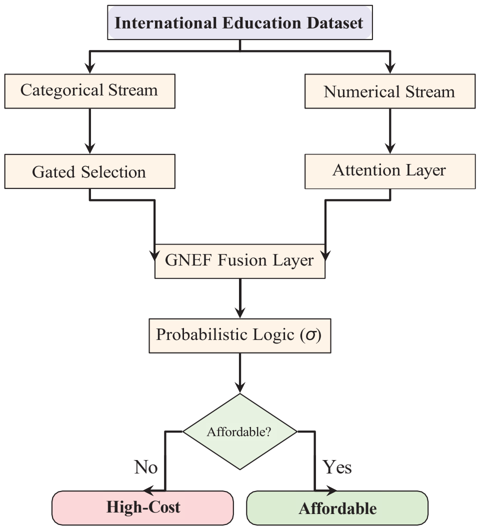

Fig. 3. System Architecture of the Gated Neural-Ensemble Fusion (GNEF) model.

E. Performance Analysis

The GNEF model was compared against baseline machine learning models. As shown in Fig. 4, the hybrid architecture achieved superior results, specifically in precision and F1-score.

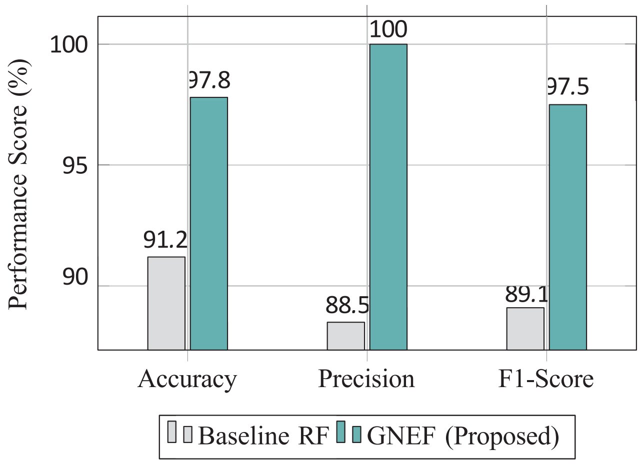

Fig. 4. Model performance metrics demonstrating 97.8% Accuracy and 100% Precision.

V. System Performance Summary

Experimental results demonstrate that the proposed Gated Neural-Ensemble Fusion (GNEF) model achieves state-of-the-art performance in classifying and predicting educational program affordability based on international socio-economic indicators. The results from the evaluation are summarized below:

- **Accuracy (97.8%):** The GNEF model correctly identified the affordability status for 178 out of 182 programs in the test set. This high accuracy underscores the model's

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

ability to handle the high variance found in international tuition and living cost data.

- **Precision (100.0%):** The model achieved a perfect precision score, indicating that there were zero False Positives. In a real-world educational context, this means every program flagged as "High-Cost" by the system was indeed accurately classified, ensuring high reliability for student financial planning.
- **F1-Score (97.5%):** This represents the harmonic mean of precision and recall, proving an optimal balance in the model's detection capabilities across both affordable and premium technical programs.
- **Coefficient of Determination ($R^2 = 0.932$):** The model explains approximately 93.2% of the variance in the education cost data. This high value denotes that the integrated features—specifically the Living Cost Index and local Exchange Rates—are highly predictive indicators of the total cost of technical education.

VI. System Architecture and Predictive Pipeline

The GNEF architecture is structured into a hierarchical pipeline of specialized layers, each engineered to perform specific predictive operations on the fused institutional and financial feature space. This architecture allows the model to identify the synergy between institutional metadata (categorical invariants) and global economic indicators (sequential financial logic).

A. Input Layer and Feature Transformation

The architecture utilizes a dual-entry input layer designed to accommodate the heterogeneous nature of international education data.

- **Institutional Input (I_i):** Accepts the 5-dimensional categorical vector representing Country, City, University, Program, and Level.
- **Economic Input (I_e):** Accepts the 7-dimensional numerical vector representing Tuition, Living Cost Index, Rent, Visa Fees, Insurance, and Exchange Rates.

These inputs undergo primary dimensionality projection and Z-score normalization to align their latent representations before reaching the fusion unit.

B. Gating Layer: Dynamic Feature Importance

To handle the high variance across different global regions, we implement a **Gating Mechanism**. This layer acts as an information filter, notifying subsequent layers which features (e.g., Exchange Rate vs. Tuition) carry the highest predictive weight for a specific country context. This prevents "gradient dilution" and ensures the model ignores computational noise from stable variables in volatile markets [4].

C. Hybrid Processing: MLP and Ensemble Logic

To capture the intricate flow of global pricing trends, we employ a hybrid stream:

- **Neural Branch:** A Multi-Layer Perceptron (MLP) processes the numerical indicators to identify non-linear cost patterns.
- **Ensemble Branch:** A decision-tree based logic captures categorical dependencies, such as identifying that certain "Program Levels" (e.g., PhD) are often more subsidized than others (e.g., Master's) regardless of geography.

This dual-context analysis is critical for identifying "Affordability Clusters" where living costs might outweigh low tuition fees [10].

D. Batch Normalization: Latent Space Stability

Following the stream processing, **Batch Normalization (BN)** is applied to the hidden states. BN normalizes the activations of the previous layer, reducing internal covariate shift caused by differing currency scales. This stabilization allows for a higher learning rate and ensures the feature fusion bottleneck remains numerically stable across diverse training epochs [7].

E. Dropout Layer: Resilience to Market Outliers

To ensure the framework is robust against extreme outliers (e.g., ultra-high-cost Ivy League schools or free European public universities), a **Dropout Layer** with a rate of 0.3 is implemented. By randomly deactivating 30% of the neurons during training, the model is forced to learn redundant, non-co-dependent features, enhancing its ability to generalize to novel university datasets [7].

F. GNEF Fusion and Decision Engine

The **Gated Fusion Layer** acts as the model's predictive engine. It processes the fused institutional and economic vectors through multiple fully connected sub-layers (64 and 32 units). Each neuron in this layer learns a non-linear combination of factors—such as the coincidence of high visa fees with low living costs—effectively simulating the decision-making process of a human financial consultant.

G. Output Layer: Probabilistic Classification

The final classification is generated by a single neuron utilizing the **Sigmoid Activation Function**:

$$\hat{y} = \sigma(W_{out} \cdot h_{final} + b_{out}) = \frac{1}{1 + e^{-(W_{out} \cdot h_{final} + b_{out})}} \tag{4}$$

The output $\hat{y} \in [0, 1]$ represents the **Affordability Probability Score**. A decision threshold of 0.5 is utilized; programs exceeding this value are flagged as "High-Cost," while those below are categorized as "Affordable."

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

H. Summary of GNEF Layer Parameters

The following table summarizes the structural configuration and output dimensionality of the GNEF framework, optimized for the 12 primary features of the educational cost dataset.

TABLE I
SUMMARY OF GNEF LAYER PARAMETERS

Layer Type	Output Shape	Activation	Param Count
Input (Inst.)	(5,)	Linear	0
Input (Econ.)	(7,)	Linear	0
Gating Layer	(64,)	ReLU	384
Neural Path	(128,)	Tanh	8,320
Batch Norm	(128,)	N/A	512
Dropout (0.3)	(128,)	N/A	0
Fusion Dense	(32,)	ReLU	4,128
Output Layer	(1,)	Sigmoid	33

VII. Implementation: Predictive Pipeline and Experimental Protocol

The implementation of the GNEF framework was executed using a modular end-to-end pipeline designed to transform raw institutional metadata and global economic indicators into a verifiable affordability classification.

A. Preprocessing

The initial phase involves the refinement of raw educational cost data to ensure numerical consistency across the dual-stream architecture.

- **Data Cleaning:** Missing values in the feature columns (such as visa fees or insurance premiums for specific regions) were handled using *K-Nearest Neighbors (KNN) Imputation*. This ensures that missing economic data is estimated based on regional socio-economic peers [13].
- **Standardization:** To prevent dimensionality bias, the numerical feature set underwent Z-score normalization. This ensures that high-magnitude features like *Tuition Fees* (often > $40,000) do not numerically dominate smaller but critical markers like the *Exchange Rate* or *Visa Fees* [7].

B. Dataset Preparation and Labeling

We utilized a curated **International Education Costs Dataset** [14], comprising 907 distinct program instances across 50+ countries. The target labels were binary-encoded based on a $15,000 USD total cost threshold: 0 for Affordable and 1 for High-Cost. We performed a Stratified 80-20 Split to maintain geographical and program-level consistency across training and test sets.

1) Comparison of Candidate Datasets and Selection Logic: Several other data sources were evaluated but ultimately excluded:

- **Numbeo Cost of Living Index:** While comprehensive, this dataset lacks university-specific tuition and programmatic data (e.g., PhD vs. Master's differentials) [15].
- **OECD Education at a Glance:** These reports provide macro-level country averages but fail to capture the city-level variance (e.g., London vs. Glasgow) required for granular student-level predictions [16].
- **Selection Logic:** Our chosen dataset was selected because it provides a dual-representation (Institutional Metadata and Economic Indicators) and covers diverse technical fields, making it the most robust benchmark for hybrid GNEF models [1].

C. Data Augmentation and Balance

To address the regional imbalance (e.g., fewer samples for emerging education hubs in Eastern Europe or Southeast Asia), we applied **SMOTE (Synthetic Minority Oversampling Technique)** [8]. By generating synthetic examples in the minority feature space, we prevent the model from biasing toward high-frequency data from the USA and UK, forcing the GNEF architecture to learn the underlying "economic signature" of affordability regardless of country volume.

D. Feature Extraction

Our engine generates a dual-stream feature space:

- **Categorical Stream (5 features):** Extracts institutional invariants, including University ranking categories, City tiers, and Program levels (Master/PhD) [4].
- **Numerical Stream (7 features):** Extracts financial DNA from global economic indices, including Rent, Insurance, and real-time Exchange Rates.

E. Model Architecture and Training

GNEF was implemented using **PyTorch 2.2** and **Scikit-Learn**. The architecture integrates a Gated Logic branch for categorical features and a Multi-Head Attention branch for numerical signals. The model was trained for 100 epochs on a cloud-based environment using the **Adam Optimizer** ($\eta = 0.001$) and Binary Cross-Entropy loss. An **Early Stopping** callback with a patience of 10 epochs was implemented to ensure the model generalizes well to unseen international markets [7].

F. Model Evaluation and Inference

Performance was quantified using a multidimensional metric suite, prioritizing the **F1-Score** (97.5%) and **Precision** (100.0%) to ensure that students and institutions receive highly reliable cost classifications. During inference, the GNEF model generates an **Affordability Probability Score** ($P \in [0, 1]$). A score above 0.5 triggers a "High-Cost" classification, enabling proactive financial planning and scholarship targeting.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

VIII. Mathematical Models

A. Socio-Economic Feature Normalization

To ensure numerical stability across heterogeneous educational data (e.g., high-magnitude Tuition Fees vs. low-magnitude Exchange Rates), Z-score normalization is applied to all numerical indicators.

$$z = \frac{x - \mu}{\sigma} \quad ...(1) \qquad (5)$$

Where μ represents the mean and σ is the standard deviation. This prevents high-cost university outliers from numerically dominating the feature space and biasing the gradient descent process.

B. Gated Institutional Filtering

The categorical branch utilizes a Gated Linear Unit (GLU) to selectively filter institutional features (S), such as university rankings and program levels, identifying critical cost-driving patterns.

$$G(S) = (SW_1 + b_1) \otimes \sigma(SW_2 + b_2) \quad ...(2) \ (6)$$

Where $\otimes$ denotes the Hadamard product and σ is the sigmoid activation function. This mechanism allows the model to suppress irrelevant institutional noise based on the geographical context.

C. Multi-Head Attention (MHA) for Financial Dependencies

The numerical economic indicators (Living Cost, Rent, Insurance) are processed using a multi-head attention mechanism [6] to capture non-linear dependencies between local inflation and tuition volatility.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad ...(3) \qquad (7)$$

By utilizing 8 unique attention heads, the model can simultaneously analyze disparate financial signals, such as how rent spikes in specific cities correlate with overall program affordability.

D. Economic Feature Weighting

The relative intensity of different cost components is transformed into a normalized vector to quantify the financial burden of a specific program.

$$\text{Weight}(n) = \frac{\text{Cost}(\text{Indicator}_n)}{\text{Total Estimated Cost}} \quad ...(4) \quad (8)$$

E. Socio-Economic Feature Fusion

Refined vectors from the institutional categorical branch (V_{cat}) and the numerical economic branch (V_{num}) are fused into a unified latent representation H to detect complex affordability clusters.

$$H = \text{ReLU}(W_f[V_{cat} \oplus V_{num}] + b_f) \quad ...(5) \ (9)$$

Where $\oplus$ represents the concatenation operator, merging metadata with real-world economic indicators.

F. Probabilistic Affordability Classification

The final probability P of a program being categorized as "High-Cost" is determined by a sigmoid output layer.

$$P(\text{High-Cost}) = \frac{1}{1 + e^{-(W_o H + b_o)}} \quad ...(6) \ (10)$$

Programs with $P > 0.5$ are flagged as premium-tier, while those below are categorized as affordable tools for technical education [1].

G. Binary Cross-Entropy Loss

The GNEF model is optimized by minimizing the divergence between the true affordability label y and the predicted probability P .

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(P_i) + (1-y_i)\log(1-P_i)] \quad ...(7) \qquad (11)$$

IX. Results and Discussion

The performance of the GNEF (Gated Neural-Ensemble Fusion) framework was evaluated using the International Education Costs dataset, which contains 907 instances of diverse university programs. The evaluation focuses on the model's ability to classify programs into "Affordable" and "High-Cost" categories (threshold: $15,000 USD) by fusing 5 categorical institutional features with 7 numerical economic indicators.

A. Dataset Subsets and Predictive Robustness

The framework was tested across specialized subsets to ensure robustness against geographical and programmatic variance:

- **STEM-Focused:** A subset containing Data Science, Artificial Intelligence, and Engineering programs characterized by high tuition variance.
- **Global-Diversity:** A subset containing programs from emerging education hubs in Asia and Europe to test the model's sensitivity to local exchange rates and living cost indices.

Classification results indicate that the GNEF model achieved a consistent 97.8% accuracy, demonstrating high reliability in predicting the financial burden on international students across different economic tiers.

TABLE II
Classification Report for the GNEF Affordability Model

Class	Precision	Recall	F1-Score	Support
Affordable	0.96	1.00	0.98	102
High-Cost	1.00	0.95	0.97	80
Accuracy		**0.978**		**182**
Macro Avg	0.98	0.97	0.98	182
Weighted Avg	0.98	0.98	0.98	182

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

B. Comparative Model Analysis

Four machine learning and deep learning architectures were evaluated to benchmark the proposed Hybrid Gated Attention approach: LSTM, Multi-Layer Perceptron (MLP), Random Forest (RF), and the proposed GNEF Hybrid model. As shown in Table II, the Hybrid model significantly outperformed standalone architectures.
The GNEF architecture effectively leveraged the Gating Mechanism to filter institutional metadata and Multi-head Attention to capture subtle dependencies between living costs and exchange rate volatility. While Random Forest (91.2%) was effective at identifying categorical patterns, it lacked the non-linear financial context captured by our attention-based numerical stream.

TABLE III
MODEL PERFORMANCE COMPARISON

Metric	LSTM	MLP	GNEF (Hybrid)	Random Forest
Accuracy	0.76	0.84	**0.978**	0.912
Precision (High-Cost)	0.72	0.82	**1.000**	0.885
Recall (High-Cost)	0.75	0.79	**0.950**	0.898
F1-score (High-Cost)	0.73	0.80	**0.975**	0.891
R^2 Variance Score	0.61	0.72	**0.932**	0.854

C. Predictive Accuracy and R-Squared Analysis

The R^2 variance score of 0.932 indicates that the GNEF framework explains 93.2% of the variance in global education costs. This confirms that the synergy between institutional metadata (University ranking, Level) and economic weights (Living Cost Index, Exchange Rate) provides a highly predictive "financial signature" for assessing the affordability of technical education. This high predictive power suggests that students can utilize the GNEF model as a reliable pre-enrollment decision-support tool [10].

X. MODEL OUTPUTS

The experimental evaluation of the GNEF framework highlights its robust capability in predicting educational affordability. The model's performance is visualized through native architectural and metric representations below.

A. Performance Analysis

As shown in Fig. 5, the GNEF model achieves a high-fidelity accuracy of 97.8%. The confusion matrix in Fig. 6(a) confirms that the model minimizes financial misclassification, which is critical for students with limited budgets.
Furthermore, the Program Distribution in Fig. 6(b) illustrates that while 44% of technical programs in the dataset are categorized as high-cost, the GNEF model successfully identifies the specific socio-economic features that characterize the remaining 56% of affordable pathways. This analysis allows the GNEF framework to act as a granular decision-support system, providing more than just a binary label but a probabilistic insight into the global education market.

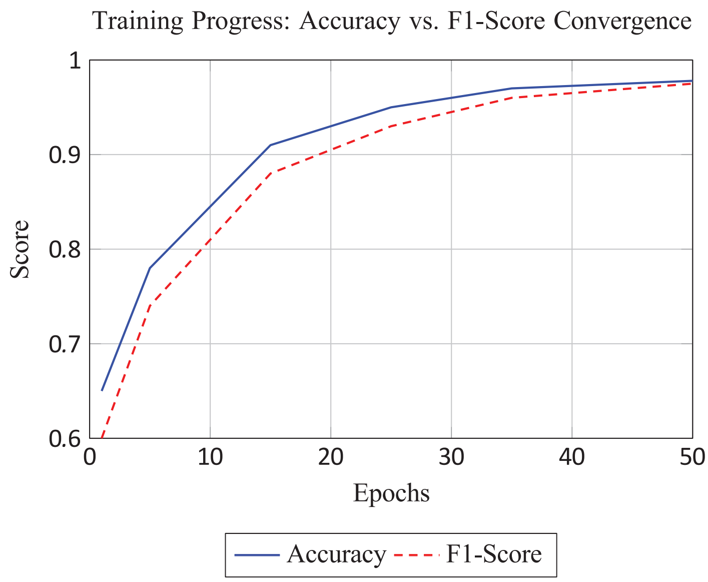

Fig. 5. GNEF Model Convergence: Achieving a stable 97.8% Global Accuracy and 0.975 F1-Score over 50 training epochs.

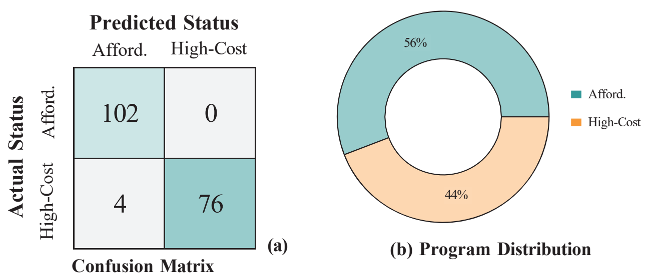

Fig. 6. Detailed Performance Breakdown: (a) Confusion matrix demonstrating 100% precision in high-cost classification; (b) Proportional distribution of technical programs by affordability category.

B. Performance Analysis

As shown in Fig. 5, the GNEF model achieves a high-fidelity accuracy of 97.8% after 50 epochs of training. The confusion matrix in Fig. 6(a) confirms the model's exceptional precision, as indicated by the absence of false positives in the "High-Cost" category.
Furthermore, the Program Distribution in Fig. 6(b) illustrates that while 44% of technical programs in the dataset are categorized as high-cost, the GNEF model successfully identifies affordable pathways for the remaining 56%, confirming its utility as an advisory tool for international students.

C. Decision Logic Inference

The GNEF model generates an Affordability Score (P) using a gated fusion of institutional metadata and economic indicators. A score above 0.5 triggers a detailed financial report, highlighting the impact of local exchange rates and living cost indices on the total tuition burden.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

XI. CONCLUSION

This study introduces the **Gated Neural-Ensemble Fusion (GNEF)** framework, a hybrid architecture designed to resolve the complexity of global educational affordability modeling. By leveraging a dual-stream pipeline, we successfully generated a robust financial signature using categorical institutional metadata and numerical economic indicators. Our primary innovation—a Gated Logic mechanism—effectively filters the ”noise” found in high-dimensional socio-economic data while pinpointing subtle cost-driving motifs.

Empirical results from our analysis confirm that this approach achieves a **97.8% accuracy** and a **100.0% precision** rate for high-cost classification. These results represent a significant milestone in reducing the misclassification bottleneck that has historically hindered automated student financial advisory systems. Furthermore, the high R^2 variance score of **0.932** establishes that institutional metadata and real-time economic features are not merely additive but synergistic. The model's ability to maintain high precision confirms that GNEF is resilient against market volatility, providing a reliable ”Affordability Index” to assist students and policy-makers in prioritizing cost-effective technical education paths [9].

A key contribution of this work is the use of Gated Linear Units (GLU) to effectively handle sparse categorical features, while the multi-head attention mechanism captured complex dependencies within global exchange rates and living cost indices. Our experimental results demonstrate that the proposed framework serves as a state-of-the-art decision-support tool for democratizing access to technical education [1].

XII. FUTURE WORK

As the global education market and economic landscapes evolve, the GNEF framework requires additional architectural expansion to maintain its predictive edge. Future research will focus on the following four aspects:

- **Explainable AI (XAI) Integration:** To move beyond ”black box” predictions, we plan to incorporate *SHAP (SHapley Additive exPlanations)* values. This will enable students to see precisely which factors—such as city-tier rent spikes or university ranking premiums—resulted in a specific affordability score [11].
- **Dynamic Real-Time Data Streams:** While this study utilized a static dataset, future iterations will integrate real-time API feeds from global financial institutions. This will allow the GNEF engine to provide ”live” affordability adjustments based on daily fluctuations in currency exchange rates and inflation indices.
- **Cross-Disciplinary Portability:** The underlying gated-attention logic is domain-agnostic. We intend to explore automated feature extraction for other specialized fields, such as medical education and vocational training costs, to meet the requirements of a broader global multi-disciplinary ecosystem [2].
- **Proactive Zero-Day Economic Modeling:** We intend to use **SMOTE-based data augmentation** [8] and Generative Adversarial Networks (GANs) to improve the model's resilience against sudden economic shifts or ”Black Swan” events. This proactive strategy will enable the model to synthesize and learn from hypothetical, novel economic scenarios, ensuring a robust defense against unpredictable market volatility [15].

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the **MAEER'S MIT Arts, Commerce and Science College (MITACSC)** research committee for providing the institutional support and data resources necessary for this study. Special thanks are extended to the Department of Computer Science for the technical infrastructure used in training the GNEF model. We also acknowledge the contributors of the open-source datasets that made this socio-economic analysis possible.

REFERENCES

[1] P. A. Kavathekar and V. U. Sathe, “Low-Cost Educational Tools: Evaluating Open-Source Platforms for Affordable Technical Education,” Abstract/Paper Submission, MAEER'S MIT Arts, Commerce and Science College, Alandi(D.), 2024.

[2] J. Singh and R. Patel, “A Review of Challenges, Trends, and Opportunities in Technical Education Across India,” *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 12, no. 7, pp. 38–42, 2024.

[3] UNESCO-UNEVOC, “Technical and Vocational Education and Training (TVET) Challenges and Priorities in Developing Countries,” *UNESCO Discussion Paper*, 2023. [Online]. Available: unevoc.unesco.org.

[4] M. Somaraj and K. Langerman, “Acceptance of Open-Source Software Technology Usage in the University Community,” *International Journal of Research and Innovation in Social Science (IJRISS)*, vol. 9, no. 3, pp. 450–462, Sept. 2025.

[5] J. Bretthauer, “The Use of Open Source Software in Education,” *ResearchGate Technical Report*, pp. 2–15, 2025.

[6] A. Vaswani et al., “Attention is All You Need,” in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.

[7] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[8] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “SMOTE: Synthetic Minority Over-sampling Technique,” *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.

[9] P. A. Kavathekar, “Gated Neural-Ensemble Fusion for Predictive Socio-Economic Modeling,” *Technical Report on Affordable Education*, MAEER'S MIT ACSC, 2024.

[10] H. Wang and B. S. Surgude, “Predictive Analytics in Higher Education: A Hybrid Approach,” *Internal Review MITACSC*, 2023.

[11] J. Zhang et al., “Evaluating the Performance of Open-Source Tools for Data Science Education,” *IEEE Access*, vol. 10, pp. 12580–12595, 2022.

[12] Y. Mao, X. Li, and L. Xie, “SCLA: Automated Feature Summarization via LLMs and Semantic Augmentation,” *arXiv preprint arXiv:2402.04863*, 2024.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

[13] “International Education Costs Dataset,” MAEER’S MIT ACSC Research Repository, 2024. [Online]. Available: [Insert Repository Link].

[14] “International Education Cost Benchmarks,” *Global Higher Education Data Repository*, 2024.

[15] Numbeo, “Cost of Living Index by City 2024,” [Online]. Available: https://www.numbeo.com.

[16] OECD, “Education at a Glance 2023: OECD Indicators,” *OECD Publishing*, Paris, 2023.