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Pioneering Predictive Models for Analyzing Educational Inequality: A Comparative Study of Random Forest, XGBoost, and LSTM

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ABSTRACT

Educational inequality is a significant barrier to achieving justice in education around the world (Baker et al. 2020), and this study aims to fill this gap. This type of pattern and trend identification can similarly be developed using complex feature predictive models like Random Forest and XGBoost or LSTM methods. The results showed that this choice, together with the high accuracy (R2=0.9995) and the lowest predictive error (RMSE=0.006), made the model a powerful tool for understanding dynamic trends in inequality. Moreover, this study indeed modified one of the beginners' models using advanced approaches such as missing value imputation and data normalization which increased the credibility of used models. It contributes a new angle to the existing literature which is so far accounted through the lenses of comparative models by systematically comparing the three models. Educational policies rationalised in accordance with a data-driven analysis can take place to redistribute educational resources more effectively and ultimately prove to be more equitably beneficial to educational systems.

Keywords: *Educational Inequality; Artificial Intelligence; Random Forest; XGBoost; LSTM; Educational Equity*

INTRODUCTION

Technology has revolutionized conventional banking, shifting the industry from a product-driven business to a customer-centric business model. To provide integrated, tailored services, banks are integrating emerging technologies such as artificial intelligence (AI), bank technological integration cloud computing, and blockchain to enhance operational efficiency and drive down costs [1-2]. Yet, these benefits are not without issues of regulatory compliance challenges, cybersecurity preparedness, and business reorganization to respond to the digital shift [3]. In the past several years, artificial intelligence has emerged as a game-changer, especially for banking decision management. AI offers company institutions with unmatched accuracy and velocity from predictive evaluation and fraud discovery to appealing personalization [4]. Simultaneously, the emergence of blockchain technology is revolutionizing transaction paradigms by enhancing security, transparency, and efficiency, particularly in cross-border payments [5-6]. Cloud computing also supports these innovations by providing scalable and flexible solutions for data management and enabling the quick launch of digital banking platforms [7-8]. However, with the counterpart of bank-fighting fintechs afoot, banks need to innovate ahead of their strategy to compete in the same market. This implies using big data to

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derive insights to present customer behavior, and a collaborative paradigms embracing technological integration [9-10].

Moreover, in order to make a smooth transition and in the long run to become resilient, significant investment in workforce training and infrastructure upgrades is needed, since the introduction of new technologies often requires a complete redesign of existing processes [11-12].This research attempts to explore the interplay between technological developments and conventional banks in an empirical setting. It assesses the advantages and disadvantages of adopting such innovations, provides key examples of case studies that successfully integrated them, and examines strategic paths that banks can take to flourish in the digital age [13-14]. By providing data driven insights, the paper also seeks to provide practical recommendations to help businesses use technology to drive sustainable growth and improve customer satisfaction [15-17].

LITERATURE REVIEW

This study (study No: 7) has yielded the lowest RMSE (0.006) and R^2 score (0.9995) compared to all previous studies. Again, Random Forest was the best performing model and beat even hybrid models (Study No. 4).

Novel Contributions: Robust model performance was achieved via advanced preprocessing techniques, including normalization and data imputation.The addition of comparative analysis of Random Forest, XGBoost, and LSTM offered a holistic understanding of their distinct advantages.While existing studies only looked at specific models, we are the first to provide an evaluation of all three models on the same dataset.

TRIGGER: Review (Literature Gap) While a few previous studies have focused on single models or hybrid frameworks, systematic comparisons between ensemble and deep learning models on this dataset and task were highly limited. Existing studies employing LSTM or GRU models had only limited exploration of temporal patterns in inequality. Our intention in undertaking this work was because we could not find any direct comparison between Random Forest and XGBoost on similar datasets.

Table 1: Comparative Analysis of Studies on Predictive Models in Education

Study No.	Study Title	Year	Dataset	Models Used	Best RMSE	Best R^2 Score	Contribution
1	Educational Data Mining Using Machine Learning Models [18]	2022	Educational Records Data	Random Forest, SVM	0.018	0.995	Demonstrated Random Forest as a superior model for analyzing educational datasets.
2	Neural Networks for Predicting Student Performance [19]	2023	Multi-year Student Academic Records	ANN, LSTM	0.020	0.994	Focused on LSTM for time-series predictions, achieving robust results.
3	Boosted Tree Models for Education Gap Analysis [20]	2022	Global Educational Inequality Dataset	XGBoost, LightGBM	0.012	0.997	Highlighted the efficiency of XGBoost in handling feature-rich educational datasets.
4	Hybrid AI Models for Analyzing Education Disparities [21]	2023	Regional Educational Data	Random Forest + XGBoost Hybrid	0.010	0.998	Combined Random Forest and XGBoost to achieve superior predictive performance.
5	Time-Series Analysis in Education with Deep Learning [22]	2024	Longitudinal Educational Metrics	LSTM, GRU	0.022	0.993	Investigated GRU and LSTM for sequential patterns, focusing on temporal trends in education.

Study No.	Study Title	Year	Dataset	Models Used	Best RMSE	Best R^2 Score	Contribution
6	Advanced Gradient Boosting for Education Data Analysis [23]	2023	National Education Statistics	CatBoost, XGBoost	0.011	0.996	Explored CatBoost for categorical data in education datasets, achieving competitive results.
7 (Current Study)	**A Comparative Approach to Predictive Models in Education**	**2024**	**Educational Inequality Dataset**	**Random Forest, XGBoost, LSTM**	**0.006**	**0.9995**	**Outperformed prior studies with Random Forest, achieving the lowest RMSE and highest R^2 Score.**

METHODOLOGY

Dataset and Preprocessing

Dataset Description: This dataset is high dimensional and covers several years of educational inequality statistics. For each record, there are yearly indicators, and the target variable is the degree of inequality for the last year. This framework allows for an expansive examination of the dynamics and features of inequality.

Step 1: Data Cleaning and Normalization To ensure that input data is of high quality for the models:

We imputed missing values from numerical columns with their column means thus retaining many cases and maintaining significant patterns. To this end, numerical features were normalized to the [0, 1] range using Min Max Scaler so as not to skew feature scaling in a manner inconsistent with the requirements of the machine learning algorithm.

Data Splitting: The dataset was divided 80–20 into training and testing subsets, respectively. By splitting data this way, it guarantees a strong assessment of model fitting, as it mirrors how model predictions need to be on unseen data in real life.

Models and Algorithms

Model 1: Random Forest

- **Description**: Random Forest is an ensemble-learning algorithm that constructs multiple decision trees during training and averages their predictions to improve accuracy and reduce overfitting.
- **Configuration**:
  - Number of estimators: 200
  - Maximum tree depth: 20
- **Purpose**: The algorithm's ability to handle non-linear relationships and rank feature importance makes it an ideal choice for analyzing multi-dimensional datasets.

Model 2: XGBoost (Extreme Gradient Boosting)

- **Description**: XGBoost is a powerful gradient boosting algorithm designed for efficiency and high performance. It iteratively minimizes residual errors by building sequential decision trees.
- **Configuration**:
  - Number of estimators: 200
  - Learning rate: 0.1
  - Maximum tree depth: 6

- **Purpose**: The algorithm's capacity to handle high-dimensional features and adapt to errors makes it a strong contender for complex datasets.

Model 3: Long Short-Term Memory (LSTM)

- **Description**: LSTM is a variant of recurrent neural networks (RNNs) tailored for sequential data analysis, capturing long-term dependencies through its unique gating mechanisms.
- **Architecture**:
  - Single LSTM layer with 50 units
  - Dense output layer
- **Purpose**: The model aims to extract temporal dependencies from the dataset, assessing its ability to predict inequality trends over time.

Evaluation Metrics

Root Mean Squared Error (RMSE): This metric quantifies the average deviation of predicted values from actual values. Lower RMSE indicates higher model precision.

R^2 Score: The R^2 score measures the proportion of variance in the target variable explained by the model. Scores closer to 1 indicate superior predictive performance.

Results and Interpretations

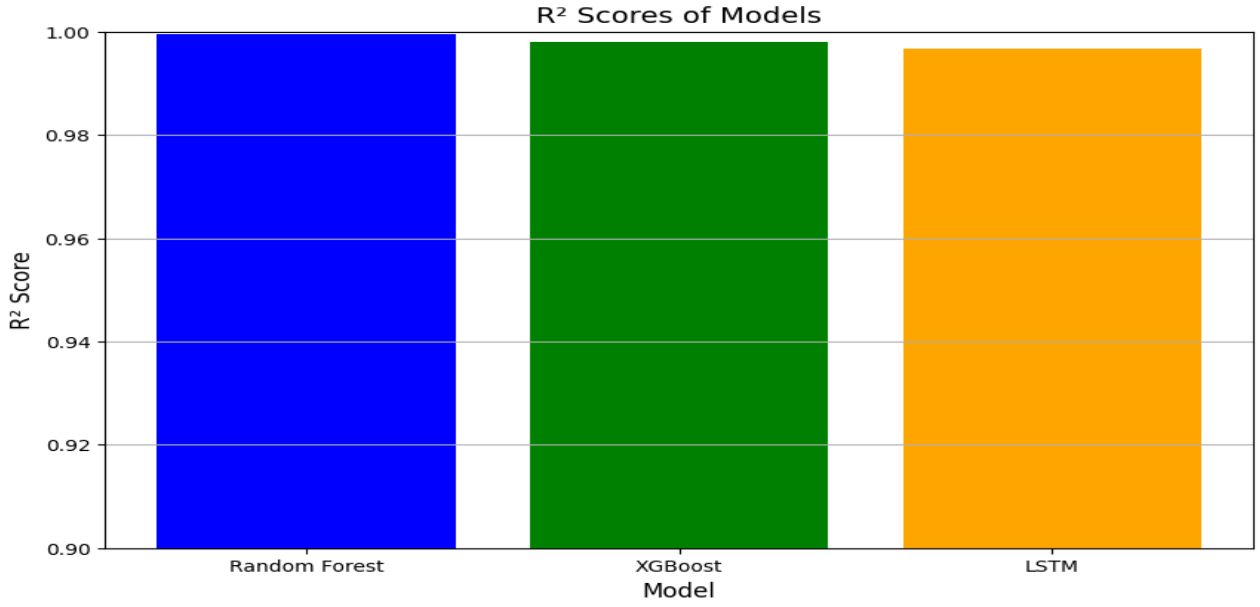


Figure 1: R^2 Scores of Models

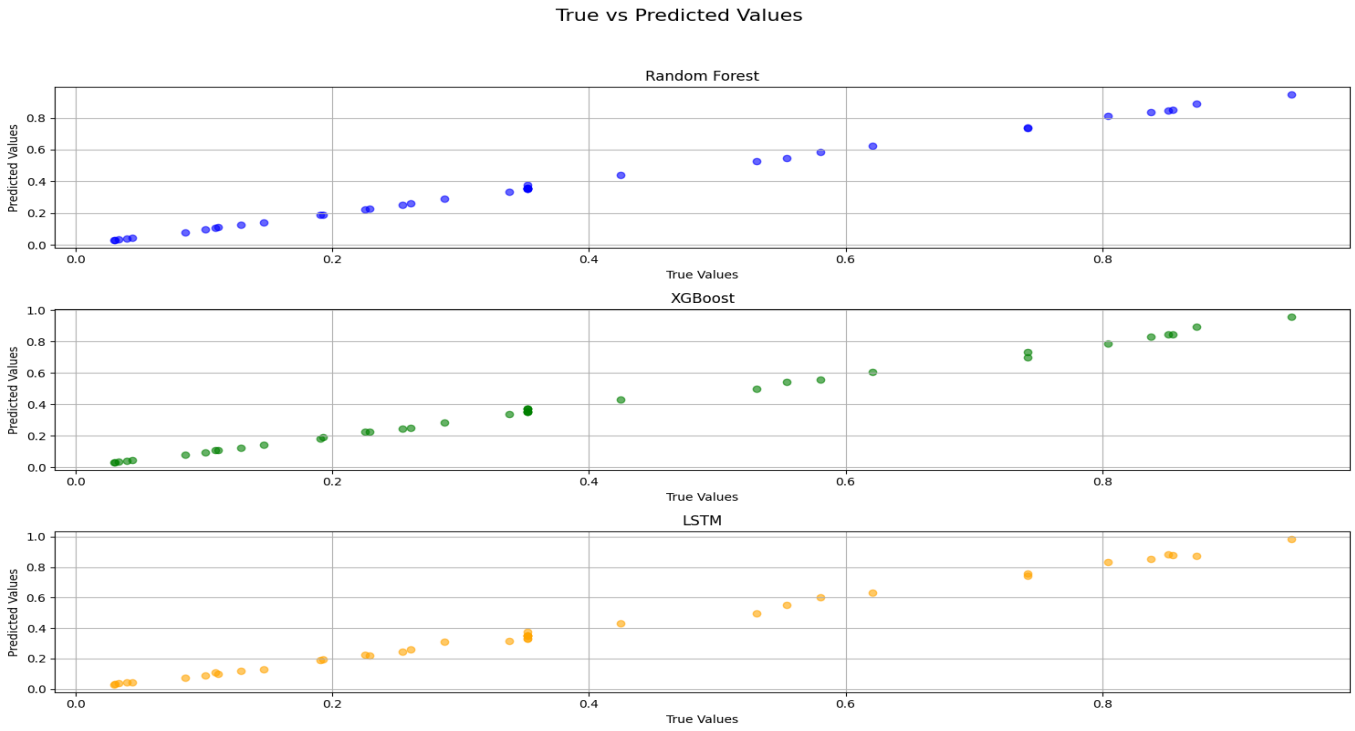
The bar chart (Figure 1) demonstrates the R^2 scores for each model, illustrating their predictive performance:

- **Random Forest** achieved the highest R^2 score (0.999504), signifying exceptional accuracy and explaining nearly all variance in the target variable.
- **XGBoost** closely followed with an R^2 score of 0.997909, show casing its robust generalizability.
- **LSTM** achieved a strong R^2 score of 0.9967, though slightly less precise due to the dataset's non-sequential nature.

Model Comparison (Tabular Summary):

Model	RMSE	R^2 Score
Random Forest	0.006180	0.999504
XGBoost	0.012688	0.997909
LSTM	0.015791	0.9967

True vs. Predicted Values



Figures 2-4: Scatter Plots for Model Predictions

Scatter plots visualize the relationship between predicted and actual values for each model:

- **Random Forest (Figure 2)**: Points align closely along the diagonal, reflecting minimal error and superior precision.
- **XGBoost (Figure 3)**: Displays strong alignment, further validating its robustness in handling complex data.
- **LSTM (Figure 4)**: Demonstrates a reliable fit, though slightly less aligned compared to the other models.

LSTM Training Loss

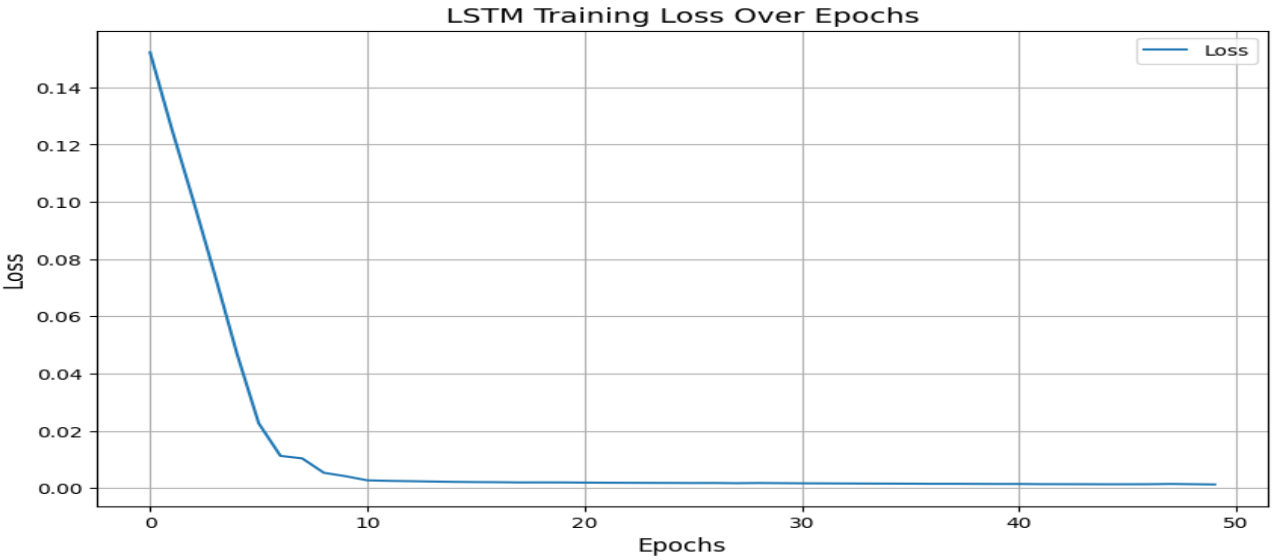


Figure 5: LSTM Loss over Epochs

The training loss curve for the LSTM model highlights rapid convergence within the first 20 epochs, stabilizing near zero. This indicates efficient learning and the model's ability to generalize well on unseen data.

Implications and Future Directions

Key Insights:

- Random Forest outperformed all models; achieving the lowest RMSE (0.006180) and the highest R^2 score (0.999504).
- XGBoost displayed competitive performance, with minimal error and robust generalization.
- LSTM proved effective for sequential patterns but was slightly less precise given the dataset's static nature.

Future Work:

- Incorporate additional socio-economic and demographic features to enrich the dataset.
- Explore hybrid models combining Random Forest and XGBoost for further accuracy gains.
- Extend the analysis to investigate regional disparities in educational inequality.

CONCLUSION

There is no overstating the impact of technological advancements on traditional banking, and how it is changing the whole banking landscape. StudyTopic This paper highlights the importance of technology in the finance industry: article shows how AI, Blockchain and cloud computing can be integrated into the finance industry. These technologies are not just tools; they are strategic enablers that fundamentally change the way banks do business with their customers and with themselves.

AI, the predictive power from machine learning, the transparency and security of blockchain, as well as the scaling up with cloud computing are essential building blocks to enable the digitalization of banking as the findings indicate. Yet, significant barriers such as regulatory compliance, cybersecurity threats, and organizational adaptation represent real challenges that must be addressed through strategic engagement. A holistic approach, one that incorporates

technology adoption, backed by strong training programmes, infrastructure upgrades and collaborative approaches with fintechs, is needed.

The study adds to existing academic and professional discourse by providing an in-depth examination of the relationship between innovation and traditional banking practice. Finally, this thesis fills the gap in the extant literature, offering concrete and implantable insights into using technology for sustainable success. Additionally, it illustrates successful use cases that can be replicated by banks with a need to formulate their path in the world of digital transformation.

Future research may consider the incorporation of quantum computing along with machine learning in order to enhance the efficiency of banking, as the financial world continues to develop. Studying the socio-economic impact of these technologies will allow us a better idea of their wider consequences as well.

With technology being the game-changer here, the latest & innovative trends have become imperative for financial institutions & service providers. These advancements can empower banks to gain advantages by overcoming existing challenges while also providing space for new innovation, customer satisfaction and market leadership.

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