APPLYING LSTM DEEP LEARNING MODEL TO PREDICT CORPORATE CAPITAL STRUCTURE: A DATA-DRIVEN APPROACH

ỨNG DỤNG MÔ HÌNH HỌC SÂU LSTM TRONG DỰ BÁO CƠ CẤU VỐN CỦA DOANH NGHIỆP: TIẾP CẬN THEO HƯỚNG DỮ LIỆU

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ABSTRACT

Capital structure plays a crucial role in corporate finance, influencing investment decisions and financial performance. Traditional econometric models have been widely used to predict capital structure; however, recent advancements in deep learning offer promising alternatives. This study explores the application of Long Short-Term Memory (LSTM) models for capital structure prediction, comparing their performance against conventional machine learning approaches. Using financial data from major corporations, we analyze the predictive capabilities of LSTM architectures. Our findings indicate that LSTM models exhibit superior accuracy in capturing complex patterns within financial datasets, demonstrating their potential as powerful tools for capital structure forecasting.

Keywords: *LSTM, capital structure prediction, deep learning, financial forecasting, time-series analysis.*

TÓM TẮT

Cơ cấu vốn đóng vai trò quan trọng trong tài chính doanh nghiệp, ảnh hưởng đến các quyết định đầu tư và hiệu quả tài chính. Các mô hình kinh tế lượng truyền thống đã được sử dụng rộng rãi để dự đoán cơ cấu vốn; tuy nhiên, những tiến bộ gần đây trong học sâu mang lại một hướng tiếp cận đầy hứa hẹn. Nghiên cứu này khám phá việc ứng dụng các mô hình LSTM trong dự đoán cơ cấu vốn, đồng thời so sánh hiệu suất của chúng với các phương pháp học máy truyền thống. Bằng cách sử dụng dữ liệu tài chính từ các tập đoàn lớn, chúng tôi phân tích khả năng dự đoán của các kiến trúc LSTM. Kết quả nghiên cứu cho thấy, mô hình LSTM có độ chính xác vượt trội trong việc nắm bắt các mẫu phức tạp trong dữ liệu tài chính, thể hiện tiềm năng của chúng như những công cụ mạnh mẽ trong dự báo cơ cấu vốn.

Từ khóa: *LSTM, dự đoán cơ cấu vốn, học sâu, dự báo tài chính, phân tích chuỗi thời gian.*

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1. INTRODUCTION

The increasing complexity of financial markets has necessitated the development of advanced predictive models to support corporate financial decision-making. Capital structure, defined by the proportion of debt and equity financing, plays a crucial role in determining a firm's financial stability and growth potential. Traditional econometric models and statistical approaches have been widely used to analyze capital structure determinants, but their ability to capture complex, nonlinear relationships in financial data is often limited. As a result, machine learning (ML) techniques, particularly deep learning models such as Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for forecasting financial trends.

LSTM, a specialized form of recurrent neural networks (RNNs), is designed to efficiently process and learn from sequential financial data, making it highly suitable for capital structure prediction. Unlike conventional models, LSTM can capture long-term dependencies and nonlinear patterns in time-series data, addressing challenges such as dynamic market conditions, firm-specific financial fluctuations, and macroeconomic changes. In the context of emerging markets, including Vietnam, capital structure decisions are influenced by regulatory environments, market liquidity, and economic volatility. Leveraging LSTM models in capital structure forecasting can provide firms with more accurate and data-driven insights, aiding in financial planning and risk management.

Vietnam's financial market has undergone significant transformation over the past two decades, driven by rapid economic growth, increased foreign investment, and evolving regulatory policies. As Vietnamese firms expand and integrate into global markets, optimizing capital structure becomes a strategic priority. However, existing research on capital structure forecasting in Vietnam remains limited, with most studies relying on traditional econometric approaches that may not fully capture the complexities of financial data in a fast-changing market.

The adoption of AI and deep learning in financial forecasting presents a promising avenue for improving predictive accuracy. LSTM networks, in particular, have demonstrated success in forecasting stock prices, interest rates, and financial ratios across global markets. Applying LSTM to capital structure prediction in Vietnam can help firms navigate financial risks, enhance investment strategies, and optimize debt-equity decisions. This study aims to fill the research gap by evaluating the effectiveness of LSTM in predicting capital structure trends within the Vietnamese financial landscape.

This study seeks to advance the application of deep learning in financial forecasting by:

Developing an LSTM-based model to predict capital structure using historical financial data from Vietnamese firms.

Comparing the predictive performance of LSTM with traditional models such as Catboosting, Support Vector Regression (SVR), and Random Forest (FR).

Assessing the implications of LSTM-based predictions for corporate financial strategy, investment decision-making, and risk management in Vietnam's emerging market.

By leveraging LSTM networks, this research aims to provide a robust and data-driven approach to capital structure forecasting, offering valuable insights for businesses, investors, and policymakers operating in Vietnam's financial markets.

2. LITERATURE REVIEW

Capital structure, defined by the proportion of debt and equity financing, plays a crucial role in corporate financial decision-making. Previous research has extensively explored the determinants of capital structure, with studies indicating that firm size, profitability, tax considerations, and market conditions significantly influence financing choices [1]. Larger firms tend to have greater access to debt financing due to lower perceived risk, while firms with higher profitability often rely more on internal funds, reducing their dependence on external debt. Additionally, studies have highlighted that institutional, cultural, and geographic factors contribute to variations in capital structure policies across different markets [2].

The emergence of AI and ML in financial modeling has provided new perspectives on capital structure prediction. Traditional econometric models, such as RF and SVR, have been widely used for financial forecasting but often struggle with capturing complex, nonlinear relationships within financial data. Artificial Neural Networks (ANNs) have been increasingly applied in financial prediction due to their ability to model intricate dependencies in data. Research has demonstrated that ANNs outperform conventional statistical models in predicting financial outcomes such as stock prices, credit risk, and macroeconomic trends [3].

Among AI-based models, LSTM networks have gained prominence for their effectiveness in time-series forecasting. Unlike traditional neural networks, LSTMs are specifically designed to retain long-term dependencies, making them particularly useful for financial time-series data, where historical trends play a critical role in future predictions

An LSTM network consists of key components that regulate information flow:

- Cell State (Ct): Stores long-term information and is controlled by different gates.

- Input Gate (it): Determines which new information from the current input should be added to the cell state.

- Forget Gate (ft): Decides which information in the cell state should be removed.

- Output Gate (ot): Selects the relevant part of the cell state to generate the output (ht).

At each time step t, the LSTM model performs the following operations:

- Forget Step: Identifies and discards irrelevant information.

$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$

- Input Step: Adds relevant information to the cell state.

$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$

$\tilde{C}_t = \tanh\,(W_c.[h_{t-1}, x_t] + b_c)$

$C_t = f_t.C_{t-1} + i_t.\tilde{C}_t$

- Output Step: Generates predictions based on the updated cell state.

$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)$

$h_t = o_t.\tanh(C_t)$

Advantages of LSTM: LSTM networks are highly effective in handling long-term dependencies, making them superior to traditional RNNs. Unlike standard RNNs, which struggle with retaining information over long sequences, LSTM employs gating mechanisms to selectively store and discard information. This enables LSTM to process complex time-series data efficiently, ensuring more reliable predictions.

Another significant advantage of LSTM is its robust performance in financial time-series analysis. Since financial data often exhibit nonlinear relationships and temporal dependencies, traditional models may fail to capture these complexities. LSTM, with its ability to model long-term dependencies, enhances forecasting accuracy, making it a valuable tool in financial decision-making.

Limitations of LSTM: Despite its advantages, LSTM has notable limitations. One of the primary challenges is its high computational complexity. Compared to conventional ML models, LSTM networks require substantial computational resources due to their large number of parameters. This can lead to increased training costs and make real-time applications challenging.

Another drawback, optimizing LSTM models can be challenging. They are prone to overfitting if not trained on sufficiently large datasets or if proper regularization techniques are not applied. Ensuring a well-balanced dataset and incorporating strategies such as dropout or batch normalization is essential to improve model generalization and stability.

Applications of LSTM in Capital Structure Prediction:

- Stock Price Forecasting: Predicts future stock price fluctuations based on historical data [4].

- Interest Rate Prediction: Helps anticipate interest rate changes for financial strategy planning [5].

- Credit Risk Analysis: Assesses loan default probabilities using historical financial data [6].

- Earnings Prediction (EPS): Forecasts corporate earnings, aiding investment decisions [7].

- Financial Market Volatility Estimation: Predicts large market movements, such as stock index fluctuations and exchange rate variations [8].

- Sentiment Analysis and Market Trend Forecasting: Uses social media and news data to predict market trends [9].

- Cash Flow Forecasting and Corporate Financial Management: Helps businesses plan financial strategies effectively [10].

Given the increasing integration of AI in financial decision-making, this study aims to evaluate the effectiveness of LSTM networks in capital structure prediction. By comparing LSTM with traditional models such as Catboosting, SVR, and RF, this research seeks to provide insights into the most suitable approach for forecasting capital structure trends in dynamic financial environments. The following sections detail the data sources, methodologies, and empirical analysis conducted to assess model performance and applicability in financial forecasting.

3. DATA AND METHODOLOGY

3.1. Data Collection and Preprocessing

The dataset includes 8 observations, each containing 15 financial ratios extracted from annual financial statements spanning the years 2015 to 2022. The data was obtained from Fiinpro, then aggregated and processed using Python to ensure consistency and accuracy. Table 1 provides detailed information on the listed companies. The selected companies are among the top ten in market capitalization on their respective stock exchanges and are publicly traded on Vietnam's three major stock exchanges: HOSE, HNX, and UPCoM.

Table 1. Data representing the stock market indices of different companies with industries

Sector	Company	Industry
HOSE	VHM	Construction and Real Estate
	FPT	Technology and Information
	GAS	Energy
HNX	IDC	Construction and Real Estate
	PVS	Energy
	KSV	Mining
UPCoM	VGI	Technology and Information
	ACV	Transportation and Warehousing
	MCH	Manufacturing

Table 2 provides a detailed overview of the financial ratios utilized in this study to develop predictive models. The capital structure is represented by the debt-to-equity (DE) ratio, while the remaining financial ratios, along with their respective formulas, are outlined to offer a clear reference for readers. The preprocessing steps, including data cleaning, normalization, and transformation, were performed using Python to enhance model reliability and predictive performance.

Table 2. Variables

Variable Name	Symbol	Definition
Dependent Variable		
Capital structure	DE	Total debt/equity
Independent Variable		
Liquid asset turnover	LAT	Revenues/cash and equivalents
Current asset turnover	CAT	Revenues/current assets
Tangible fixed assets	TFA	Revenues/tangible fixed assets
Asset turnover	AT	Revenues/assets
Equity turnover	EQT	Revenues/equity
Profitability	ROE	Net income/equity
Profitability	GROSS	Gross margin
Profitability	EBITDA	Ebitda margin
Profitability	NETINC	Net income margin
Liquidity	CUR	Current assets/current liabilities
Liquidity	QUR	(Cash and short investments)/ current liabilities
Liquidity	STDE	Current liabilities/equity
Solvency	TLTA	Total liabilities/total assets
Solvency	COVER	EBIT/interest expenses
Solvency	TLE	Total liabilities/equity

To enhance the dataset and improve model accuracy, we employed a time-series interpolation technique to enrich the data. This method allowed us to generate additional observations by estimating missing values based on historical trends, ensuring a more comprehensive and continuous dataset. By leveraging time-series interpolation, we maintained the integrity of financial patterns while addressing potential data gaps.

3.2. Model Development

Our methodology begins with comprehensive data preprocessing. The dataset consists of key financial ratios that influence capital structure, including profitability, liquidity, solvency, and turnover metrics. To ensure consistency in scale and prevent dominance of variables with larger numerical ranges, min-max normalization is applied across all features. This transformation standardizes the dataset within a defined range, enhancing the efficiency and stability of the learning process.

Once preprocessed, the data is formatted into a time-series structure, as LSTM models require sequential input to recognize trends over time. A sliding-window approach is employed, where historical financial data points are used to predict future values. This method allows the model to learn from past patterns and make more accurate projections about capital structure dynamics.

To evaluate performance, the dataset is split into training and testing sets, ensuring that the model is exposed to sufficient historical data for learning while reserving a portion for unbiased assessment. The LSTM architecture is designed with multiple layers to enhance its ability to capture complex dependencies. The network consists of stacked LSTM layers, followed by a dense output layer responsible for generating the final prediction. Hyperparameter tuning, including adjustments to the number of units, learning rate, and batch size, is performed to optimize predictive performance.

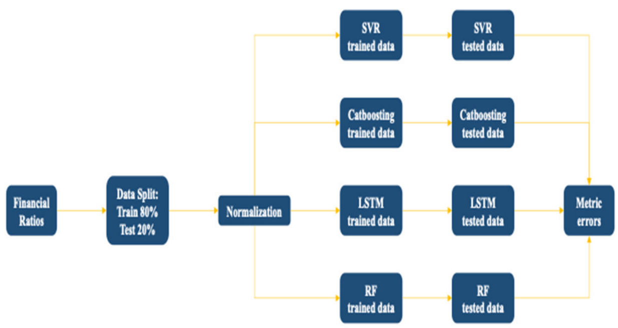

Fig. 1. Methodology

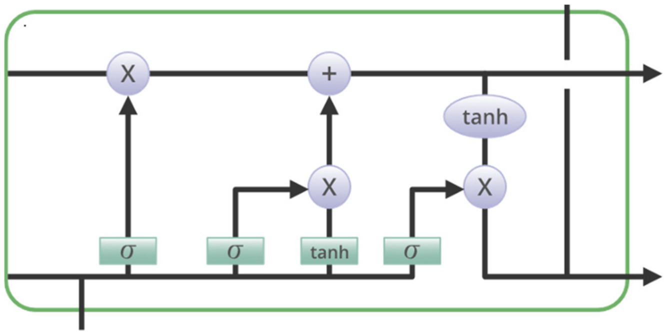

Fig. 2. LSTM structure

To prevent overfitting, an early stopping mechanism is integrated, which monitors validation loss and halts training when no further improvement is observed after two consecutive epochs. The LSTM architecture consists of a stacked structure, beginning with an initial LSTM layer configured with return_sequences=True to ensure sequential outputs for deeper layers. Two additional LSTM layers, each with 100 units, further process the time-dependent features. A final LSTM layer with 50 units extracts the most relevant information before passing it to a Dense output layer, which produces a single prediction value.

The model is trained using the Adam optimizer, with Mean Squared Error (MSE) as the loss function. Performance is evaluated using multiple metrics, including R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The training process runs for a maximum of 100 epochs, with a batch size of 32, ensuring efficient learning.

$$\mathrm{MAE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|x_i - \bar{x}_i|}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}$$

By leveraging historical financial data formatted as sequential inputs using a sliding-window approach, the model learns patterns in capital structure fluctuations. The integration of early stopping ensures generalization to unseen data, reducing the risk of overfitting. The proposed LSTM model is benchmarked against traditional ML techniques, including SVR, RF, and CatBoosting, demonstrating its robustness in financial forecasting.

3.3. Performance Evaluation

To assess the effectiveness of our proposed LSTM-based model for capital structure prediction, we utilize two widely recognized error metrics: MAE and RMSE. These metrics provide insights into the accuracy and reliability of the predictive models, with lower values indicating superior performance. Definitions and interpretations of these metrics can be referenced in the study by Chicco et al [11].

Table 3 presents a comparative evaluation of LSTM against traditional ML models, including CatBoosting, SVR, and RF, across multiple companies.

Table 3. Algorithm metric errors

Company	Metrics	LSTM	Catboost	SVR	RF
VHM	MAE	**0.00051**	0.10189	0.12507	0.10054
	RMSE	**0.00065**	0.11715	0.12591	0.11597
FPT	MAE	**0.00219**	0.10191	0.12507	0.10047
	RMSE	**0.00256**	0.11716	0.12591	0.11591
GAS	MAE	**0.00131**	0.10189	0.12507	0.10047
	RMSE	**0.00144**	0.11714	0.12591	0.11591
IDC	MAE	**0.00054**	0.10191	0.12507	0.10046
	RMSE	**0.00062**	0.11715	0.12591	0.11589
PVS	MAE	**0.00103**	0.10188	0.12507	0.10043
	RMSE	**0.00134**	0.11713	0.12591	0.11587
KSV	MAE	**0.00517**	0.10191	0.12507	0.10046
	RMSE	**0.00583**	0.11715	0.12591	0.11589
VGI	MAE	**0.00271**	0.10191	0.12507	0.10044
	RMSE	**0.00274**	0.11716	0.12591	0.11588
ACV	MAE	**0.00112**	0.10188	0.12507	0.10045
	RMSE	**0.00123**	0.11713	0.12591	0.11589
MCH	MAE	**0.00515**	0.10191	0.12507	0.10056
	RMSE	**0.00582**	0.11715	0.12591	0.11599

The results indicate that LSTM consistently outperforms all competing models, demonstrating superior predictive capability with the lowest error values across all examined companies. For instance, in the case of VHM, LSTM achieves an MAE of 0.00051 and an RMSE of 0.00065, significantly lower than CatBoost (0.10189 MAE, 0.11715 RMSE), SVR (0.12507 MAE, 0.12591 RMSE), and RF (0.10054 MAE, 0.11597 RMSE). Similar trends are observed across other companies, reinforcing LSTM's effectiveness in capital structure prediction.

Among traditional ML models, CatBoost and RF exhibit relatively better performance than SVR. However, both models still fall considerably short in comparison to LSTM, as evidenced by their consistently higher MAE and RMSE values. SVR, in particular, records the highest error rates across all cases, indicating its limited capability in capturing the complexities of financial time-series data. The superior performance of LSTM can be attributed to its ability to capture long-term dependencies and nonlinear patterns inherent in financial data, a crucial advantage in capital structure forecasting. Conversely, tree-based models such as CatBoost and RF, while robust in handling structured data, lack the sequential memory mechanisms necessary for effectively modeling temporal dependencies, resulting in higher predictive errors.

To further analyze the robustness of LSTM, we evaluate its performance for different forecasting windows using VHM data, as shown in Table 4.

Table 4. Forecasting VHM metrics for different windows

Window	MAE	RMSE
90 days	**0.00259**	**0.00272**
120 days	**0.00399**	**0.00446**
180 days	**0.00433**	**0.00534**

The results reveal that shorter forecasting windows yield more accurate predictions. Specifically, a 90-day window achieves the lowest MAE (0.00259) and RMSE (0.00272), while increasing the forecast horizon to 180 days leads to higher errors (MAE = 0.00433, RMSE = 0.00534). This indicates that while LSTM effectively captures short-term patterns, predictive uncertainty increases over extended periods due to accumulating forecast errors and potential structural changes in financial data.

These findings underscore the efficacy of deep learning approaches, particularly LSTM, in financial forecasting applications. By effectively learning complex relationships within sequential data, LSTM proves to be the most reliable model for capital structure prediction, offering substantial advantages over conventional ML methods.

4. RESULTS AND DISCUSSION

The developed models for the *DH* and *MRR* are optimized using AMGA, which has the capacity of finding the optimal solution of a multi-objective problem. It is tough work to determine the optimal process parameters for simultaneous improving machining responses. Additionally, processing factors have complex effects on the technical outputs. The optimizing issue can be described as follows:

The empirical findings from our study highlight the superiority of LSTM models in predicting capital structure over traditional ML models such as CatBoost, SVR, and RF. The significantly lower MAE and RMSE values obtained from the LSTM model across all tested companies indicate that deep learning methods can effectively capture complex financial patterns and long-term dependencies. The ability of LSTM to model nonlinear relationships and sequence-dependent data provides a distinct advantage in financial forecasting, particularly in dynamic and volatile markets like Vietnam.

Our results align with prior research suggesting that deep learning models outperform conventional econometric approaches in financial time-series analysis. While traditional models such as RF and SVR struggle with capturing intricate dependencies in sequential data, LSTM's memory gating mechanisms allow it to retain and utilize long-term financial trends effectively. This capability is especially crucial for capital structure forecasting, where historical financial decisions significantly impact future financial strategies.

Additionally, the comparison among traditional models reveals that CatBoost and RF exhibit relatively better performance than SVR, though both still fall short of LSTM. SVR's relatively poor predictive performance may be attributed to its inability to effectively model time-series data, reinforcing the need for models specifically designed to handle sequential dependencies in financial forecasting.

This study contributes to the advancement of deep learning applications in financial forecasting by demonstrating the effectiveness of LSTM in capital structure prediction. Our research aligns with the growing adoption of AI-driven methodologies in corporate finance and provides a comparative analysis against traditional models, including CatBoosting, SVR, and RF. By benchmarking the predictive accuracy of LSTM, this study offers valuable insights into the advantages of memory-based neural networks in capturing complex financial trends. Furthermore, our work expands the literature on financial forecasting in emerging markets, particularly in Vietnam, where economic and regulatory conditions influence corporate capital structure decisions. The findings suggest that LSTM models can serve as a robust analytical tool for firms, investors, and policymakers seeking data-driven financial planning solutions.

The findings of this study offer important implications for corporate finance professionals, investors, and policymakers operating in Vietnam's financial markets. Companies can leverage LSTM-based predictions to optimize their debt-equity structure, ensuring financial stability and long-term growth. The ability of LSTM to capture complex financial patterns makes it a valuable tool for risk management, enabling firms to identify early warning signals for financial distress and implement proactive strategies. Investors can integrate AI-driven capital structure forecasts into their decision-making models, improving risk assessment and portfolio management. Additionally, regulators can utilize AI-driven insights to formulate policies that enhance financial market stability, transparency, and efficiency.

While this study provides strong evidence supporting the effectiveness of LSTM in capital structure prediction, several areas warrant further investigation. Future research could explore the integration of alternative data sources, such as macroeconomic indicators, sentiment analysis from financial news, and alternative datasets, to improve predictive accuracy. Another promising direction involves developing hybrid AI models that combine LSTM with attention mechanisms or transformer-based architectures to enhance forecasting performance. Additionally, assessing the application of LSTM under different market conditions, including financial crises or extreme economic events, can provide insights into the model's robustness. Finally, implementing real-time capital structure forecasting models could be beneficial for financial institutions and investors, offering practical insights for immediate decision-making in dynamic financial environments.

5. CONCLUSION

This study demonstrates the superiority of the LSTM model in capital structure prediction compared to traditional ML approaches such as CatBoost, SVR, and RF. By effectively capturing temporal dependencies and nonlinear patterns, LSTM consistently achieves lower prediction errors, underscoring its robustness in financial forecasting. Empirical results across multiple companies confirm that LSTM significantly outperforms conventional models, particularly SVR, which struggles with the complexities of financial time-series data.

Furthermore, an analysis of different forecasting horizons reveals that prediction accuracy declines as the time window extends. While LSTM performs optimally in short-term forecasting, its error margins increase for longer forecasts. This highlights the challenge of long-term financial prediction and suggests the potential benefits of hybrid deep learning architectures or attention mechanisms to enhance forecasting accuracy over extended periods.

The findings of this study have important practical implications for corporate finance, investment strategies, and risk management. Accurate capital structure predictions can support financial decision-makers in optimizing funding strategies and mitigating risks. Future research could explore the integration of advanced architectures, such as Transformer-based models, or the inclusion of macroeconomic indicators to further improve predictive performance and applicability in dynamic financial environments.

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