

Applying LSTM Recurrent Neural Networks to Predict Revenue

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Abstract. Predicting a company's revenue is not a trivial task. Attempting to identify a sales pattern for a store's products, considering all possible variables, both internal and external to the business, is a complex task. For companies that sell products, finding a way to predict next day's revenue helps maintain lean inventory, among numerous other factors. As result, fewer resources are wasted in the form of stagnant products, and there are less expenses in purchasing supplies. The main motivation for this study is to accurately forecast a company's revenue for the days, following the prediction day-only for companies that sell products and disregarding those that offer services. To achieve this goal, here, considering a real scenario, we evaluate the use of the Long Short-Term Memory (LSTM) type of Recurrent Neural Network, known for their superior ability to capture long-term temporal dependencies, outperforming traditional forecasting models in this domain. For our experiments, we employ a single real data model across various LSTM architectures, iteratively refining our approach to approximate an ideal state for future revenue prediction. This study not only validates the effectiveness of LSTM networks in handling the temporal complexity inherent in sales data but also investigates the impact of different architectural configurations on forecasting accuracy. By doing so, we aim to identify a robust model that can serve as a reliable tool for businesses in their inventory and supply chain management strategies.

Keywords: Revenue · Prediction · RNN · LSTM

1 Introduction

Well-managed companies aim to achieve three objectives: increased customer satisfaction, increased revenue, and reduced expenses. For such, entrepreneurs need to address various day-to-day questions related to cash flow, future revenues, the cost of purchasing raw materials and finished products, the volume

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of stagnant inventory, among others. Furthermore, companies must be flexible to respond rapidly to competitive and market changes. They must benchmark continuously to achieve best practice [8].

In the dynamic landscape of business, anticipating future sales becomes a pivotal challenge for entrepreneurs striving to make informed decisions, which is a crucial part of company strategy. Competitive strategy is about being different [8]. To follow this process, suppose a scenario where a business owner could harness the power of advanced technologies to predict future sales with remarkable accuracy.

The main goal of this work is to assist business owners in partially or fully addressing some of the mentioned questions, as well as others related, since answering these questions will contribute to achieving the above-mentioned objectives. Knowing how to find a value close to future revenue not only brings the direct benefit of more resources to the company but also entails indirect benefits, such as better-managed and leaner inventory. This, in turn, leads to another indirect benefit, which is the reduction of the company's costs, since the lean production philosophy considers inventory a form of waste that should be minimized [16].

There are several ways to assist a business owner in achieving their objectives. A financial consultant could provide this service due to their highly specialized knowledge. However, machine learning models could also be used, provided that those capable of handling complex time series are selected [1].

This article delves into the realm of predictive analytics, specifically focusing on the application of Long Short-Term Memory (LSTM) networks. By exploring the potential of LSTM networks in forecasting future sales, it aims to empower business owners with valuable insights, allowing them to navigate the complexities of their operations with greater foresight and efficiency. The integration of cutting-edge technologies in sales prediction not only aligns with the pursuit of increased revenues but also sets the stage for more streamlined inventory management and cost reduction, ultimately contributing to the holistic success of a business.

The Long Short-Term Memory (LSTM) type of Recurrent Neural Networks (RNNs) is a machine learning model that performs well with complex time series, handling variable sequences and non-linear data [7]. Therefore, it has been chosen for the data analysis in this problem due to its intrinsic nature.

The data for training the model were retrieved from the database of an online system called My Bucks [4], owned by a company affiliated with Neural Tec [13] called Blue Forge. All the data used are real, as it was decided that fictitious data would not be used for the study at any point. Furthermore, the available volume was substantial, which would provide more security for the neural network training process. The data was grouped by day and presented to the Neural Network with nineteen features: the sales date, the company, the total revenue for the day, among others. The granularity of the data that is used as an input for time-series forecasting, is an important factor in the process of prediction [7].

The study's objective is to analyze data from 10 previous days before a specified date and attempt to predict the revenue for the following day. If this process

proves successful, it would be extended to more subsequent days. However, if unsuccessful, the model's training data would be enriched with new features for further model training and accuracy analysis.

Various neural network architectures were chosen to train the dataset, aiming to find the one that best adapts-that is, the one that best predicts future revenue. This article will present the best architecture, and its result will be displayed to validate its quality.

This article has four sections: related work, methodology, experimental analysis and conclusion. The related work section will present the literature review and compare other articles to this work. The methodology section will indicate how the data was pre-processed and will briefly explain the algorithms used for prediction. Then, the experimental analysis section will be presented, displaying the chosen data format, the configuration used for algorithm comparison, the analysis criteria used to find the best algorithm, and the obtained results of best architecture. Finally, a conclusion will be presented regarding the most successful algorithm to be used for the sales prediction problem.

2 Related Work

This section aims to provide a comprehensive overview of previous studies and relevant research that underpin and contextualize the present work. It addresses a variety of theoretical approaches, methodologies, and findings that have contributed to the development of the field under study.

Related works are organized according to specific themes and topics, allowing for a clearer understanding of the evolution of knowledge in the area. Each work is succinctly summarized, highlighting its significant contributions and its connections to the objectives and methodology adopted in this article.

By exploring related works, it is possible to identify gaps in existing knowledge, unresolved challenges, and opportunities for additional contributions. This section serves as a solid foundation for the argument and relevance of the present study while acknowledging and valuing the contributions of previous researchers.

In [12], the authors provide a tutorial-like introduction to Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN), originally developed as supplementary material for Artificial Intelligence lectures. It emphasizes understanding LSTM-RNN's evolution since the early nineties, noting changes in notation and representation in today's publications. The article highlights the significance of LSTM-RNN and its potential to improve machine learning algorithms, offering valuable insights into their workings and motivating further development within the machine learning community.

In [1], the research aims to develop a reliable sales trend prediction mechanism using data mining techniques to optimize revenue generation in today's data-driven business environment, particularly in the E-commerce industry. Accurate sales forecasting is crucial for effective enterprise planning and decision-making, impacting resource management and market growth. By employing data mining techniques, vast amounts of data can be transformed into actionable

insights, facilitating sound budgeting and strategic planning across functional areas. The study focuses on selecting appropriate approaches for precise sales forecasting, involving extensive data analysis and the evaluation of prediction algorithms. The research findings, methodologies, and future directions are discussed comprehensively, emphasizing the importance of predictive analytics in driving business success. The authors compare machine learning techniques such as Generalized Linear Model (GLM), Decision Tree, and Gradient Boosted Trees (GBT), concluding that the GBT algorithm had the best predictive performance. Despite not employing neural network techniques, the article proved useful in studying data preprocessing techniques for sales prediction.

In [7], the text discusses the application of artificial intelligence, particularly deep neural networks like Long Short-Term Memory (LSTM) with CNN-LSTM (Convolutional Neural Network and Long Short-Term Memory) and Convolutional Long Short-Term Memory (ConvLSTM), in time series analysis and forecasting, addressing challenges such as economic complexity and data granularity. It highlights the importance of sentiment analysis in automated opinion classification, particularly in processing large volumes of textual data. The paper proposes a model for company revenue prediction using deep learning techniques, leveraging quantitative stock data and news sentiments as input features, with a focus on sequence classification for binary forecasting.

In [11], the paper addresses the importance of sales forecasting for business decision-making, particularly in resource allocation, cash flow management, and early risk identification. It discusses the use of machine learning techniques, specifically time series models, such as Auto Regressive Integrated Moving Average (ARIMA) and Long Short Term Memory (LSTM) networks, for sales prediction. ARIMA models are explained in terms of their parameters and their application to stationary time series, while LSTM networks are highlighted for their ability to handle sequence dependence. The paper proposes a comparative study of ARIMA, SARIMA, and LSTM models for profit prediction, emphasizing data collection, model development, and forecasting for the next five years. It is structured to discuss literature review, model building, result analysis, and conclusion in subsequent sections.

In [2], a study was conducted on the insurance industry. The insurance industry serves crucial functions in dispersing risks, compensating losses, financing, and social management, contributing to the stability of people's living standards and social stability. With China emerging as a dominant force in the global insurance market, witnessing significant growth in premium income, now ranking third globally, its importance to the national economic system as a financial pillar and GDP growth driver cannot be overstated. As China's economy transitions to a "new normal" characterized by innovation-driven growth, predicting premium income scale has become a pertinent concern. Long Short-Term Memory (LSTM) neural networks, known for their ability to capture long-term relationships in time series data, offer promising prospects for accurate prediction in the financial domain, notably in stock market forecasting, underscoring their applicability and effectiveness across various fields.

In [3], the authors conduct a comparative study for retail sales prediction using LSTM and ARIMA networks. Environmental concerns, particularly regarding food waste, have become increasingly urgent. The disposal of expired or unsold food by grocery stores not only has significant negative environmental impacts but also poses economic implications. To address this, more accurate sales forecasting methods are crucial. By utilizing historical sales data and patterns, time-series forecasting approaches, such as Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN), have been employed. Among these, Long Short-Term Memory (LSTM) models have gained attention for their ability to remember long-term information in time-series data. Hence, this study focuses on using LSTM and ARIMA models to predict future sales, aiming to mitigate food waste and promote environmental sustainability while optimizing economic outcomes for grocery stores.

In [9], a comparison was made between two RNN models for predicting sales of medium-sized restaurants. The challenge of forecasting sales in small and medium-sized restaurants, often hindered by limited data and resources for analysis, is crucial for efficient employee scheduling and cost-effectiveness. Traditionally, sales predictions are made intuitively or through economic modeling, focusing on factors like guest counts and sales dollars. Despite the shift towards machine learning methods, including neural networks like LSTM, empirical evidence suggests mixed results compared to traditional statistical models like ARIMA. Recent research emphasizes the importance of accurate forecasting methodologies, particularly in the restaurant industry, highlighting the need for comprehensive studies to compare various machine learning techniques and traditional models. This paper aims to address this gap by conducting a thorough survey of forecasting models using real-world data, aiming to identify optimal methods for predicting sales with an emphasis on accuracy and reproducibility.

In [14], a study is conducted on predicting high and low prices of soybeans futures using an LSTM network. Predicting price movements in financial time series is essential for investors to mitigate risks and maximize returns, constituting a significant challenge in finance. Neural networks, renowned for their nonlinear fitting capabilities, have been extensively employed in this endeavor. Researchers have utilized models like the backpropagation (BP) neural network for price prediction, with recent advancements focusing on deep learning techniques such as the long short-term memory (LSTM) neural network. While LSTM models offer improved accuracy, noise in closing prices poses a challenge, prompting exploration into predicting high and low prices of futures. Despite limited research in this area, this paper employs LSTM networks to forecast high and low prices of soybean futures, yielding promising results that, when combined with a simple trading strategy, demonstrate the potential for substantial profits.

In [6], the authors propose an approach based on Long Short-Term Memory with Particle Swam Optimization (LSTM-PSO) for sale forecasting in E-commerce companies. The advancement of economic development and technology, alongside the evolution of logistics systems, has significantly reshaped

the purchasing behavior of Chinese consumers, particularly with the rise of e-commerce technology. During the 2019 Double 11 shopping festival in China, various e-commerce platforms shattered sales records, with Tmall alone generating RMB 10 billion in sales within 1 min and 36 s, leading to a total transaction volume of RMB 268.4 billion and 1.292 billion logistics orders. Sales forecasting, crucial for both traditional businesses and modern e-commerce platforms, aids managers in decision-making processes such as call center preparation, logistics scheduling, and resource allocation. However, e-commerce companies face unique challenges due to the dynamic online environment and the influence of marketing behavior on consumer shopping patterns, necessitating sophisticated analytical models like neural networks for accurate sales forecasting. This paper proposes a novel Long Short-Term Memory (LSTM) based approach for sales forecasting in e-commerce companies, optimizing model parameters using Particle Swam Optimization (PSO) metaheuristic. Experimental results demonstrate the effectiveness of the proposed approach in forecasting accuracy, underscoring the importance of advanced machine learning techniques in addressing the complexities of e-commerce sales forecasting. The study proved to be particularly useful due to the context of e-commerce companies, as they could also utilize the technique presented in this study.

In [15], employing a blend of lightGBM (Light Gradient Boosting Machine) and LSTM, this study proposes an effective model for predicting supply chain sales, emphasizing its accuracy, efficiency, and relevance for strategic decision-making in industrial settings. In recent years, the e-commerce and logistics industries' development has transformed supply chain demand's scope and pace, necessitating enterprises to swiftly respond to customer needs to maintain competitiveness. However, increased uncertainty due to complex social relationships and fluctuating market demands has led to excessive costs within the supply chain. Addressing this challenge has become the focal point for supply chain stakeholders. Leveraging big data analysis and AI technologies for accurate long-term sales forecasting is increasingly crucial, offering vital technical support for crafting supply chain solutions. While various prediction models have been proposed, many linear models lack accuracy and stability. To enhance interpretability without compromising accuracy, this paper combines deep learning with traditional machine learning methods, employing an LSTM model for data mining and integrating it with a lightGBM model for its strong interpretability. Through comparative experiments using three sales datasets, the paper demonstrates the proposed model's effectiveness in forecasting supply chain sales, contributing to enhanced predictive accuracy and interpretability.

Sales forecasting serves as a cornerstone for firms in estimating sales revenue and shaping production, operational, and marketing strategies. Despite the ubiquitous understanding that forecasts are inherently imperfect, accurate predictions are crucial for avoiding losses and optimizing operational efficiency. This necessity is particularly pronounced for products with short lifecycles, where traditional time series forecasting models may falter due to limited historical data availability. Inaccurate sales forecasts can lead to inventory imbalances, cus-

tomer dissatisfaction, and operational challenges, impacting a company's financial health and capital management. To address these challenges, this study explores effective short-term sales forecasting methods, experimenting with different training timeseries lengths, window sizes, and sentiment analysis techniques. The proposed LSTM model combined with sentiment analysis showcases innovation and underscores the significance of accurate sales forecasting in enabling companies to adapt to market dynamics and achieve cost savings, potentially propelling them to industry leadership. In [10], the study introduces a model for short-term goods demand forecasting in E-commerce, integrating LSTM with sentiment analysis of consumer feedback from 'taobao.com'. Results highlight the efficacy of promptly adjusting sentiment weights to enhance forecast accuracy, enabling precise predictions even with limited historical data. The proposed LSTM approach demonstrates high accuracy in forecasting goods with short-term demands.

3 Methodology

3.1 Dataset

For this study, data was extracted from an online financial system called My Bucks [4]. Sales data from three hundred companies between January 2018 and December 2023 were consulted, and the data was grouped by the day of the sale.

The dataset obtained encompasses nineteen features, including sales date, company name, and daily sales figures for each company. A total of 28,049,723 records were extracted from the database. These records were subsequently aggregated based on sales date and company, resulting in a consolidated total of 4,312,935 entries.

3.2 Model Development

A CSV file was generated with this data for processing by a Python program. All data features were standardized to prevent outliers from interfering with the training process.

After standardization, the dataset was split into training and testing data at a ratio of 70%/30%, respectively. Only after this split were the data presented to the LSTM model. The data was further divided into training and validation sets at an 80%/20% ratio, respectively.

The neural network hyperparameters and experimental details are provided in Sec. 4.2.

3.3 Model Evaluation

Following the training process, the goal was to attempt to predict the revenue for the next day. If successful, the process would be extended to predict revenue for subsequent days. However, if unsuccessful, the data would be enriched with new features, and a new training cycle would commence.

4 Experimental Analysis

A CSV file was constructed from the extracted data to be presented to the model for training. Figure 1 illustrates the revenues of three randomly chosen companies from the three hundred in the dataset during the consulted period.

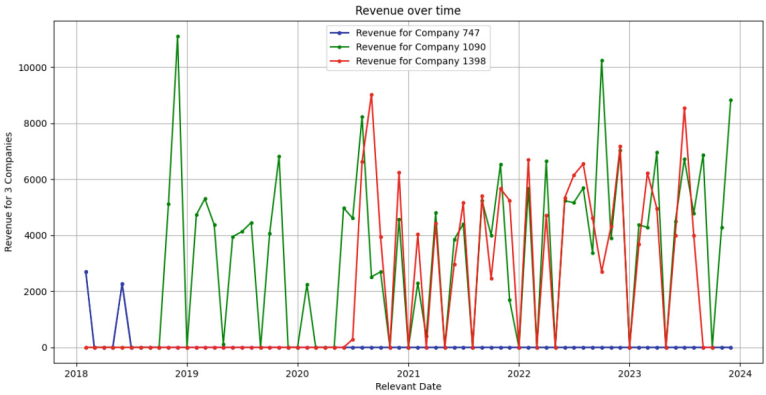

Fig. 1. Revenue of three companies over time

The IQR (Interquartile Range) technique was used to remove outliers and the data was standardized on a scale between 0 and 1, as there are no negative numbers in the dataset, given that it pertains to revenues, i.e., sales of companies. After standardization, the data was split into two sets: training and testing, in a ratio of 70%/30%, respectively. Thus, 3,019,054 records were used for training and 1,293,881 were used for testing.

Due to the nature of LSTM networks, data sequences were prepared with a size according to the chosen configuration to analyze past data. Initially set to analyze the past 10 d, several sequences with subsets of 10 d each were created.

Finally, during the training of all architectures studied, the training data was further split into two sets: training and validation, in a ratio of 80%/20%, respectively.

4.1 Algorithm and Computational Environment Configuration

For model training and subsequent data prediction, a Dell Inspiron 15 5000 notebook, with an Intel Core i7 processor running at 2.7 GHz and 8 gigabytes of memory, operating on Windows 10 64-bit OS build version 19045.3693, was used. In addition to the machine used previously, Google Colab [5] was also utilized with the configuration being CPU hardware accelerator (neither GPU nor TPU were used).

The chosen Python version was 3.7.9. For data manipulation, the Pandas library version 1.3.5 and Numpy version 1.21.6 were utilized. The SKLearn

library version 1.0.2 was used for data standardization and splitting into training and testing sets. The Keras library version 2.11.0 was employed for the LSTM neural network.

4.2 Analysis Criteria

The dataset was used to train three different neural network architectures. This study will present the best one, which was considered the winner among them all.

The configuration of the best architecture is presented next:

- LSTM layer with 50 neurons;
- Dense layer with 1 neuron;
- LSTM layer uses the tanh activation function;
- Dense layer use the linear activation function;
- Optimizer: Adaptive Moment Estimation (Adam) with a learning rate of 0.0001;
- Loss function: Mean Squared Error (MSE);
- Number of training epochs: 10;
- Batch size: 100.

Figure 2 illustrates the neural network architecture whose configuration was previously mentioned.

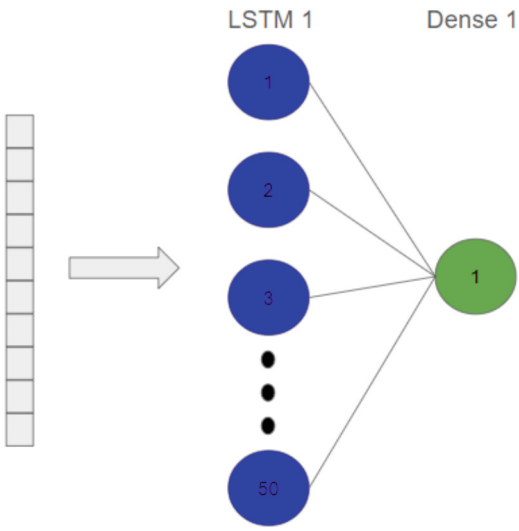

Fig. 2. Best Architecture

Figure 3 shows the training graph with the loss values for training data and this training was done using the batch training method of the Keras package.

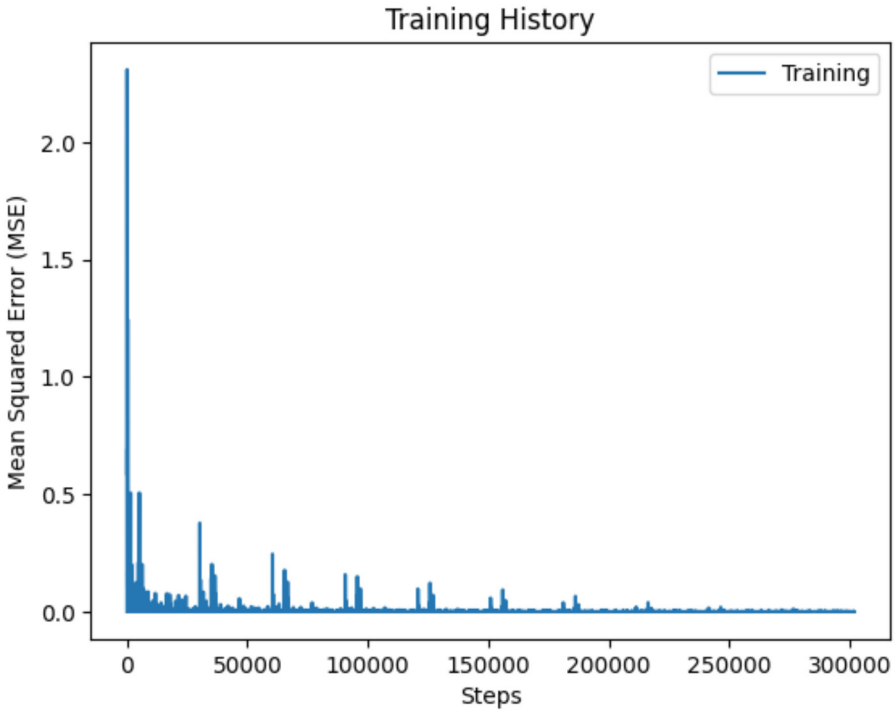

Fig. 3. Training History of Best Architecture

Following the training phase, the prediction algorithm was employed to forecast outcomes for both the training and test datasets. This step was undertaken to evaluate the accuracy of the predictions in relation to the original data, thereby assessing the model's performance.

Figure 4 shows the relationship between the original and predicted values in the train dataset. As it can be seen in the comparison between the two sets, the values are very close, indicating that the model can generalize well considering the training set.

Figure 5 shows the relationship between the original and predicted values in the test dataset. As seen in the comparison between the two sets, the values are relatively close, indicating that the model can generalize with the test set, although not as well as with the training set.

Figures 6 and 7 present boxplot graphs comparing the original data with the predicted data in the training and test datasets, respectively. Both graphs demonstrate that the data points are closely aligned, indicating a high degree of similarity between the original and predicted data and suggesting a good level of prediction accuracy, albeit some outliers can be observed in the test data.

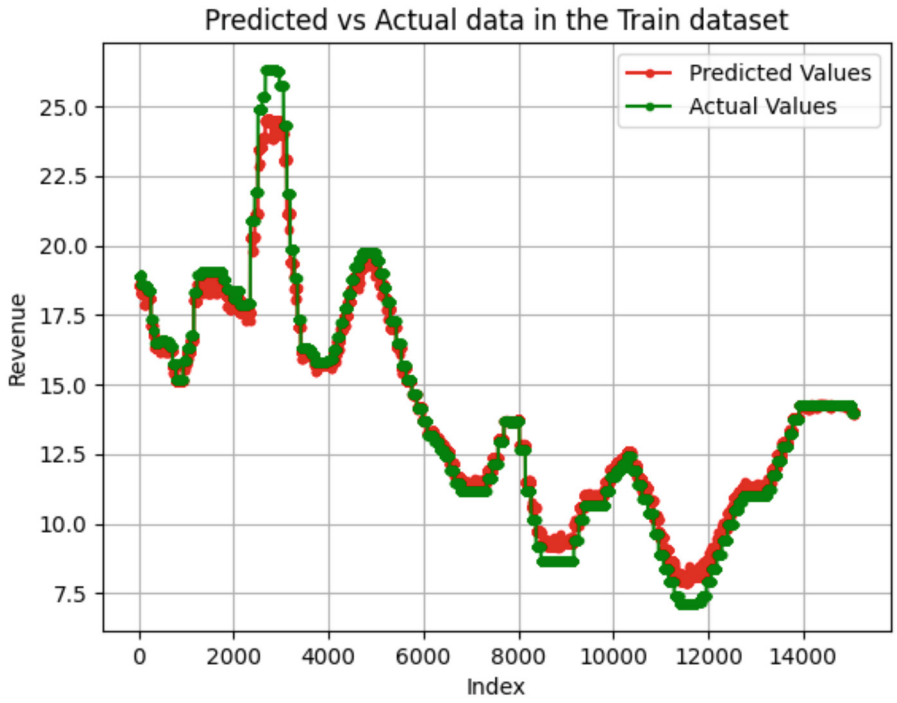

Fig. 4. Predicted vs Original Values in the Train Dataset

4.3 Results

Three distinct architectures were trained, with one emerging as the superior choice based on the outcomes detailed in the preceding section. Table 1 shows the comparison among them. Subsequently, further details regarding the training process of the most effective architecture is provided.

Table 1. Architectures Comparison

Architecture	Train Time (s)	Evaluation Loss	Evaluation MAE	Train Mean Error	Test Mean Error
Arch 1	6032.767805501	0.008931690827012062	0.0705975890159607	0.5106907777806268	1.6352886355469594
Arch 2	7076.006256432	0.105632567421456789	0.0976432567854321	0.6532507004224589	2.3567894783635373
Arch 3	9155.245678363	0.245742467853246487	0.1156894246783666	0.8422225673214567	2.9964245678534680

The selected architecture demonstrated good generalization, evidenced by the relatively modest average error observed on the test set. However, to enhance the model's robustness and predictive accuracy, exploring additional architectures and expanding the dataset to include more features is advisable. This expansion could involve integrating new data directly from the database (internal) as well as incorporating external information, such as consumer sentiment

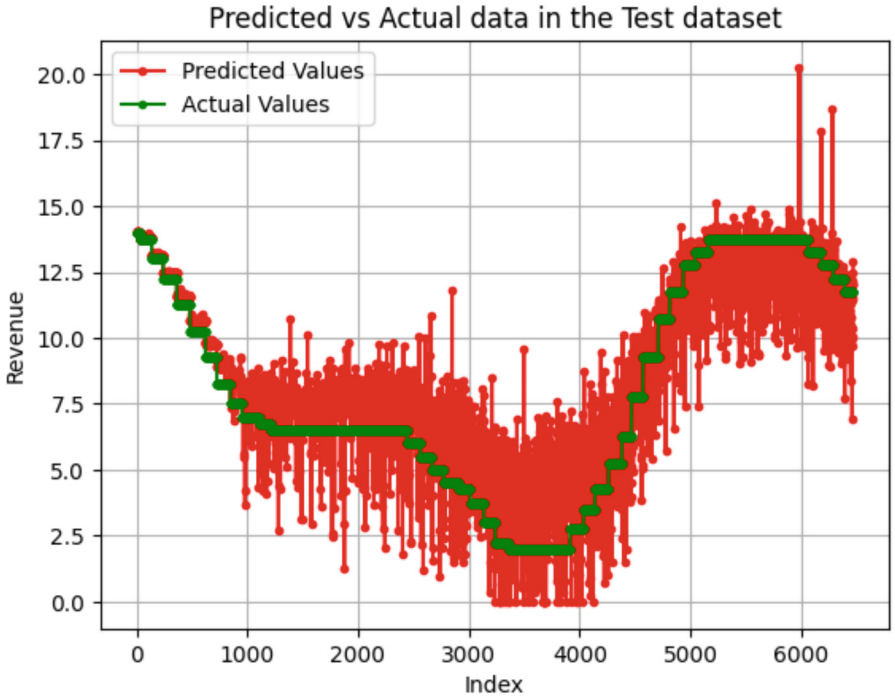

Fig. 5. Predicted vs Original Values in the Test Dataset

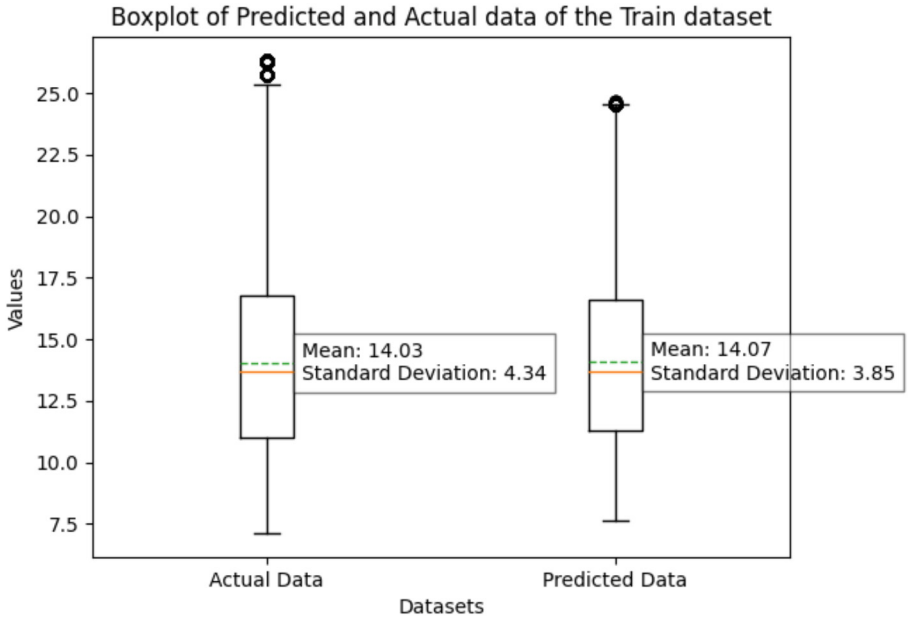

Fig. 6. Boxplot with Actual and Predicted Data in the Train Dataset

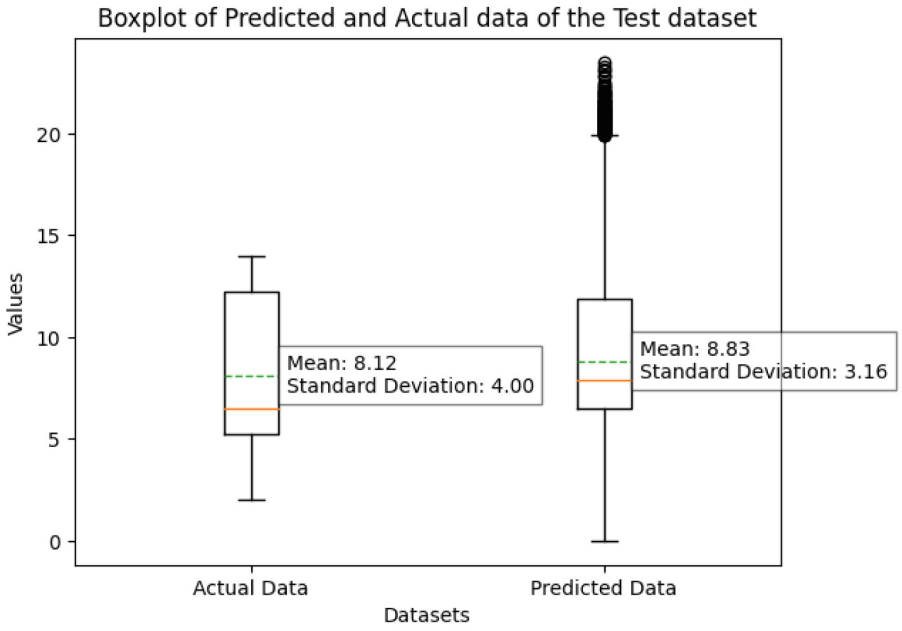

Fig. 7. Boxplot with Actual and Predicted Data in the Test Dataset

analysis related to the companies under study. Moreover, increasing the volume of records for analysis will likely contribute positively to future experiments' depth and reliability.

4.4 Discussion

The outcomes derived from the LSTM model hold significant value for any company that can provide its dataset for future revenue forecasting. Organizations adopting this analytical process benefit from enhanced planning and strategic execution. Moreover, they can minimize inefficiencies in purchasing processes, thereby reducing operational costs.

Ensuring a company's longevity necessitates optimizing its processes through the continuous and systematic application of sophisticated, accurate technologies. These technologies are essential for deciphering complex datasets and converting them into clear, actionable insights for decision-makers. This approach not only streamlines management but also supports the strategic alignment of business operations, contributing to sustainable growth and efficiency.

5 Conclusion

Discovering an automated method to forecast a company's revenue based on its billing history can significantly propel its growth by enabling more effective

inventory management and providing estimates of future cash flows. However, selecting the most suitable machine-learning technique for this intricate task is far from straightforward. The neural networks explored in this study shed light on the challenge of generalization within the confines of the available data. It became evident that quantitative and qualitative enhancement of the dataset is essential for neural network models to improve their generalization capabilities. Achieving an optimal equilibrium between the volume and quality of data and the sophistication of algorithms holds the potential to increase the longevity of companies that implement this strategy markedly.

Future work might explore a broader array of machine learning algorithms, including ensemble methods and deep learning variations, to identify models offering superior generalization capabilities. Additionally, incorporating real-time data analytics and exploring the impact of external factors, such as market trends and economic indicators, on revenue predictions could further refine the accuracy of these models.

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