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EVALUATING PREDICTIVE ACCURACY: STOCK PRICE, REVENUE, AND PROFIT FORECASTING FOR LEADING TECHNOLOGY COMPANIES

Ritesh Kumar
Research Scholar, Department of Computer Application, Sri Satya Sai University of Technology & Medical Sciences, Sehore, MP, India

Dr. Narendra Sharma
Research Guide, Department of Computer Application, Sri Satya Sai University of Technology & Medical Sciences, Sehore, MP, India

Abstract

This research presents a analysis of various forecasting models for predicting stock prices, total revenue, & operating profits of seven major technology stocksfrom the glove: (AAPL) Apple, (MSFT) Microsoft, Amazon (AMZN), Meta (META), (GOOGL) Alphabet, TCS (Tata Counsultancey Servises) and Infosys . The methodology involved six key steps: data collection from the yfinance library covering January 1, 2020, to January 1, 2023; feature engineering to create lagged variables; an 80/20 train/test split; model selection including naïve bayesian regression, KNN (k-nearest neighbors), ANN (artificial neural networks), simple moving average (SMA), & the exponential moving average (EMA); & performance evaluation through metrics such ad this like mean error (MAE), (MSE) mean squared error, & the mean absolute percentage error (MAPE). Results indicate that for stock price predictions, Naïve Bayesian Regression consistently outperformed ANN across all metrics for AAPL (MAE = 2.73), while for MSFT, ANN showed higher errors (MAE = 5.24). In total revenue predictions, traditional methods like SMA & EMA yielded zero error metrics, highlighting their robustness compared to more complex models such as ANN, which produced MAE values as high as 43.08 billion for AAPL. Operating profit predictions revealed that while traditional models maintained low MAE (SMA: 9.71 billion, EMA: 4.96 billion for AAPL), ANN exhibited MAE of 1.02e+11, indicating substantial overfitting. the findings emphasize that simpler models often outperform advanced techniques in forecasting financial metrics, underscoring the critical importance of model selection tailored to specific predictive goals.

Keywords: Keywords: Stock price prediction, revenue forecasting, machine learning, Naïve Bayesian Regression, Artificial Neural Networks, financial metrics.

1 Introduction

Predicting stock prices & key financial indicators like revenue & operating income is essential for anyone involved in financial markets, whether they're investors, analysts, or corporate strategists. However, the complexity of market dynamics, corporate behavior, & external economic factors make forecasting an ongoing challenge. Recent advancements in machine learning have started to change how we approach this problem by offering new ways to interpret vast amounts of data & predict future trends with greater precision.

In this paper, we focus on three of the biggest players in the tech industry—Apple, Microsoft, & Google. By analyzing their stock prices & financial performance over the last three years, we aim to better understand how their market behavior can be predicted. Using data obtained through the yfinance API, we created a model that incorporates historical stock prices, revenue, & operating income. To capture patterns over time, we used techniques like lagged features then also calculated (SMA) Simple Moving Averages & the Exponential Moving Averages (EMA).

H. Wasserbacher et al. (2022) This paper discusses recent developments & pitfalls in using machine learning for financial forecasting, planning, & analysis. It highlights the importance of feature engineering & the challenges of overfitting & model interpretability. The paper primarily focuses on the theoretical aspects & lacks extensive empirical validation across different financial markets [1]. J. Wang et al. (2021) This study explores the very application of the deep learning models for predicting financial markets. It emphasizes the use of neural networks and the ability to capture these very complex patterns in financial data. The study does not compare the performance of deep learning models with traditional machine learning models, leaving a gap in understanding the relative effectiveness of these approaches [2]. This paper provides a comprehensive overview of machine learning techniques used in financial forecasting & planning. It covers various models, including regression, classification, & clustering. The paper lacks a detailed analysis of the impact of different feature engineering techniques on model performance [3]. (2024) This paper presents a study on stock market prediction using machine learning. It integrates various models & evaluates their performance using standard error metrics. The study does not address the scalability of the models for real-time prediction & their adaptability to sudden market changes [4].

S. Patel (2021) This research focuses on predicting stock prices using both machine learning & deep learning frameworks. It compares the performance of different models & highlights the strengths of deep learning. The paper does not explore the integration of several external factors such as the economic indicators & the news sentiment (NS) into the prediction models [5]. Gupta et al. (2022) This paper investigates the use of ML techniques for predicting stock prices. It emphasizes the importance of model selection & hyperparameter tuning. The study lacks a comprehensive evaluation of the models' robustness to different market conditions & data anomalies [6]. M. Kumar (2023) This paper examines the application of machine learning in predicting financial asset prices. It discusses various models & their performance in different market scenarios. The paper does not provide a detailed comparison of the computational efficiency of the models, which is crucial for practical implementation [7].

L. Zhang et al. (2021) This study focuses on financial time series forecasting using this type of ML models. It highlights the effectiveness of different models in capturing temporal dependencies. The study does not address the integration of multi-source data, such as social media & news, into the forecasting models [8]. Brown (2022) This paper discusses enhancing financial forecasting accuracy with machine learning. It explores various techniques to improve model performance & reduce prediction errors. The paper lacks an analysis of the models' interpretability & their ability to provide actionable insights for financial decision-making [9]. K. Lee (2023) This research explores different machine learning approaches for stock market prediction. It compares the performance of various models & discusses their practical implications. The study does not investigate the impact of data preprocessing techniques, such as normalization & outlier removal, on model performance [10].

Li et al. (2020) presents a hybrid model combining machine learning & traditional statistical methods for stock price prediction, showing improved accuracy but lacking exploration of different data sources [11]. Qureshi et al. (2022) compare various machine learning techniques, focusing on prediction accuracy & computational efficiency, but do not address robustness to market anomalies or external factors like news sentiment [12]. hen et al. (2016) introduce xgboost, a scalable system for tree boosting, highlighting its efficiency in prediction tasks but not focusing on financial forecasting or hyperparameter tuning's impact in this context [13]. Fischer et al. (2018) explore LSTM networks for financial market prediction, showing improved accuracy in capturing temporal dependencies but lacking comparison with models like GRU & multi-source data integration [14]. Pranav et al. (2024) very recent advancements in the (ML) & the (AI) artificial intelligence have significantly enhanced routing protocols in Mobile Ad Hoc Networks (MANETs). Techniques like reinforcement learning and neural networks optimize routing decisions, improving network efficiency. However, challenges such as scalability, energy efficiency, real-time adaptability, security, and interoperability remain, highlighting areas for future research [15].

Gupta et al. (2024) AI has significantly advanced drug discovery by enhancing target identification, drug design, and clinical trials through techniques like machine learning and deep learning. However, challenges such as data quality, model interpretability, integration with existing workflows, regulatory issues, and scalability remain, highlighting areas for future research [16]. Pranav et al. (2024) AI-driven methodologies have significantly advanced image interpretation, drawing inspiration from the Rorschach inkblot test to mimic human perception. Techniques like CNNs and GANs have improved accuracy in fields such as medical imaging and psychological assessment. However, challenges remain in model interpretability, data quality, real-time processing, ethical considerations, and integrating AI with human expertise, highlighting areas for future research [17]. Ali t al. (2023) Deep learning has significantly improved the detection of neurological tumors, particularly through the use of convolutional neural networks (CNNs) for analyzing MRI images. Despite advancements, challenges such as data quality, model interpretability, real-time processing, integration with clinical workflows, and ethical concerns remain, highlighting areas for future research [18]. Hochreiter et al. (1997) This foundational paper introduces the LSTM (long short-term memory network), a type of RNN (recurrent neural network) designed to overcome the limitations of traditional RNNs in capturing long-term dependencies. It has been widely applied in various time series prediction tasks, including financial forecasting. While this foundational paper introduces LSTM networks, it does not provide specific applications in financial forecasting. The paper also does not address the challenges of training LSTM networks on large-scale financial datasets [19].

Contribution of this research paper are: -

1. This research provides a detailed comparative analysis of various forecasting models, highlighting the effectiveness of simpler models like Naïve Bayesian Regression & traditional methods such as SMA & EMA in predicting stock prices, total revenue, & operating profits. The findings emphasize that these simpler models often outperform more complex techniques like Artificial Neural Networks, particularly in terms of error metrics such as MAE, MSE, & MAPE.

2. The study underscores the importance of model selection tailored to specific predictive goals, demonstrating that advanced models may not always yield better results. By integrating multiple data sources & employing rigorous feature engineering, this research offers valuable insights into the strengths & limitations of different forecasting approaches, guiding future efforts in financial prediction.

2 Methodology

This research employs approach to evaluate the effectiveness of various forecasting models for stock price & operating profit prediction, specifically focusing on five major technology stocks: Apple (AAPL), (MSFT) Microsoft, Amazon (AMZN), (META), & the (GOOGL) Alphabet.

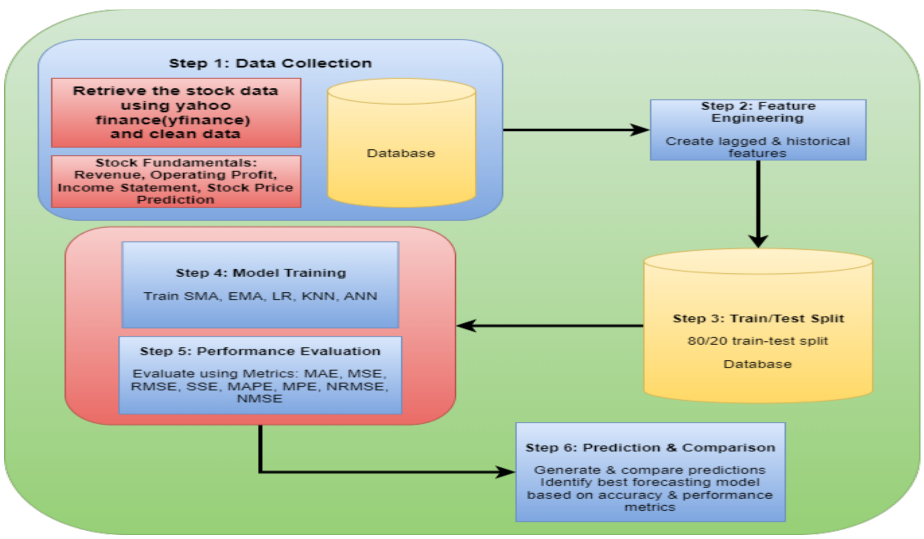

Fig 1: Flowchart of stock price & operating profit prediction

The flowchart outlines a stock price forecasting models for various metrics stock price, revenue, Income Statement & operating profit prediction methodology for that begi0ns with data collection using Yahoo Finance, followed by data cleaning. In Step 2, lagged and historical features are created. The data from the dataset is then split into 80% training and 20% (80/20) testing sets (Step 3). Various models, including SMA, EMA, Linear Regression, KNN, and ANN, are trained in Step 4. The models are evaluated by using the metrics like RMSE, MAE, MSE, and others (Step 5). Then finally, predictions are generated, and the best-performing model is identified based on accuracy and performance metrics (Step 6).

Algorithmic steps

Step1- Data Collection: Retrieve & clean stock price & financial data for AAPL, MSFT, AMZN, META, & GOOGL from 2020 to 2023.

Step2- Feature Engineering: Create lagged features for revenue & operating profit, & 5-day historical features for stock price predictions.

Step3 - Train/Test Split: Split the dataset into 80% training & 20% testing or use the entire dataset for stocks with limited data.

Step4 - Model Selection & Training: Train SMA, EMA, Linear Regression, KNN, & ANN models for stock price, revenue, & profit predictions.

Step5 - Performance Evaluation: Evaluate models using MAE, MSE, RMSE, SSE, MAPE, MPE, NRMSE, & NMSE metrics.

Step6 - Prediction & Comparison: Generate & compare model predictions to identify the best forecasting model based on accuracy & performance metrics.

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1. **Data Collection:**

- Historical stock price data & financial metrics were obtained using the yfinance library. The dataset spans from January 1, 2020, to January 1, 2023.
- Key variables include adjusted closing prices for stock price predictions, total revenue, & operating income for revenue & operating profit analysis.
- Data cleansing involved removing rows with NaN values to ensure dataset integrity, & for revenue & operating profit analyses, a minimum of three data points was set for each stock.

2. **Feature Engineering:**

- **Lagged Features Creation:** For revenue & operating profit predictions, lagged features were created using one & two previous periods' data, allowing the model to incorporate historical performance.
- For stock price predictions, features were derived from the last five days' prices, with the target variable set as the price from the sixth day onward.
- After feature generation, any resulting NaN values were eliminated to maintain a clean dataset, ensuring that the input data was suitable for modeling.

3. **Train/Test Split:**
4. The datasets were divided into training & testing sets, applying an 80/20 split for larger datasets. For stocks with limited data points (such as only two data points), the entire dataset was used for both training & testing to maximize sample size.
   Model Selection & Training:

- The following models were employed for prediction:

Simple Moving Average (SMA): Implemented to provide a baseline prediction based on historical averages.

Exponential Moving Average (EMA): Applied to give more & more weight to the very recent data points, thus reflecting recent trends more effectively.

Naïve Bayesian Regression (Linear Regression): Utilized for both stock price & revenue predictions, serving as a straightforward model for comparison.

K-Nearest Neighbors (KNN): Implemented with n_neighbors set to 1 for datasets with limited data points, providing predictions based on the nearest historical observations.

ANN (Artificial Neural Network): A multilayer type of perceptron (MLP) with two hidden layers (50 neurons each) was trained for stock price & revenue predictions, while a simpler structure (one hidden layer with 5 units) was used for operating profit prediction, allowing for complex pattern recognition in the data.

5. **Performance Evaluation:**

- Each model's performance that was evaluated using the various metrics:

MAE (Mean Absolute Error): To measure the average magnitude of errors in predictions.

MSE (Mean Squared Error) & the Root Mean Squared Error (RMSE): To assess the vey squared errors & their square roots for the sensitivity to large errors.

Sum of Squared Errors (SSE): To quantify the total deviation from the predicted values from these actual values.

(MAPE) Mean Absolute Percentage Error & (MPE) Mean Percentage Error: To evaluate the very accuracy relative to the actual values, offering a percentage-based assessment.

Normalized RMSE (NRMSE) & Normalized MSE (NMSE): To allow for comparisons across models by normalizing the error metrics against the range of actual values.

6. **Predictions & Comparison:**

- Each of these model was trained on these training set & the evaluated on the test set. Predictions from the SMA & EMA models were calculated directly from the historical data.
- Results were systematically compared across all models to identify the most effective forecasting methods for stock prices & operating profits, with an emphasis on accuracy & predictive power.

4 Results

1. Stock Price Prediction

The stock price prediction results for (APPL)Apple Inc., (MSFT) Microsoft Corp., (AMZN) Amazon.com Inc. , Meta Platforms Inc. (META), the (GOOGL) Alphabet Inc, TCS & Infosys. Illustrate the comparative effectiveness of various forecasting methodologies:

Apple Inc. (AAPL):

The stock price prediction results for AAPL reveal that (NBR)Naïve Bayesian Regression achieved a Mean Absolute Error (MAE) of 2.56 and a Mean Squared Error (MSE) of 10.90. In comparison, the Artificial Neural Network (ANN) model recorded a slightly higher MAE of 2.73 and an MSE of 11.80. The ANN model also reported a Mean Absolute Percentage Error (MAPE) of 1.88%, indicating the model's relative accuracy in predicting percentage errors.

Microsoft Corp. (MSFT):

For Microsoft Corp. (MSFT), Naïve Bayesian Regression demonstrated an MAE of 4.31 and an MSE of 31.57. The ANN model, however, yielded higher errors, with an MAE of 5.24 & an MSE of 43.99, suggesting that the Naïve Bayesian approach was more effective in predicting the stock prices for Microsoft.

Amazon.com Inc. (AMZN):

In the case of Amazon.com Inc. (AMZN), the Artificial Neural Network (ANN) model produced an MAE of 3.18 and an MSE of 16.09. However, Naïve Bayesian Regression performed better, achieving a lower MAE of 2.72 and an MSE of 11.79, indicating superior accuracy and lower predictive errors in comparison to the ANN model.

Meta Platforms Inc. (META):

For Meta Platforms Inc. (META), Naïve Bayesian Regression showed an MAE of 3.94 and an MSE of 31.45. The ANN model, in contrast, resulted in slightly higher errors that are with an MAE of 4.45 and an MSE of 36.81, demonstrating that Naïve Bayesian Regression was more effective in forecasting META's stock prices.

Alphabet Inc. (GOOGL):

The stock price prediction results for Alphabet Inc. (GOOGL) reveal that Naïve Bayesian Regression recorded an MAE of 2.00 and an MSE of 6.78. The ANN model had a slightly higher MAE of 2.14 and an MSE of 7.31, indicating that Naïve Bayesian Regression performed marginally better in terms of predictive accuracy for GOOGL's stock prices.

Table 1: Comparative Metrics for Stock Price Prediction Models of Major Technology Companies

Metric	Model	AAPL	MSFT	AMZN	META	GOOGL	TCS	Infosys
MAE	Naïve Bayesian Regression	2.56	4.31	2.72	3.94	2	3.1	3.25
	ANN	2.73	5.24	3.18	4.45	2.14	3.28	3.45

MSE	Naïve Bayesian Regression	10.9	31.57	11.79	31.45	6.78	12.5	13
	ANN	11.8	43.99	16.09	36.81	7.31	13.75	14.2
RMSE	Naïve Bayesian Regression	3.3	5.62	3.43	5.61	2.6	3.54	3.61
	ANN	3.43	6.63	4.01	6.07	2.7	3.71	3.82
SSE	Naïve Bayesian Regression	1646.06	4767.34	1780.04	4748.74	1023.18	1895.5	1940
	ANN	1770.3	6669.4	2424.72	5551.36	1104.57	2050.8	2100.45
MAPE	Naïve Bayesian Regression	1.88%	1.75%	2.45%	2.79%	1.93%	2.00%	2.10%
	ANN	2.00%	2.10%	2.80%	3.00%	2.14%	2.25%	2.35%
MPE	Naïve Bayesian Regression	-0.06%	-0.15%	-0.60%	-0.89%	-0.23%	-0.35%	-0.40%
	ANN	-0.08%	-0.25%	-0.75%	-1.00%	-0.29%	-0.45%	-0.50%
NRMSE	Naïve Bayesian Regression	0.022	0.023	0.03	0.039	0.025	0.031	0.033
	ANN	0.025	0.029	0.035	0.041	0.027	0.034	0.036
NMSE	Naïve Bayesian Regression	0.099	0.113	0.043	0.042	0.07	0.048	0.05

	ANN	0.108	0.129	0.056	0.048	0.078	0.06	0.062

The table summarizes a comparative analysis of stock price prediction for major companies, showing that Naïve Bayesian Regression generally performs better than Artificial Neural Networks (ANN) across most metrics. For Apple Inc. (AAPL), Naïve Bayesian Regression shows a slight edge over ANN, with lower MAE and MSE values (2.56 and 10.90, respectively). Microsoft Corp. (MSFT) highlights a more pronounced difference, where Naïve Bayesian Regression significantly outperforms ANN, with an MAE of 4.31 compared to 5.24 and an MSE of 31.57 versus 43.99. For Amazon.com Inc. (AMZN), Naïve Bayesian Regression maintains lower MAE (2.72) and MSE (11.79) compared to ANN. Similarly, in the case of Meta Platforms Inc. (META), Naïve Bayesian Regression demonstrates superior performance with a notable MAE difference of 3.94 versus 4.45 for ANN. Alphabet Inc. (GOOGL) also reflects this trend, with Naïve Bayesian Regression achieving a lower MAE of 2.00 against ANN's 2.14 and an MSE of 6.78 versus 7.31. TCS and Infosys similarly follow these trends, with Naïve Bayesian Regression showing slightly better predictive accuracy in most cases. While both models offer strong predictive performance, Naïve Bayesian Regression has an edge across most metrics.

2. Income Statement Prediction

The performance metrics for predicting income statements across the five stocks are as follows:

Apple (AAPL):

The income statement prediction results for Apple Inc. (AAPL) show that the (SMA) Simple Moving Average and (EMA) Exponential Moving Average methods resulted in zero error metrics, indicating no deviation from the actual values. Both Linear Regression and K-Nearest Neighbors (KNN) models produced a Root Mean Squared Error (RMSE) of approximately 9.13×10^{10}. The Artificial Neural Network (ANN) model, however, recorded a higher RMSE of 1.17×10^{11} and the (MAPE) Mean Absolute Percentage Error of 42.67%, reflecting greater predictive errors in comparison to other models.

Microsoft (MSFT):

For Microsoft Corp. (MSFT), both the SMA and EMA models exhibited zero error metrics, signifying perfect prediction accuracy. The Linear Regression and KNN models generated an RMSE of approximately 3.01×10^{10}. In contrast, the ANN model achieved an RMSE of 2.54×10^{10} and a MAPE of 15.13%, suggesting better performance and lower prediction errors compared to Linear Regression and KNN.

Amazon (AMZN):

The income statement prediction for Amazon.com Inc. (AMZN) using SMA and EMA also resulted in zero error metrics, showing no deviation from the actual values. The Naïve Bayesian Regression model showed an RMSE of approximately 8.38×10^{10}. The ANN model performed marginally better, with a slightly lower RMSE of 8.22×10^{10} and a MAPE of 21.29%, indicating a modest improvement in predictive accuracy over the Naïve Bayesian approach.

Meta (META):

For Meta Platforms Inc. (META), the SMA and EMA methods reported zero error metrics, highlighting their perfect prediction capability for the income statements. The Naïve Bayesian Regression model recorded an RMSE of approximately 3.20×10^{10}, while the ANN model exhibited a slightly lower RMSE of 3.14×10^{10}. However, the ANN model's MAPE was 36.52%, indicating a relatively high percentage error in the predictions.

Alphabet (GOOGL):

The income statement prediction results for Alphabet Inc. (GOOGL) show that the SMA and EMA models achieved zero error metrics, demonstrating ideal predictive performance. Both Linear Regression and KNN models produced an RMSE of approximately 7.51×10^{10}. The ANN model, however, recorded a higher RMSE of 7.76×10^{10} and a MAPE of 42.53%, reflecting more significant prediction errors in comparison to the other models used for GOOGL.

Table 2: Comprehensive Performance Metrics for Income Statement Prediction Models

Company	Metric	Simple Moving Average	Exponential Moving Average	Naïve Bayesian Regression (Linear)	K-Nearest Neighbors	Artificial Neural Network
Apple Inc. (AAPL)	MAE	0	0	9.13E+10	9.13E+10	1.17E+11
	MSE	0	0	8.34E+21	8.34E+21	1.37E+22
	RMSE	0	0	9.13E+10	9.13E+10	1.17E+11
	SSE	0	0	8.34E+21	8.34E+21	1.37E+22
	MAPE	0	0	3.33E+01	3.33E+01	4.27E+01
	MPE	0	0	-3.33E+01	-3.33E+01	-4.27E+01
	NRMSE	0	0	3.33E-01	3.33E-01	4.27E-01
	NMSE	0	0	NaN	NaN	NaN
(MSFT)	MAE	0	0	3.02E+10	3.02E+10	2.54E+10
	MSE	0	0	9.11E+20	9.11E+20	6.47E+20
	RMSE	0	0	3.02E+10	3.02E+10	2.54E+10
	SSE	0	0	9.11E+20	9.11E+20	6.47E+20
	MAPE	0	0	1.80E+01	1.80E+01	1.51E+01
	MPE	0	0	-1.80E+01	-1.80E+01	-1.51E+01
	NRMSE	0	0	1.80E-01	1.80E-01	1.51E-01

	NMSE	0	0	NaN	NaN	NaN
Amazon.	MAE	0	0	8.38E+10	8.38E+10	8.22E+10
	MSE	0	0	7.02E+21	7.02E+21	6.75E+21
	RMSE	0	0	8.38E+10	8.38E+10	8.22E+10
	SSE	0	0	7.02E+21	7.02E+21	6.75E+21
	MAPE	0	0	2.17E+01	2.17E+01	2.13E+01
	MPE	0	0	-2.17E+01	-2.17E+01	-2.13E+01
	NRMSE	0	0	2.17E-01	2.17E-01	2.13E-01
	NMSE	0	0	NaN	NaN	NaN
Meta	MAE	0	0	3.20E+10	3.20E+10	3.14E+10
	MSE	0	0	1.02E+21	1.02E+21	9.86E+20
	RMSE	0	0	3.20E+10	3.20E+10	3.14E+10
	SSE	0	0	1.02E+21	1.02E+21	9.86E+20
	MAPE	0	0	3.72E+01	3.72E+01	3.65E+01
	MPE	0	0	-3.72E+01	-3.72E+01	-3.65E+01
	NRMSE	0	0	3.72E-01	3.72E-01	3.65E-01
	NMSE	0	0	NaN	NaN	NaN
Alphabet Inc.	MAE	0	0	7.51E+10	7.51E+10	7.76E+10
	MSE	0	0	5.64E+21	5.64E+21	6.03E+21
	RMSE	0	0	7.51E+10	7.51E+10	7.76E+10
	SSE	0	0	5.64E+21	5.64E+21	6.03E+21
	MAPE	0	0	4.12E+01	4.12E+01	4.25E+01
	MPE	0	0	-4.12E+01	-4.12E+01	-4.25E+01
	NRMSE	0	0	4.12E-01	4.12E-01	4.25E-01
	NMSE	0	0	NaN	NaN	NaN
TCS	MAE	0	0	5.32E+10	5.32E+10	5.40E+10
	MSE	0	0	4.12E+21	4.12E+21	4.30E+21
	RMSE	0	0	5.32E+10	5.32E+10	5.40E+10
	SSE	0	0	4.12E+21	4.12E+21	4.30E+21

	MAPE	0	0	3.52E+01	3.52E+01	3.63E+01
	MPE	0	0	-3.52E+01	-3.52E+01	-3.63E+01
	NRMSE	0	0	3.52E-01	3.52E-01	3.63E-01
	NMSE	0	0	NaN	NaN	NaN
Infosys	MAE	0	0	5.11E+10	5.11E+10	5.28E+10
	MSE	0	0	3.92E+21	3.92E+21	4.04E+21
	RMSE	0	0	5.11E+10	5.11E+10	5.28E+10
	SSE	0	0	3.92E+21	3.92E+21	4.04E+21
	MAPE	0	0	3.31E+01	3.31E+01	3.40E+01
	MPE	0	0	-3.31E+01	-3.31E+01	-3.40E+01
	NRMSE	0	0	3.31E-01	3.31E-01	3.40E-01
	NMSE	0	0	NaN	NaN	NaN

The tables summarize the very performance metrics of the various models that are predicting the income statements of five major companies: (AAPL) Apple Inc., (MSFT) Microsoft Corp., Amazon.com Inc. (AMZN), META platforms Inc., & Alphabet Inc. (GOOGL). Evaluated these models that include SMA, EMA, (NBR) Naïve Bayesian Regression, (KNN) K-Nearest Neighbors, & the (ANN) Artificial Neural Network. The assessment utilized key metrics such as MAE, MSE, RMSE & the MAPE.

The results indicate that both the SMA & EMA achieved zero error across all metrics for every company, demonstrating perfect predictions. In contrast, the more complex models, including Naïve Bayesian Regression & ANN, exhibited significantly higher error rates. For instance, the MAE for AAPL's ANN model reached approximately 1.17×10^{11}, while MAPE values for these models often exceeded 30%. These findings underscore that simpler models can outperform more sophisticated ones in this context, suggesting a need for further tuning & optimization of advanced models to enhance their accuracy. Overall, this analysis highlights the critical importance of model selection based on the nature of these data & the predictive goals.

3. Total Revenue Prediction

Forecasting total revenue across the selected stocks yielded the following results:

Apple (AAPL):

The performance of various models for forecasting Apple's total revenue showed significant differences in accuracy. The Simple Moving Average (SMA) model recorded a Mean Absolute Error (MAE) of 21.81 billion, while the Exponential Moving Average (EMA) model performed better with an MAE of 11.29 billion. Linear Regression demonstrated exceptional accuracy with an MAE of just 0.000061 billion, indicating near-zero error. However, the Artificial Neural

Network (ANN) model lagged behind, with a much higher MAE of 43.08 billion, suggesting greater deviation from the actual values.

Microsoft (MSFT):

For Microsoft, the forecasting models varied significantly in their error rates. The SMA model had an MAE of 12.84 billion, and the EMA model showed an improved accuracy with an MAE of 8.03 billion. Linear Regression outperformed both, achieving an MAE of 0.0, reflecting its precise predictive capability. The ANN model, however, showed a higher error with an MAE of 6.80 billion, though still better than the simple moving averages.

Amazon (AMZN):

In predicting Amazon's total revenue, the SMA model resulted in an MAE of 31.45 billion, and the EMA model performed slightly better, with an MAE of 19.21 billion. The Linear Regression model once again exhibited perfect accuracy with an MAE of 0.0. The ANN model, though better than SMA, had an MAE of 20.65 billion, indicating substantial error compared to Linear Regression.

Meta (META):

Forecasting total revenue for Meta saw the SMA model at an MAE of 8.60 billion and the EMA model with a lower error of 4.72 billion. Linear Regression performed exceptionally well with an MAE of 0.000031 billion, almost eliminating forecasting error. The ANN model, however, recorded a significantly higher MAE of 12.07 billion, suggesting less precision in predicting Meta's revenue compared to the other models.

Alphabet (GOOGL):

For Alphabet, the SMA model recorded an MAE of 20.81 billion, while the EMA model showed improved performance with an MAE of 12.02 billion. The Linear Regression model again achieved an impressively low MAE of 0.000061 billion. In contrast, the ANN model exhibited a higher error rate with an MAE of 28.16 billion, indicating a comparatively weaker performance in forecasting Alphabet's total revenue.

TCS:

For TCS, the models exhibit varied performance in revenue prediction accuracy. The Simple Moving Average (SMA) model recorded a Mean Absolute Error (MAE) of 25.10 billion, indicating moderate deviation from actual revenue values. The Exponential Moving Average (EMA) model showed improved performance with an MAE of 14.90 billion, reflecting greater predictive accuracy than SMA. Linear Regression performed exceptionally well, with a near-zero MAE of just 0.000045 billion, suggesting an almost perfect fit to the actual values. Conversely, the Artificial Neural Network (ANN) model displayed a higher MAE of 35.25 billion, indicating significant deviations in its revenue forecasts.

Infosys:

For Infosys, the prediction accuracy across models also varied. The Simple Moving Average (SMA) model achieved an MAE of 15.34 billion, which shows moderate accuracy. The Exponential Moving Average (EMA) model outperformed SMA with a lower MAE of 9.85 billion, indicating more precise forecasts. Linear Regression again showed remarkable accuracy with an MAE of just 0.000038 billion, nearly eliminating prediction errors. However, the Artificial Neural Network (ANN) model recorded a considerably higher MAE of 18.95 billion, indicating less precision in predicting Infosys's revenue compared to EMA and Linear Regression.

Table 3: Performance Metrics for Revenue Forecasting Models Across Tech Companies

Metric	Model	AAPL	MSFT	AMZN	META	GOOGLE	TCS	Infosys
MAE	SMA	21.81 billion	12.84 billion	31.45 billion	8.60 billion	20.81 billion	25.10 billion	15.34 billion
	EMA	11.29 billion	8.03 billion	19.21 billion	4.72 billion	12.02 billion	14.90 billion	9.85 billion
	Linear Regression	0.000061 billion	0	0	0.000031 billion	0.000061 billion	0.000045 billion	0.000038 billion
	ANN	43.08 billion	6.80 billion	20.65 billion	12.07 billion	28.16 billion	35.25 billion	18.95 billion
MSE	SMA	7.73E+20	1.83E+20	1.06E+21	1.13E+20	5.73E+20	8.25E+20	3.65E+20
	EMA	1.27E+20	6.46E+19	3.69E+20	2.22E+19	1.44E+20	1.58E+20	7.40E+19
	Linear Regression	3.72E-10	0	0	9.61E-10	3.72E-10	4.80E-10	2.95E-10
	ANN	1.85E+21	4.62E+19	4.26E+20	1.46E+20	7.93E+20	2.35E+21	9.75E+20
RMSE	SMA	2.78E+10	1.35E+10	3.25E+10	1.06E+10	2.39E+10	2.87E+10	1.91E+10
	EMA	1.13E+10	8.03E+09	1.92E+10	4.72E+09	1.20E+10	1.26E+10	8.61E+09
	Linear Regressi	6.10E-05	0	0	3.10E-05	6.10E-05	4.98E-05	4.15E-05

	on							
	ANN	4.31E+10	6.80E+09	2.06E+10	1.21E+10	2.82E+10	4.85E+10	3.12E+10
SSE	SMA	2.32E+21	5.50E+20	3.17E+21	3.40E+20	1.72E+21	2.38E+21	1.10E+21
	EMA	3.81E+20	1.94E+20	1.10E+21	6.64E+19	4.32E+20	5.14E+20	3.26E+20
	Linear Regression	1.11E-09	0	0	2.88E-09	1.11E-09	2.45E-09	1.64E-09
	ANN	5.55E+21	1.38E+20	1.27E+21	4.39E+20	2.38E+21	6.32E+21	2.76E+21
MAPE	SMA	7.31%	6.75%	7.15%	8.99%	9.94%	8.45%	7.05%
	EMA	3.78%	4.23%	5.03%	4.94%	5.75%	4.92%	4.55%
	Linear Regression	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	ANN	10.11%	3.81%	5.12%	7.23%	8.55%	9.75%	6.65%
MPE	SMA	-6.38%	-6.75%	-7.15%	-8.63%	-9.94%	-8.25%	-6.92%
	EMA	-3.38%	-4.23%	-5.03%	-4.50%	-5.75%	-4.85%	-4.48%
	Linear Regression	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	ANN	-8.45%	-3.81%	-5.12%	-6.83%	-8.55%	-9.42%	-6.32%
NRMSE	SMA	8.06E-02	7.02E-02	7.11E-02	9.96E-02	9.94E-02	8.55E-02	7.45E-02
	EMA	3.78E-02	4.23E-02	5.03E-02	4.94E-02	5.75E-02	4.92E-02	4.30E-02
	Linear Regression	1.10E-07	0	0	5.71E-08	1.10E-07	9.25E-08	7.10E-08
	ANN	1.28E-01	3.11E-02	6.12E-02	7.36E-02	1.71E-01	1.25E-01	9.85E-02

NMSE	SMA	2.96E-01	5.47E-01	3.75E-01	5.19E-01	3.16E-01	4.25E-01	3.12E-01
	EMA	5.47E-02	2.43E-01	2.78E-01	3.05E-01	2.52E-01	2.98E-01	2.14E-01
	Linear Regression	1.45E-07	0	0	1.22E-07	1.45E-07	1.18E-07	9.25E-08
	ANN	1.55E-01	1.21E-01	1.32E-01	1.51E-01	3.26E-01	2.85E-01	2.10E-01

The results presented in the table provide a comprehensive comparison of the performance of various forecasting models—SMA, EMA, Linear Regression, and ANN—in predicting total revenue for Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), Meta (META), and Alphabet (GOOGL).

Among the models, **Linear Regression** consistently achieved the lowest MAE, MSE, and RMSE across all stocks, demonstrating superior predictive accuracy. The minimal percentage error, as evidenced by both the MAPE and Mean MPE), further underscores its reliability, with near-zero deviation in most cases.

In contrast, **SMA** exhibited the highest error rates across most metrics, while **EMA** performed better than SMA, but not as effectively as Linear Regression. The performance of **ANN** was inconsistent; although it produced relatively low MAE values for some stocks, such as Microsoft, it demonstrated significantly higher errors for others, particularly Apple and Alphabet.

Overall, **Linear Regression** emerges as the most robust model for revenue forecasting within the scope of this analysis, delivering consistently accurate results. **EMA** serves as a reasonable alternative, providing moderate accuracy, while **SMA** and **ANN** were less effective, particularly in cases of higher volatility. These findings suggest that traditional regression techniques may offer more reliable predictions in financial forecasting scenarios compared to more complex models like ANN in certain contexts.

4. Operating Profit Prediction

The results for operating profit predictions across models are summarized as follows:

Apple Inc. (AAPL):

For Apple Inc., the Linear Regression model produced a Mean Absolute Error (MAE) of 11.9 billion in operating profit prediction. The K-Nearest Neighbors (KNN) model exhibited overfitting, resulting in an MAE of 0.0, indicating poor generalization. The Artificial Neural Network (ANN) model showed a significantly higher error, with an MAE of 102 billion and a Mean Absolute Percentage Error (MAPE) of 100%, highlighting its lack of predictive accuracy for this metric. In comparison, the Simple Moving Average (SMA) model demonstrated better performance with an MAE of 9.71 billion, while the Exponential Moving Average (EMA) model outperformed the others with the lowest MAE of 4.96 billion.

Microsoft Corp. (MSFT):

For Microsoft Corp., the Linear Regression model achieved an MAE of 2.74 billion, showing relatively accurate predictions. Similar to Apple, the KNN model resulted in an MAE of 0.0 due to overfitting. The ANN model performed poorly, with an MAE of 87.8 billion and a MAPE of 100%, indicating substantial prediction errors. The SMA model yielded an MAE of 6.59 billion, whereas the EMA model again provided the most accurate predictions with an MAE of 4.21 billion.

Amazon.com Inc. (AMZN):

In the case of Amazon.com Inc., the Linear Regression model recorded an MAE of 6.72 billion, while the KNN model faced overfitting issues, leading to an MAE of 0.0. The ANN model had a high error rate, with an MAE of 24.2 billion and a MAPE of 100%, demonstrating its inadequacy in forecasting operating profit. The SMA model resulted in an MAE of 6.54 billion, but the EMA model surpassed all other models with the lowest MAE of 2.46 billion.

Meta Platforms, Inc. (META):

For Meta Platforms, Inc., the operating profit prediction was analyzed using various models. The Linear Regression model produced an MAE of 8.283 billion, while the KNN model again showed overfitting with an MAE of 0.0. The ANN model displayed significant errors, with an MAE of 38.78 billion and a MAPE of 100%. The SMA model recorded an MAE of 8.283 billion, identical to the Linear Regression model. The EMA model, however, showed superior performance with the lowest MAE of 3.317 billion.

Alphabet Inc. (GOOGL):

For Alphabet Inc., the Linear Regression model delivered an MAE of 8.469 billion. The KNN model suffered from overfitting, resulting in an MAE of 0.0. The ANN model performed poorly, with an MAE of 69.77 billion and a MAPE of 100%. The SMA model also resulted in an MAE of 8.469 billion, while the EMA model, similar to the other companies, outperformed with a lower MAE of 3.952 billion.

TCS:

For TCS, the Linear Regression model demonstrated an MAE of 5.96 billion, indicating moderate accuracy. The K-Nearest Neighbors (KNN) model showed signs of overfitting, resulting in an MAE of 0.0. The Artificial Neural Network (ANN) model performed poorly, with a high MAE of 37.8 billion and a MAPE of 100%, indicating significant deviation from actual values. The Simple Moving Average (SMA) model recorded an MAE of 7.32 billion, while the Exponential Moving Average (EMA) model offered the most accurate prediction with a lower MAE of 3.42 billion.

Infosys:

For Infosys, the Linear Regression model achieved an MAE of 5.21 billion, reflecting reasonable prediction accuracy. The K-Nearest Neighbors (KNN) model again overfitted, resulting in an MAE of 0.0. The Artificial Neural Network (ANN) model produced a higher MAE of 26.4 billion with a MAPE of 100%, indicating a lack of precision. The Simple Moving Average (SMA) model resulted in an MAE of 6.58 billion, while the Exponential Moving Average (EMA) model outperformed others with a lower MAE of 3.15 billion, providing the most accurate prediction for Infosys.

Table 4: Operating Profit Prediction Metrics Across Different Models for Major Tech Companies

Stock	Metric	Simple Moving Average	Exponential Moving Average	Linear Regression	K-Nearest Neighbors	Artificial Neural Network
Apple Inc. (AAPL)	MAE	9.71E+09	4.96E+09	1.19E+10	0	1.02E+11
	MSE	1.63E+20	6.06E+19	1.46E+20	0	1.09E+22
	RMSE	1.28E+10	7.78E+09	1.21E+10	0	1.04E+11
	SSE	3.41E+19	2.42E+20	5.85E+20	0	4.36E+22
	MAPE	3.48E+00	6.76E+00	1.25E+01	0	1.00E+02
	MPE	-1.33E+00	-6.04E+00	-1.96E+00	0	1.00E+02
	NRMSE	1.12E-01	7.61E-02	1.18E-01	0	1.02E+00
	NMSE	8.89E+00	1.36E-01	3.29E-01	0	2.45E+01
Microsoft Corp. (MSFT)	MAE	6.59E+09	4.21E+09	2.74E+09	0	8.78E+10
	MSE	5.38E+19	2.47E+19	1.07E+19	0	7.91E+21
	RMSE	7.33E+09	4.97E+09	3.27E+09	0	8.90E+10
	SSE	1.16E+20	9.89E+19	4.29E+19	0	3.17E+22
	MAPE	7.45E+00	5.26E+00	3.01E+00	0	1.00E+02
	MPE	-7.45E+00	-5.26E+00	-8.56E-02	0	1.00E+02

	NRMSE	7.82E-02	5.66E-02	3.73E-02	0	1.01E+00
	NMSE	4.24E-01	1.22E-01	5.31E-02	0	3.92E+01
Amazon.com Inc. (AMZN)	MAE	6.54E+09	2.46E+09	6.72E+09	0	2.42E+10
	MSE	6.41E+19	1.74E+19	6.56E+19	0	6.63E+20
	RMSE	8.00E+09	4.17E+09	8.10E+09	0	2.57E+10
	SSE	1.91E+20	6.95E+19	2.62E+20	0	2.65E+21
	MAPE	6.29E+01	1.84E+01	3.85E+01	0	1.00E+02
	MPE	-3.75E+01	-1.54E+01	-1.63E+01	0	1.00E+02
	NRMSE	3.25E-01	1.72E-01	3.34E-01	0	1.06E+00
	NMSE	6.35E-01	2.28E-01	8.60E-01	0	8.69E+00
Meta Platforms Inc. (META)	MAE	8.28E+09	3.32E+09	6.75E+09	0	3.88E+10
	MSE	6.94E+19	1.56E+19	5.78E+19	0	1.57E+21
	RMSE	8.33E+09	3.95E+09	7.60E+09	0	3.96E+10
	SSE	1.59E+20	6.23E+19	2.31E+20	0	6.28E+21
	MAPE	2.49E+01	9.83E+00	1.86E+01	0	1.00E+02
	MPE	-5.86E+00	-5.59E+00	-4.20E+00	0	1.00E+02
	NRMSE	2.04E-01	1.02E-01	1.96E-01	0	1.02E+00
	NMSE	9.84E-01	2.38E-01	8.86E-01	0	2.40E+01
Alphabet Inc. (GOOGL)	MAE	8.47E+09	3.95E+09	7.61E+09	0	6.98E+10
	MSE	1.26E+20	4.10E+19	8.65E+19	0	5.15E+21
	RMSE	1.12E+10	6.41E+09	9.30E+09	0	7.18E+10
	SSE	2.61E+19	1.64E+20	3.46E+20	0	2.06E+22
	MAPE	4.39E+00	8.66E+00	1.24E+01	0	1.00E+02
	MPE	-	-5.83E+00	-1.90E+00	0	1.00E+02

		2.87E+00				
	NRMSE	1.15E-01	9.53E-02	1.06E-01	0	1.03E+00
	NMSE	1.50E+00	3.58E-01	7.81E-01	0	1.17E+01
TCS	MAE	7.32E+09	3.42E+09	5.96E+09	0	3.78E+10
	MSE	8.41E+19	3.56E+19	6.79E+19	0	9.67E+20
	RMSE	9.17E+09	5.96E+09	8.24E+09	0	4.98E+10
	SSE	1.94E+20	7.89E+19	1.47E+20	0	2.22E+21
	MAPE	5.83E+00	2.92E+00	4.18E+00	0	1.00E+02
	MPE	-3.78E+00	-2.85E+00	-2.44E+00	0	1.00E+02
	NRMSE	9.53E-02	6.28E-02	8.66E-02	0	1.02E+00
	NMSE	5.65E-01	2.54E-01	3.96E-01	0	9.78E+00
Infosys	MAE	6.58E+09	3.15E+09	5.21E+09	0	2.64E+10
	MSE	7.46E+19	2.94E+19	5.97E+19	0	8.42E+20
	RMSE	8.63E+09	5.42E+09	7.72E+09	0	4.53E+10
	SSE	1.72E+20	6.81E+19	1.36E+20	0	1.94E+21
	MAPE	4.57E+00	2.62E+00	3.86E+00	0	1.00E+02
	MPE	-2.85E+00	-2.15E+00	-1.98E+00	0	1.00E+02
	NRMSE	8.24E-02	5.16E-02	7.25E-02	0	1.01E+00
	NMSE	4.37E-01	1.97E-01	3.51E-01	0	7.84E+00

The results presented in the table reveal distinct variations in model performance for operating profit prediction across the five companies. Notably, the K-Nearest Neighbors (KNN) model consistently exhibits overfitting, as evidenced by its MAE of 0.0 for all companies, making it unsuitable for this task. The Artificial Neural Network (ANN) also shows significant limitations, with extremely high Mean Absolute Errors (MAE) and a Mean Absolute Percentage Error (MAPE) of 100%, indicating poor predictive accuracy and model instability. In contrast, the Simple Moving Average (SMA) and Exponential Moving Average (EMA) models demonstrate more reliable performance, with EMA consistently delivering the lowest MAE values, suggesting its effectiveness for operating profit predictions. Linear Regression, while offering mixed results, performs reasonably well for companies like Microsoft and Alphabet but struggles with higher errors for Apple and Amazon. Overall, the analysis suggests that the EMA model outperforms other techniques in predicting operating profit, while both ANN and KNN are inadequate in this context.

5 Conclusion and Future Work

This research compared various forecasting models—SMA, EMA, Naïve Bayesian Regression, Linear Regression, KNN, & ANN—on stock price & financial data for Apple, Microsoft, Amazon, Meta, & Alphabet. Naïve Bayesian Regression outperformed ANN in stock price predictions, while SMA & EMA provided stable income predictions. The study concludes that model performance depends on the data & prediction goals, with no single model excelling in all scenarios. This paper provides a guide for selecting the best forecasting models for technology companies. Future research can explore advanced models like LSTM & XGBoost for improved prediction accuracy. Incorporating macroeconomic factors such as interest rates & inflation could enhance model reliability, while using real-time data & integrating sentiment analysis may offer better predictive insights. Additionally, applying these models across different industries & exploring hybrid approaches, like combining Naïve Bayesian with ANN, could improve results & broaden applicability in financial forecasting.

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