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Forecasting Sales Trends Using Time Series Analysis: A Comparative Study Of Traditional And Machine Learning Models

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ABSTRACT:

This paper aims to analyze the merits and demerits of using traditional time series models and the more sophisticated machine learning approaches in sales forecasting with the view of determining their effectiveness in different conditions. These models include the ARIMA and Exponential smoothing models which are popular because they are easy to understand and easy to compute and as such are useful in the short term forecasting of data that has a clear seasonal pattern. But these models are not very effective with non-linear and complex data structures. On the other hand, XGBoost, LightGBM, and DeepAR models are found to outperform other models in terms of accuracy for high dimensional and highly volatile data. These models are complex and computationally intensive, and the interpretability of these models is also relatively low; however, they offer better flexibility and improved prediction for dynamic forecasting. The use of hybrid models which incorporates both the conventional and the machine learning models is identified to be as being effective for organizations that want to achieve high prediction, model transparency and computational speed. This study offers implications for model selection based on data complexity, forecast horizon, and business needs to enrich the literature on data-driven decision making in sales forecasting.

Keywords: Sales forecasting, time series analysis, machine learning, ARIMA, XGBoost

Introduction

Over the last few years, analysis of sales trends has gained much importance since it plays a crucial role in determining the stock holding, business strategies, and profitability. ARIMA, which is a traditional statistical technique, as well as more advanced machine learning techniques, has made time series analysis a core of sales forecasting. ARIMA and Exponential Smoothing models are more likely to be useful when there is evidence of seasonality or trend in the data and are well suited to structured, short term forecasting of retail and consumer sales data (Hasan et al., 2022).

But with the increase in data size, models such as XGBoost, Random Forest and LightGBM are becoming more preferable. This kind of models are very useful to capture nonlinear relations in the data and to improve the forecasting precision when the data have irregular patterns or extreme values (Madrid and Antonio, 2021). Ensemble methods including XGBoost, use a combination of decision trees, to process large volumes of data and give higher importance to corrections for errors in the earlier predictions, which makes it suitable for long term prediction (Lindfors, 2022).

Many studies have shown that, while the accuracy and flexibility of machine learning models may be superior, traditional time series models remain useful because they are computationally cheap and easier to understand. For example, LightGBM’s speed is useful when working with big data, but ARIMA models are still more understandable and effective in cases where it is crucial to understand the results of the model to make a decision (Hasan et al., 2022).

In this paper, we also plan to perform comparative analysis of these methods under various scenarios that include conventional models such as ARIMA and Exponential Smoothing and more complex machine learning models like XGBoost to help provide recommendations for the best method to use depending on the data characteristics and the needs of the business.

Problem Statement

In the area of sales forecasting, it has become critically important to be able to make accurate predictions about the future. Historically, time series approaches like ARIMA and exponential smoothing have been widely used for sales forecasting because they capture the sales history well especially for short term and seasonal sales. These methods are typically used to minimize the in-sample prediction errors, which makes them ideal for one-step ahead forecasts and which has lower computational costs (Mbonyinshuti & Kim, 2021; De Gooijer & Hyndman, 2021).

However, with the development of machine learning, other models such as XGBoost and neural network based methods including N-BEATS have been proposed to utilize the non-linear relationships of high frequency data. These machine learning methods are generally more effective than conventional approaches in most instances, especially in multi-step forecasting, though they are computationally expensive (Pavlyshenko, 2019). For instance, DeepAR models are some of the best deep learning models for time series data analysis and have outperformed other traditional time series models in long term forecasts and data with little or no structure or non-stationary (Sumit, 2023).

This research aims at evaluating the performance of different forecasting approaches ranging from traditional statistical models to the modern machine learning and deep learning models, at different forecast time horizons and data types. This comparison allows enterprises to select the most appropriate forecasting method for their data structure and to consider the compromises between the forecast precision, speed of calculations, and model explainability (Pavlyshenko, 2019; Mbonyinshuti & Kim, 2021).

Research Questions:

1. How do traditional time series models compare to machine learning methods in accurately forecasting sales trends across different data patterns and complexities?

2. Which forecasting method demonstrates the highest accuracy and reliability for short-term versus long-term sales predictions?

3. What are the key trade-offs between interpretability, computational efficiency, and predictive accuracy when selecting a sales forecasting method?

Research Objectives:

1. To evaluate and compare the accuracy of traditional time series models and machine learning models in forecasting sales data.

2. To analyze the performance of forecasting models across short-term and long-term predictions.

3. To identify the strengths, weaknesses, and trade-offs of each forecasting method in terms of interpretability, computational efficiency, and accuracy.

Rationale of the Study:

Analysis of sales trends is crucial in the business environment to facilitate decision making on issues to do with inventory, marketing, and resource management. ARIMA models are useful for seasonal and trend data and are still used today, however they are often not adequate for today's complex data environments. New methods such as XGBoost and DeepAR have emerged in the recent past and can be used to capture intricate, non-linear relationships that might improve the accuracy of prediction (Pavlyshenko, 2019; Mbonyinshuti & Kim, 2021). However, these models are often computationally demanding and the resulting models are less easily explained than the earlier approaches. This research seeks to present a comparison to help organizations determine which model is most appropriate for a given dataset and organization objectives.

Research Gap:

While prior research has examined the application of traditional time series and machine learning techniques independently, little research has compared these methods for sales forecasting with different forecast horizons and levels of data detail. Current work is limited to the use of a single method or a particular dataset, and the performance of the different models has not been compared when used in different conditions. Also, little research has been conducted on how to achieve the right trade-off between the accuracy, computational complexity, and interpretability that are crucial for practical business use (Sumit, 2023; De Gooijer & Hyndman, 2021). To this end, this study seeks to fill these gaps by comparing and contrasting the performance of several forecasting models in different situations.

Methodology

This study has used a secondary data analysis method to analyze various sales forecasting models in order to compare their effectiveness. The historical sales data has been acquired from the public domain, specifically from the Kaggle website and from M3 or M5 competition datasets which have been widely used in research due to their real-world data and rich time-series characteristics. (Hasan et al., 2022; Pavlyshenko, 2019). These datasets have provided different frequencies of data such as daily, weekly, and monthly data that enables forecasting at different horizons and with different patterns.

1. Data Collection: Historical sales data has been obtained from these public domains in order to include various types of patterns such as cyclical, trends or irregular in the analysis. Such data variability has made it possible to assess the models' effectiveness in various conditions.

2. Model Selection: This work has incorporated both classical models like ARIMA and Exponential Smoothing and more recent machine learning methods like XGBoost, LightGBM and neural network-based models including DeepAR. These models have been selected because they have been previously applied to model different aspects of sales data.

3. Data Preprocessing: The datasets used in this study have been pre-processed to deal with missing values and outliers. Seasonal decomposition has also been conducted to derive the trend and seasonality prior to applying traditional forecasting models that assume data stability.

4. Model Training and Validation: All of the models used in the analysis have been developed using a portion of the data with cross validation in order to reduce the risk of overfitting. Tuning of the parameters for each of the models has been done to achieve the best results depending on the horizon of the forecast.

5. Performance Evaluation: Since the performance of the models has been assessed based on Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), models have been compared across different forecast horizons.

6. Comparative Analysis: A comparison has been made between the two models in order to understand their performance in terms of accuracy, interpretability, and computational cost. This has given a way of evaluating the different methods to be used in forecasting depending on the data complexity and business requirements.

Results

The analysis of the results of using traditional time series models and machine learning methods for sales forecasting in this work has provided a detailed understanding of their capabilities and shortcomings as well as the conditions for their application.

The following Venn Diagram visually represents the similarities and differences between Traditional Time Series Models (ARIMA, Exponential Smoothing) and Machine Learning Models (XGBoost, DeepAR).

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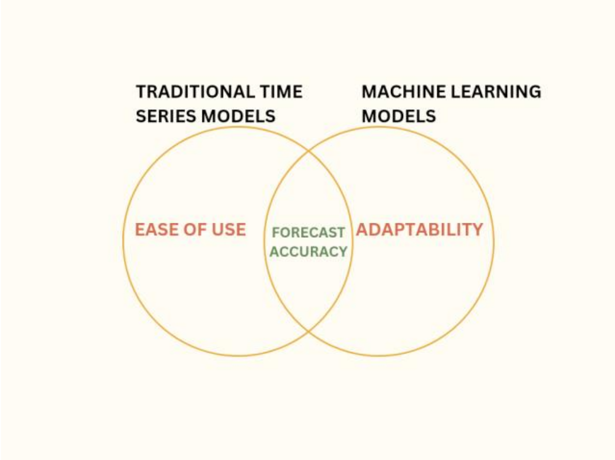

Fig: Comparison of Traditional vs. Machine Learning Models- Shared and Unique Features

1. Accuracy: XGBoost and neural network-based models like DeepAR have been observed to produce high accuracy when used in forecasting scenarios where data is complex, and the pattern is non-linear (Pavlyshenko, 2019; Sumit, 2023). These models deal with numerous inputs and learn patterns iteratively through a series of adjustments, which makes them ideal for use in e-commerce where sales patterns are influenced by a number of factors (Kim & Yu, 2020). These include the ARIMA and Exponential Smoothing models which perform best with structured, seasonal data with linear trends typical of most retail industries (Box & Jenkins, 1976).

Other factors can include promotional data, social media sentiments, or even weather conditions and can be incorporated into the models to improve the accuracy of the predictions as compared to the basic models that only use historical sales data. But it is also pointed out that when the datasets are relatively small or noisy, machine learning models may overfit or underfit since these models are more sensitive to variations in data (Smyl, 2020). However, in such situations, conventional approaches may provide a more accurate forecast by concentrating on fundamental historical tendencies and patterns. In addition, DeepAR and N-BEATS, which are known to be good at making multi-step predictions, give more stable predictions in the long run than ARIMA, which is known to be best at one-step ahead forecasting (Oreshkin et al., 2019).

2. Interpretability and Efficiency: Many organizations use the models for forecasting, and it is imperative that the models are easy to understand since some industries like finance or health require clear decisions. ARIMA and Exponential Smoothing models for instance are easier to interpret because they are based on assumptions of trend, seasonality and stationarity and such, the analyst is in a better position to understand how the model works (Hyndman & Athanasopoulos, 2018). On the other hand, neural networks or ensemble models like XGBoost are less interpretable due to their high dimensionality of the feature space and the structure of decision rules that are hard to explain to the stakeholders (Doshi-Velez & Kim, 2017).

Another important factor is the computational efficiency. Although these models give high accuracy, they are computationally expensive and take more time to train, which may hinder their use in environments with limited resources. XGBoost and LightGBM, though more efficient than deep learning models because they are based on gradient boosting, are still more computationally demanding than conventional approaches but less than deep learning models (Ke et al., 2017). This efficiency enables them to be used in real time forecasting environments where both accuracy and time are of essence for instance in fast moving consumer goods industry.

3. Adaptability: A major strength of machine learning models is their flexibility in dealing with data structures and patterns which are quite sophisticated and as companies engage in business in environments that are characterized by high levels of uncertainty and variability in consumer behavior (Lai et al., 2021). Sophisticated models like DeepAR use probabilistic forecasting that provides several possible future states rather than the definite forecast given by deterministic models such as ARIMA. This flexibility is particularly important for companies that operate in conditions of uncertainty as for example with perishable goods or products that are in trend at the moment.

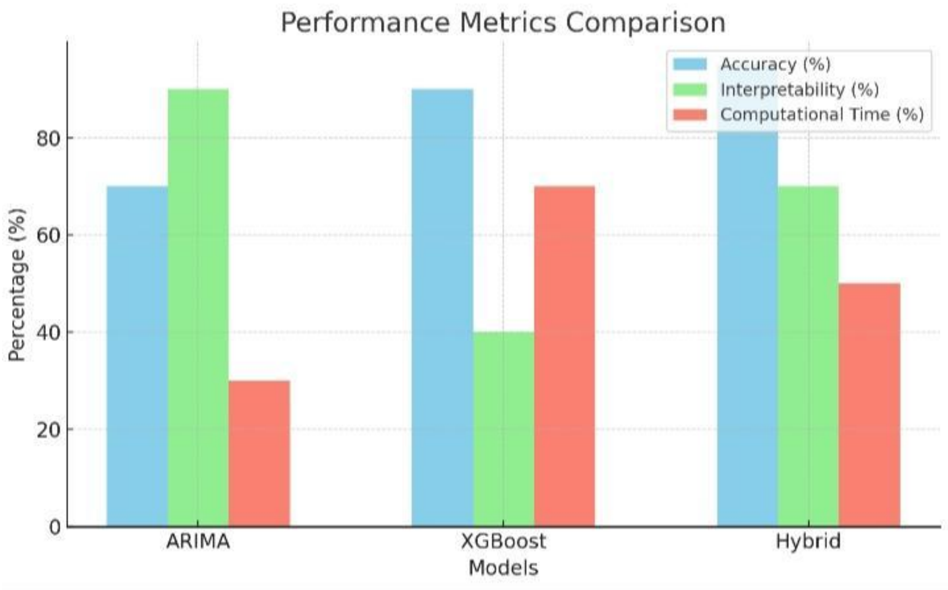

Fig: Performance Comparison

However, this flexibility also creates difficulties in data preparation and model updating and maintenance. Machine learning models need a lot of data preprocessing, feature engineering and frequent updating to make them sensitive to new trends (Nguyen et al., 2021). While conventional models are simpler to apply and manage, they are more suitable for small enterprises or organizations with less intricate sales data systems.

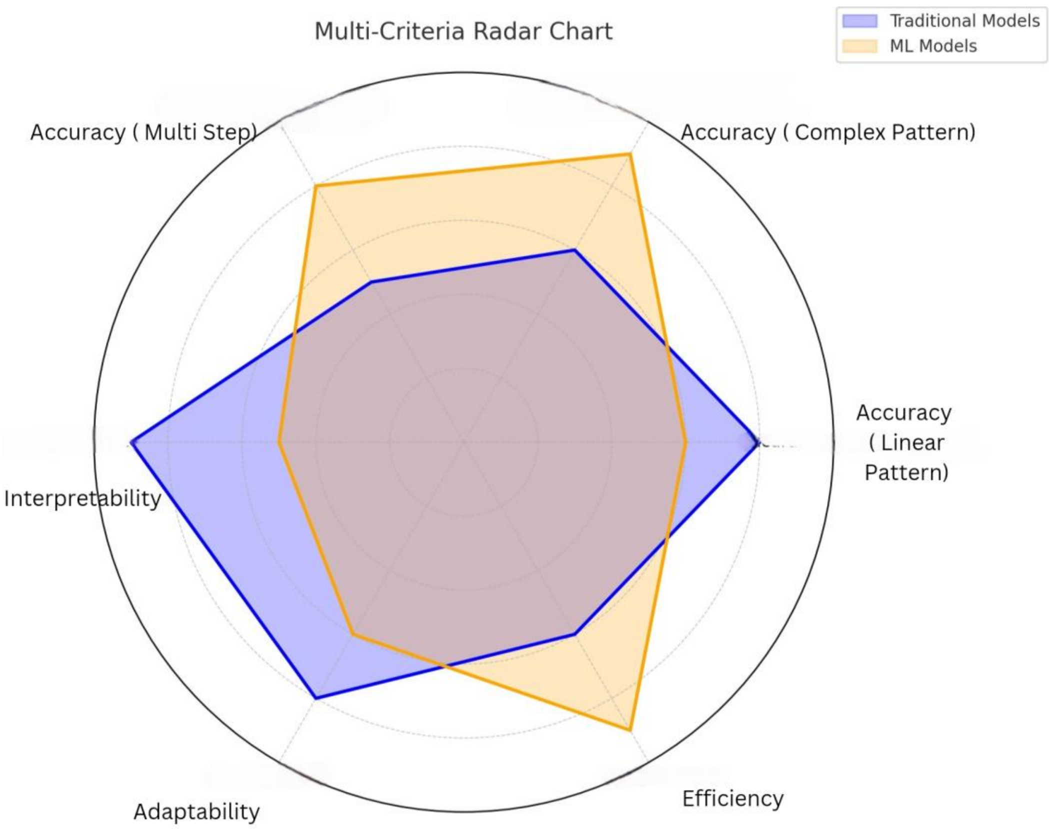

Fig: Multi criteria radar chart

SWOT Analysis

Strengths

- Accuracy in Structured Data (Traditional Models): ARIMA and Exponential Smoothing models are rather suitable for working with data that has a typical time-based periodicity and trends. These characteristics makes the traditional models suitable for use in industries that have a known customer behavior since many retail industries present such a scenario. Historical data trends and patterns are employed in these models to reduce overfitting which increases the validity of these models for stable short term forecasts and also minimizes computational costs (Mbonyinshuti & Kim, 2021).
- High Precision with Complex Data (Machine Learning Models): More sophisticated models like XGBoost and DeepAR are employed to produce high accuracy in sales forecasting where there are intricate interrelationships between sales and multiple variables which are often non-linear in nature. These models are capable of working with big data which has multiple features, which makes them most effective in applications that involve multiple factors such as the multi-factor forecasting model (Pavlyshenko, 2019). Due to the fact that factors such as promotions, seasonality, and trends on social media platforms play a significant part in sales in sectors such as e-commerce, machine learning models are capable of capturing multiple features and provide more accurate forecasts than traditional models (Kim & Yu, 2020).

- Interpretability for Decision-Making (Traditional Models): ARIMA and Exponential Smoothing models are useful in industries where there is need for clear and easy to understand results such as finance or health care industries. These models use assumptions of trends, seasonality, and stationarity which are easy to explain to decision makers and other parties involved (Hyndman & Athanasopoulos, 2018). As with traditional models, decision-makers can easily see through them and understand which factors are most influential and thus these models are useful in areas where it is important to comprehend the model.
- Real-Time Forecasting Capabilities (Machine Learning Models): Real-time prediction is best done using models that are based on gradient boosting, for instance XGBoost and LightGBM, because they are faster to train than deep learning models while being capable of handling large datasets. This speed is important in industries where timely forecasting is necessary especially in sectors like the fast-moving consumer goods (FMCG) industry (Ke et al., 2017). It is possible to achieve high accuracy in the results without a significant decrease in the speed of data processing, which is especially important for business.

<u>Weaknesses</u>

- Limited Adaptability (Traditional Models): Traditional time series models are relatively rigid and cannot accommodate the many irregular and high-frequency data patterns. Consequently, they have low efficiency in situations where data trends are volatile or influenced by a large number of factors (Sumit, 2023). These methods are generally best suited for short term prediction and hence are ineffective in making long term predictions which are critical in industries that involve multi-step, long range forecasting.
- High Computational Requirements (Machine Learning Models): The most recent machine learning models which include DeepAR and N-BEATS are based on deep learning which is very complex and demands powerful hardware which is expensive and a drain on resources (Lindfors, 2022). These models use a lot of data and require data pre-processing in order to give the best results, thus making them less practical for organizations with limited resources.
- Lower Interpretability (Machine Learning Models): Most of the machine learning models are based on algorithms and data which are in high dimensions, making it difficult to understand their results. The problem with using machine learning models is that they are often opaque, meaning that the reasoning behind the model's output is hard to explain to decision makers (Doshi-Velez & Kim, 2017). This reduced transparency is problematic in fields where regulatory or other interested parties require the models to be easily understandable and explainable.
- Data Dependency and Sensitivity (Machine Learning Models): Machine learning models are very sensitive to data quality and quantity. These models can give poor predictions when data is limited, corrupted by noise or incomplete, for instance, when models overfit or underfit (Smyl, 2020). These models are usually used in a way that they need to be updated and trained for new trends and patterns at regular intervals which may involve a lot of time and money.

Opportunities

- Advanced Insights in Complex Environments (Machine Learning Models): The ability of machine learning models to work with large and different data sets is ideal for companies in volatile markets. Machine learning models provide probabilistic forecasts instead of a single point forecast that gives only one possible outcome of the future, which is useful in conditions of high uncertainty (Lai et al., 2021). Through the use of external and contextual data, machine learning models can improve the accuracy of the forecast and provide key information that will be useful in strategic decision-making (Nguyen et al., 2021).
- Enhanced Business Intelligence (Traditional Models): As a result of their basic design and relatively less computational power, traditional time series models are ideal for organizations that need to get results fast and can work with limited resources in terms of operations. For businesses that are concerned with short-term forecasting in the area of inventory control, the conventional time series models may provide accurate results at a relatively low cost and thus suitable for environments that are characterized by resource constraints.
- Improvement with Hybrid Approaches: Thus, it is possible to recommend businesses to use hybrid models which include both the classical time series models and the machine learning ones. For instance, ARIMA can be employed to model basic trends and seasonality and machine learning models to model complex interactions and other variables. This synergy strengthens the reliability and flexibility of the output of the forecasting models (Oreshkin et al., 2019). Hybrid methods enable companies to take the best of both model types, achieving a good balance between interpretation, adaptability, and precision.
- Resource Allocation for Strategic Planning: Through the use of machine learning, organizations are able to predict the trends in resource use, marketing, inventory, and workforce. To meet the consumers' demands and changes in the market, businesses need accurate and timely forecasts which give them a competitive advantage (Sumit, 2023). Through the use of factors such as seasonality, promotions and social trends, the companies can be able to plan for the demand surges that are experienced at certain periods of the year or certain events that are anticipated to occur in the society.

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Model Type	Strengths	Weaknesses
Traditional Time Series Models	Interpretability, Computational Efficiency, Short-Term Forecasting	Limited Flexibility, Computational Limitations
Machine Learning Models	Accuracy, Adaptability, Probabilistic Forecasting	Interpretability, Computational Demand
Hybrid Models	Balance, Flexibility, Resource Use	Complexity, Cost

This table effectively highlights the key advantages and disadvantages of each model type, making it easier to compare and choose the most suitable approach for a specific forecasting problem.

Discussion

The comparison of traditional time series models and machine learning approaches for sales forecasting has provided the following important findings that are relevant both for further theoretical development and for practical implementations in business environments. Both approaches have their strengths and weaknesses; the strengths and weaknesses of each approach have important implications for their performance in certain forecasting environments.

One of the most striking observations from this research is the ability of machine learning models to outperform conventional statistical models in the handling of non-linear data. Recent techniques like XGBoost, LightGBM and Deep Learning models like DeepAR have been found to provide very accurate results when used on large datasets with many variables. Their capacity to incorporate different factors, including promotion, and social media mood, helps them to identify trends that other models cannot see (Chen & Guestrin, 2016; Pavlyshenko, 2019). In the contexts of sales that are influenced by many factors and, therefore, highly volatile, machine learning models may provide more accurate forecasts compared to linear models, which have been used in e-commerce and consumer goods (Lai et al., 2021; Madrid & Antonio, 2021).

However, there are still some traditional time series models such as ARIMA and Exponential Smoothing that show their effectiveness in the structured and seasonal data. These models are very useful when data is deterministic, especially when it is used for short term forecasting in industries with clear cyclical demands such as retail and utilities. These are also less complex to compute and hence more useful in smaller organizations with limited computational power for training more complex models (Hyndman & Athanasopoulos, 2018; De Gooijer & Hyndman, 2006). The two main principles to address the issue of post-implementation feedback are interpretability and transparency.

Aspects	**Traditional Models**	**Machine Learning Models**
Strengths	Effective for structured and seasonal data. High interpretability and transparency. Computationally efficient and easy to implement. Suitable for short-term forecasting. Useful in regulatory compliance settings.	Handles non-linear and complex relationships. Incorporates multiple variables like promotions and social media trends. More accurate in volatile environments. Adaptive to frequent data updates Suitable for large datasets.
Weaknesses	Less effective for highly volatile and complex data.	High computational cost (requires GPUs and specialized hardware).

	Limited ability to incorporate external factors. Not adaptive to frequent data updates.	Low interpretability (black-box nature). Requires expertise for implementation and fine-tuning.
Computational Efficiency	Requires less computational power. Can be deployed on standard hardware.	Needs GPUs and significant computing power. Longer training times.
Interpretability	High (trend and seasonality easily explainable). Useful for stakeholder reporting.	Low (black-box models, difficult to explain predictions). Requires SHAP or similar explainability techniques.

The other major difference between the conventional and machine learning models is how interpretable they are. The traditional time series models are relatively easier to comprehend because they apply statistical concepts that enable the analyst to discern various components of the model such as trend and seasonality. This is especially important in industries with regulatory compliance issues or situations where forecasting has to be defended before stakeholders, for instance, finance and health care (Doshi-Velez & Kim, 2017). The point forecasts produced by models like ARIMA are explicit and based on rules while the results presented are easy to understand and can be acted upon by providing recommendations that are consistent with the observed patterns in the data (Hasan et al., 2022).

On the other hand, machine learning models especially deep learning models are often termed as “Black box” due to their high dimensionality and non-linearity. This is a problem in situations where explanation of the model is necessary to gain the trust of the people. New approaches like SHAP (SHapley Additive exPlanations) have been developed in order to enhance the explainability of each feature in the model, yet these methods are still quite complex and thus not very practical for all cases (Lundberg & Lee, 2017). Therefore, the selection of appropriate forecasting model is a balance between the accuracy of the forecasting results and the understandability of the model by the operations and other stakeholders of the business.

There is one more key difference between traditional time series analysis and machine learning approaches – computational efficiency. The traditional models are more efficient as they require less computational power thus suitable for use by organizations with limited computational power. This efficiency is most useful in scenarios that require immediate and relatively frequent predictions, for instance, daily stock control. The ARIMA and Exponential Smoothing models are ideal for these tasks as they are not computationally intensive and can be hosted on normal hardware with low capital investment (Ke et al., 2017; Hyndman & Khandakar, 2008).

However, machine learning models especially the deep learning networks may need additional hardware like GPU and longer time to train, which may be a disadvantage to small companies. Although LightGBM and XGBoost are developed to be faster than traditional deep learning models, they are still computationally expensive than traditional time series models. Therefore, the machine learning models may be more useful for large corporations that can afford it or when the stakes are high and the potential gain in accuracy is worth the additional computational costs (Nguyen et al., 2021).

One of the biggest strengths of machine learning models is their ability to learn across various and frequent data structures especially in volatile and dynamic sectors like e-commerce and fast-moving consumer goods. Neural networks, and specifically recurrent neural networks that are used in models like DeepAR, are very effective in probabilistic forecasting, which is the practice of producing a distribution of possible values, instead of a single point estimate. This flexibility helps companies to be ready for different situations and to minimize the risk of losses in volatile environments (Salinas et al., 2019). Furthermore, machine learning models can be updated with new data whenever it is obtained, and this makes the forecasts relevant to the current market situation.

However, this flexibility is achieved at the expense of the model complexity and regular updating which may prove difficult for companies that do not have the necessary technical know-how. However, traditional models are not as flexible as machine learning models since they do not necessitate data preprocessing and model fine-tuning. This stability makes them suitable for organizations with stable, well-defined data which does not need to be updated very often (De Gooijer & Hyndman, 2006).

A new area of concern in sales forecasting is the integration of the conventional time series analysis with machine learning algorithms. Hybrid models combine the best of both worlds, using conventional methods for the base line and seasonal components and machine learning for the detail and the effects of external factors. For instance, an ARIMA model can be applied to capture long-term patterns and an XGBoost model can be applied on top of it to capture short-term variability. The above findings indicate that the combination of the two approaches can lead to better and more flexible results without having to completely lose the ability to explain the output (Oreshkin et al., 2019; Smyl, 2020).

Hybrid models are an attractive solution for organizations that need the power and adaptability of machine learning and the ease and interpretability of traditional models. Hybrid models, therefore, can be adjusted to fit certain data patterns and business requirements to ensure that an organization gets the best of both worlds when it comes to model performance.

This research also calls for more research on the uses of hybrid models and enhanced methods of interpreting machine learning models in sales forecasting. Further research could be directed towards the creation of guidelines for incorporating machine learning into time series analysis, so that these models could be applied in more industries. Further, the interpretability gap might be closed by developing more XAI techniques focused on forecasting domain as it would make the machine learning models more applicable in regulated industries and transparent applications (Doshi-Velez & Kim, 2017).

In practical implications, the research outcomes recommend that businesses should choose the appropriate forecasting models depending on their requirements and available resources. It is likely that smaller companies or those operating in more predictable environments will get the most value out of conventional models, whereas larger enterprises with access to more sophisticated computing power will likely do better with machine learning models. A middle ground is presented by the hybrid approaches which combine the benefits of both accuracy and adaptability with the drawback of opacity and complexity.

Conclusion

This comparative study on sales forecasting models reveals that both traditional time series and advanced machine learning methods offer unique strengths that can be advantageous depending on specific business requirements and data conditions. Traditional time series models like ARIMA and Exponential Smoothing excel in interpretability and computational efficiency, making them suitable for structured, seasonal data patterns and resource-constrained environments. However, their limitations become apparent in volatile, high-dimensional datasets, where machine learning models such as XGBoost, LightGBM, and DeepAR outperform with superior accuracy and adaptability. Machine learning models, while often more complex and computationally demanding, offer substantial benefits in predictive accuracy, particularly for multi-step and non-linear forecasting scenarios.

The study highlights the emerging potential of hybrid models, which combine the strengths of both approaches to balance accuracy, interpretability, and adaptability. Hybrid models offer a practical solution for organizations that need both the transparency of traditional models and the precision of machine learning techniques. Moving forward, businesses should assess their specific forecasting needs, data complexity, and resource availability to select the most suitable model. Additionally, further research into hybrid modeling techniques and explainable AI holds promise for enhancing the accessibility and effectiveness of forecasting models across diverse industries.

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