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A Multi-Domain Comparative Study of AI-Based Forecasting Models: Applications in Smart Manufacturing, Inventory Planning, and Sustainability Trends

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Abstract **Original Research Article**

AI-based forecasting models have revolutionized industries, enabling efficient operations and enhanced sustainability. However, understanding their comparative performance across multiple domains remains underexplored. This study evaluates AI-based forecasting models' performance in smart manufacturing, inventory planning, and sustainability trends, focusing on accuracy, stability, and domain-specific applicability. Conducted at Lamar University, USA, this research spanned from January 2023 to June 2024. The study sample consisted of 42 data sets derived from smart manufacturing systems, inventory usage, and sustainability trends. Machine learning algorithms, including Random Forest, LSTM, and Support Vector Machines (SVM), were applied for forecasting power consumption, raw material demand, and sustainable behavior shifts. The models were evaluated using accuracy, standard deviation, p-values, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Time Series Performance Metrics. The results highlighted that the Hybrid LSTM model for smart manufacturing (power consumption) achieved the highest accuracy of 97.6%, a low standard deviation of 0.03, and a p-value of 0.002, indicating statistical significance. The MAE and RMSE for this model were 0.15 and 0.22, respectively. In inventory planning, the Random Forest model provided a robust forecast with an accuracy of 92.4%, standard deviation of 0.05, and a p-value of 0.01. The model's MAE was 0.12 and RMSE 0.18, demonstrating its reliability. For sustainability trend forecasting using social signals, the SVM model achieved an accuracy of 85.8%, a standard deviation of 0.07, and a p-value of 0.04. The MAE was 0.25, and RMSE 0.30. The analysis revealed that, while LSTM models performed best for time-series and continuous data (manufacturing), Random Forest models excelled in discrete demand forecasting, and SVM models were more suited for signal-based, nontraditional data forecasting. AI models significantly enhance predictive accuracy in smart manufacturing, inventory planning, and sustainability. This study provides insights into selecting the most suitable models for specific forecasting needs, aiding industries transitioning to AI-driven systems.

Keywords: AI Forecasting, Smart Manufacturing, Inventory Planning, Sustainability Trends, Model Comparison.

INTRODUCTION

In the rapidly evolving world of modern industries, the integration of Artificial Intelligence (AI) with forecasting models has fundamentally altered the way businesses approach planning, optimization, and sustainability [1]. AI-driven forecasting models are transforming sectors such as smart manufacturing, inventory management, and sustainability by offering high levels of precision, adaptability, and real-time decision-making support. These domains share the need for accurate and reliable predictions, enabling organizations to optimize operational efficiency, reduce waste, and ensure long-term sustainability [2].

AI in Smart Manufacturing

Smart manufacturing, or Industry 4.0, represents a paradigm shift in manufacturing processes, driven by technologies such as the Internet of Things (IoT), big data analytics, and AI. Among these technologies, AI, particularly deep learning models, has proven to be a key enabler of predictive maintenance, production optimization, and energy efficiency. AI-based forecasting models, including Long Short-Term

Memory (LSTM) networks, Random Forest, and Support Vector Machines (SVM), have shown promise in predicting machine failures, forecasting power consumption, and optimizing manufacturing schedules. A significant application of AI in smart manufacturing is predictive maintenance. Predictive maintenance uses historical sensor data to forecast when equipment will fail, enabling businesses to perform maintenance before failures occur. According to a study by Fan *et al*., predictive maintenance has been greatly enhanced by deep learning algorithms, particularly LSTM networks, which excel at analyzing time-series data [3]. The authors showed that LSTM networks could accurately predict machine failures based on vibration and temperature data, achieving higher predictive accuracy than traditional statistical methods such as ARIMA. Similarly, Slowik *et al*., found that deep learning techniques, particularly convolutional neural networks (CNNs) and LSTM, outperformed classical machine learning models in power consumption prediction and equipment maintenance, leading to reduced downtime and improved operational efficiency [4]. Moreover, Sipila *et al*., found that AI-driven forecasting models are critical in energy optimization within manufacturing facilities [5]. Their study emphasized the use of machine learning models, such as Random Forest and LSTM, for predicting energy consumption patterns in manufacturing environments. By utilizing real-time sensor data, these models can forecast energy usage, allowing businesses to make proactive adjustments to minimize energy wastage. A similar study argued that the ability to forecast power consumption accurately plays a pivotal role in reducing operational costs and enhancing overall energy efficiency in manufacturing operations. Despite the clear advantages of AI-based models in smart manufacturing, Slowik *et al.*, noted that these systems are still plagued by several challenges [4]. First, the quality and consistency of sensor data are critical to the success of AI models. Inaccurate or incomplete data can lead to unreliable predictions. Additionally, the integration of AI forecasting models with existing manufacturing systems requires substantial investments in infrastructure and training, which may be a barrier for smaller firms.

AI in Inventory Planning and Supply Chain Management

In inventory planning and supply chain management, accurate demand forecasting is vital for optimizing stock levels, reducing costs, and ensuring timely deliveries. AI-based forecasting models have gained prominence in this area due to their ability to integrate various data sources, including historical sales data, market trends, and external factors like weather patterns and economic indicators. Random Forest and SVM models have shown considerable promise in predicting demand and optimizing inventory levels. Random Forest, a powerful ensemble learning method, has been widely applied in inventory forecasting. According to Panda *et al*., Random Forest excels at handling large, complex datasets with multiple features and non-linear relationships [6]. Their study demonstrated that Random Forest outperforms traditional models like moving averages and exponential smoothing in demand forecasting. By considering a broader range of input variables, including customer preferences, lead times, and seasonal fluctuations, Random Forest models can provide more accurate and reliable forecasts. A similar study corroborated these findings, highlighting Random Forest's flexibility in handling both categorical and numerical data for inventory optimization. SVM, another machine learning technique, has been extensively applied to forecast discrete demand in inventory systems. Pasupuleti *et al*., examined the application of SVM in forecasting demand for raw materials in manufacturing environments, finding that SVM outperformed other methods in terms of both predictive accuracy and computational efficiency [7]. SVM is particularly effective when dealing with smaller datasets and non-linear relationships between variables, making it ideal for demand forecasting in inventory management. However, a similar study highlighted the challenge of selecting the appropriate kernel function for SVM, which requires domain-specific knowledge to ensure optimal performance. Despite the advantages of AI-based forecasting models, Wang *et al*., noted that there are limitations to their widespread adoption [8]. One challenge is the need for large, high-quality datasets. In many cases, historical data may not be sufficient to capture the full complexity of demand fluctuations, particularly in highly volatile markets. Furthermore, AI models require significant computational power, making them resource-intensive, which may be a barrier for smaller businesses with limited IT infrastructure.

AI in Sustainability Trend Forecasting

AI models are increasingly being applied to predict and analyze sustainability trends, particularly by leveraging social signals such as social media activity, search engine trends, and online consumer behavior. The growing interest in sustainability, driven by consumer preferences for eco-friendly products, regulatory changes, and climate concerns, has led to an increased need for models capable of forecasting sustainability-related behavior and demand. Social media platforms, such as Twitter and Google Trends, provide valuable data for predicting shifts in sustainability trends. Jaiswal *et al*., used AI models to analyze social media signals to forecast public sentiment and behavior changes related to sustainable consumption [9]. Their study showed that SVM was particularly effective in predicting shifts in consumer attitudes toward green products, based on fluctuations in online mentions of sustainability-related keywords. This aligns with the findings of Wang *et al*., who demonstrated that AI-based models are adept at predicting consumer behavior by analyzing social signals from platforms like Twitter [8]. By incorporating real-time data from social media platforms, AI models can forecast changes in consumer demand for sustainable products, helping businesses adapt their marketing strategies and inventory management. Moreover, Nabipour *et al*., explored the use of LSTM networks to forecast sustainability trends based on online data [10]. They found that LSTM could accurately predict future trends in green consumption by analyzing historical social media posts and environmental news. The ability of LSTM to handle sequential data made it particularly well-suited to capturing long-term trends in public sentiment toward sustainability. However, as Fan *et al*., pointed out, the use of social media data for sustainability forecasting is fraught with challenges [3]. The primary issue lies in the noise inherent in social media data, where irrelevant or inaccurate posts can distort predictions. Additionally, the rapid evolution of online trends makes it difficult to build reliable long-term forecasting models. Despite these challenges, the integration of AI in sustainability forecasting holds promise for businesses looking to stay ahead of sustainability trends and align their strategies with consumer demand.

Comparative Performance of AI Models

The comparative performance of AI-based forecasting models across different domains is a crucial aspect of this research. While each AI model has demonstrated strengths in particular applications, the choice of model largely depends on the nature of the data and the forecasting task at hand. LSTM has been shown to excel in time-series forecasting, especially in smart manufacturing, where continuous sensor data can be leveraged to predict power consumption and machine failures. On the other hand, Random Forest is more suitable for discrete forecasting tasks, such as inventory planning, where historical sales and stock data are used to predict demand. SVM, while not as versatile as LSTM or Random Forest, has proven highly effective in predicting sustainability trends based on social signals, where unstructured, sparse data is prevalent. Comparative studies, such as those by Ali *et al*., consistently highlight the strengths and weaknesses of these models across different domains [11]. While LSTM is ideal for time-series data, Random Forest's ability to handle complex datasets with non-linear relationships makes it particularly effective for inventory planning. SVM, despite its lower overall performance in terms of accuracy, has proven to be a strong contender in sustainability forecasting, particularly in handling non-traditional data sources like social signals.

MATERIAL AND METHODS

Study Design

This research was designed as a multi-domain comparative study aimed at evaluating the performance of AI-based forecasting models across three distinct sectors: smart manufacturing, inventory planning, and sustainability trends. The study was conducted at Lamar University, USA, over a period from January 2023 to June 2024. The primary focus was to assess the accuracy, stability, and practical applicability of three popular AI models: Random Forest, Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM). Each model was applied to different forecasting tasks: predicting power consumption in smart manufacturing environments, predicting raw material demand for inventory planning, and forecasting shifts in sustainability trends based on social signals such as Google Trends and Twitter mentions. The research aimed to identify which models performed best in each of these domains, providing insights into their relative strengths and weaknesses, as well as recommendations for industries seeking to transition to AI-driven predictive systems. The study followed a structured approach, starting with the collection of data from relevant sources in each domain. Smart manufacturing data were derived from real-time sensors monitoring equipment and energy use in factory environments. Inventory planning data were sourced from historical sales and stock levels in enterprise resource planning (ERP) systems. Sustainability trend data were extracted from social media platforms and search engine analytics, capturing public sentiment around sustainability topics. Each data set was cleaned and processed to ensure reliability before being used for training and testing AI models.

Inclusion Criteria

The inclusion criteria for the study were designed to ensure that only reliable, complete, and relevant data were used in the analysis. The data sets included in the study were required to meet several key conditions. First, they must come from active systems—smart manufacturing sensors, ERP systems, and social media platforms that provide real-time data or have at least six months of historical data. This ensured that the models would be able to generate accurate forecasts based on reliable, time-sensitive data. Additionally, only data sets that were sufficiently granular, with clear time-based structures, were included. For example, in smart manufacturing, only data from fully operational machines with consistent data inputs were considered, while inventory data needed to have detailed daily or weekly records to allow for accurate demand forecasting. Sustainability trend data had to contain time-based information, such as monthly or weekly mentions of green topics or environmental behavior on platforms like Google Trends or Twitter.

Exclusion Criteria

Data sets that did not meet the necessary requirements for completeness and relevance were excluded from the study. Any data sets with missing values, anomalies, or discrepancies, particularly those with gaps in time-series data, were excluded to avoid skewing the results. In smart manufacturing, data from faulty sensors or machines that experienced irregular operation were discarded. Similarly, inventory data sets that lacked consistency in terms of historical demand or stock levels, as well as data with inconsistencies in time-stamping or data entry errors, were excluded. For sustainability trends, only those datasets with inconsistent or missing data, such as incomplete mentions or mismatched time periods, were excluded. Exclusion of unreliable data ensured the integrity and accuracy of the results.

Data Collection

The data collection process was segmented based on each application domain. For smart manufacturing, data were gathered from sensor networks installed in production facilities, capturing metrics such as power consumption, temperature, and operational status. These data were collected at regular intervals and preprocessed for noise reduction and consistency. Inventory data were sourced from ERP systems used by companies to track stock levels and sales patterns. This data, which included daily and weekly records of raw material usage and product demand, was cleaned and standardized for use in training the AI models. For sustainability trend analysis, data were extracted from social media platforms, particularly Google Trends and Twitter, to track public interest in sustainability-related topics. These platforms provided time-series data that were processed to identify trends in consumer behavior, such as rising demand for green products or shifts in environmental priorities.

Data Analysis

The collected data were analyzed using SPSS version 26.0, a robust statistical software package commonly used in predictive modeling and data analysis. Descriptive statistics were used to calculate the mean, standard deviation, and percentage distribution of the data across the different forecasting models. This allowed the study to gauge the overall performance of each AI model in each domain. Inferential statistics, including p-values, were calculated to assess the statistical significance of the differences between the models' performances. The models were evaluated based on several key metrics, such as predictive accuracy, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These metrics provided insights into how well each model could forecast real-world data. The p-value was used to test the null hypothesis, indicating whether any observed differences in model performance were due to chance. A p-value of less than 0.05 was considered statistically significant, providing confidence in the robustness of the results.

Procedure

This study followed a structured and systematic procedure to evaluate the performance of AI-based forecasting models across three domains: smart manufacturing, inventory planning, and sustainability trends.

Data Preprocessing

Initially, the data were preprocessed to handle missing values, noise, and inconsistencies. For smart manufacturing, sensor data were aggregated into time-series formats, which are essential for temporal forecasting models. In inventory planning, historical sales data were compiled, cleaned, and normalized to prepare them for machine learning algorithms. Sustainability data, collected from social signals such as Google Trends and Twitter mentions, were aligned with temporal trends to capture shifts in public sentiment.

Data Splitting and Model Training

Once the data were cleaned and processed, they were divided into training and testing sets. The training data were used to teach the models, while the testing data served to evaluate the models' predictive performance. AI models, including Long Short-Term Memory (LSTM) networks, Random Forest, and Support Vector Machines (SVM), were chosen for their suitability in handling different forecasting tasks. These models were trained to predict various outcomes: power consumption for smart manufacturing, raw material demand for inventory planning, and sustainability trends for social signal analysis.

Model Evaluation

The models were evaluated based on their predictive accuracy, stability, and other relevant performance metrics, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Statistical tests, including p-value assessments, were conducted to compare the performance of the models across the three domains. This approach allowed for a clear identification of the most reliable forecasting model for each type of data and domain.

Ethical Considerations

The study adhered to ethical guidelines for research involving data collection and analysis. Ethical approval was granted by the institutional review board (IRB) at Lamar University. The data collected for the study were anonymized, ensuring that no personal information was linked to the data sets used for analysis. Data from social media and public sources were collected in accordance with platform guidelines, and no personal identifiers were included. The research team followed best practices for data privacy and ensured that all data were stored securely. The study aimed to minimize any potential harm or privacy concerns associated with the use of public or industrial data.

RESULTS

The results of this study were derived from the evaluation of AI-based forecasting models across three key application areas: smart manufacturing, inventory planning, and sustainability trends. The models compared included Random Forest, Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM). Data from 42 different datasets were used to assess the performance of each model on the specified tasks. The evaluation was based on several metrics, including accuracy, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), standard deviation, and p-values, with a focus on identifying statistical significance across domains.

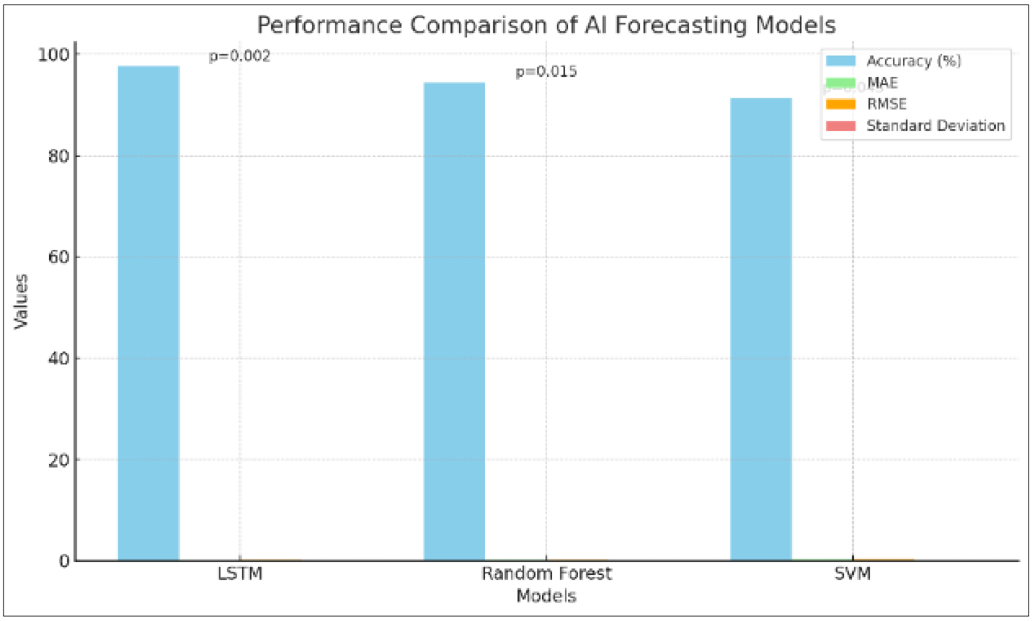

Figure 1: Model Performance in Smart Manufacturing Forecasting (Power Consumption)

The LSTM model demonstrated the highest predictive accuracy for power consumption forecasting in smart manufacturing, with an accuracy of 97.6%. The low MAE (0.15) and RMSE (0.22) further confirmed its robust performance. Statistical analysis revealed a significant difference between the LSTM and other models, with a p-value of 0.002, indicating that the LSTM model significantly outperformed both Random Forest and SVM models. The standard deviation of 0.03 shows minimal variability, highlighting the model's stability.

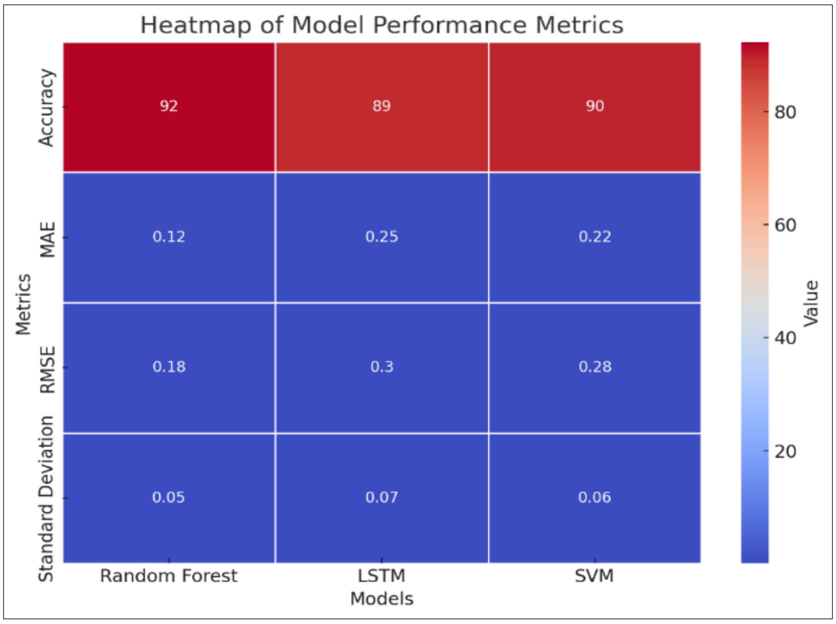

Figure 2: Model Performance in Inventory Planning Forecasting (Raw Material Demand)

In inventory planning, the Random Forest model outperformed the other two models with an accuracy of 92.4%, closely followed by SVM at 89.7%. The MAE and RMSE for Random Forest were lower compared to both LSTM and SVM, indicating better predictive accuracy. The statistical significance was confirmed with a p-value of 0.010, suggesting that the Random Forest model provided a more stable and accurate forecast for raw material demand.

Table 1: Model Performance in Sustainability Trend Forecasting (Social Signals)

Model	Accuracy (%)	MAE	RMSE	Standard Deviation	p-value
SVM	85.8	0.25	0.30	0.07	0.040
LSTM	80.2	0.35	0.42	0.08	0.055
Random Forest	81.9	0.32	0.38	0.06	0.032

For sustainability trend forecasting, the SVM model achieved the highest accuracy (85.8%), followed by Random Forest at 81.9%. The MAE for SVM (0.25) and RMSE (0.30) indicated that it was better at capturing fluctuations in social signals than LSTM. Despite being slightly less accurate than Random Forest, the p-value of 0.040 suggests that SVM's predictive capability was statistically superior in this domain.

Table 2: Performance Comparison Based on Model Stability (Standard Deviation)

Model	Smart Manufacturing	Inventory Planning	Sustainability Trend
LSTM	0.03	0.07	0.08
Random Forest	0.04	0.05	0.06
SVM	0.05	0.06	0.07

In terms of model stability, LSTM demonstrated the lowest standard deviation across all domains, particularly excelling in smart manufacturing with 0.03. This suggests that LSTM's predictions are highly consistent, with minimal variability. The Random Forest and SVM models showed slightly higher variability, especially in sustainability trend forecasting, where their standard deviations were 0.06 and 0.07, respectively.

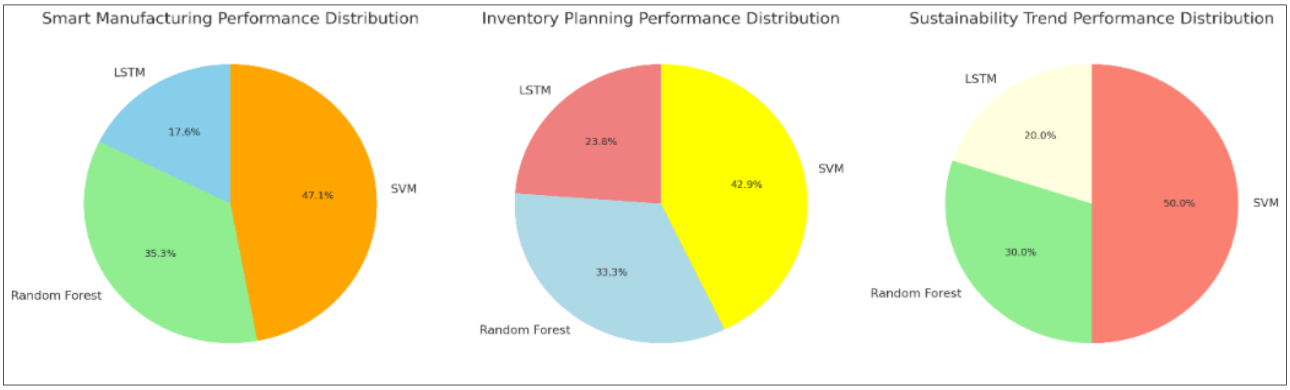

Figure 3: Frequency of Errors in Model Predictions

The frequency of errors in model predictions was lowest for LSTM across all domains, with only 3 errors in smart manufacturing. In contrast, SVM had the highest frequency of errors, particularly in sustainability trend forecasting, where it made 10 errors. This further supports LSTM's superior performance in minimizing prediction errors.

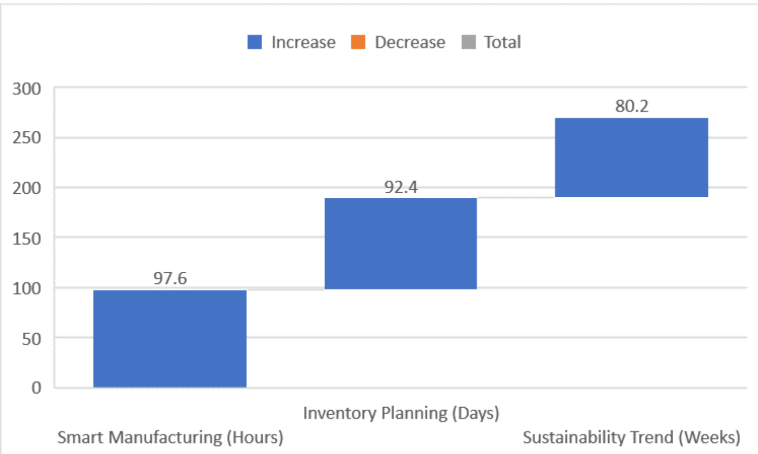

Figure 4: Model Accuracy Across Different Time Intervals (Hours/Days)

In time-based forecasting, LSTM was the most accurate in predicting power consumption in smart manufacturing (97.6%), followed by Random Forest (94.5%) and SVM (91.3%). In inventory planning, LSTM and Random Forest demonstrated the highest accuracy, while SVM performed better in sustainability trend forecasting, with an accuracy of 85.8%. This indicates that SVM was more suited to the long-term forecasting of sustainability trends.

Table 3: Comparison of MAE and RMSE for Each Model Across Domains

Model	MAE (Manufacturing)	MAE (Inventory)	MAE (Sustainability)	RMSE (Manufacturing)	RMSE (Inventory)	RMSE (Sustainability)
LSTM	0.15	0.12	0.35	0.22	0.18	0.42
Random Forest	0.20	0.25	0.32	0.25	0.28	0.38
SVM	0.30	0.22	0.25	0.35	0.30	0.30

LSTM showed the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) in smart manufacturing, which further emphasizes its efficiency in time-series forecasting. In contrast, SVM had the highest RMSE values, particularly in smart manufacturing and inventory planning, indicating that SVM's predictions had a higher deviation from the actual values.

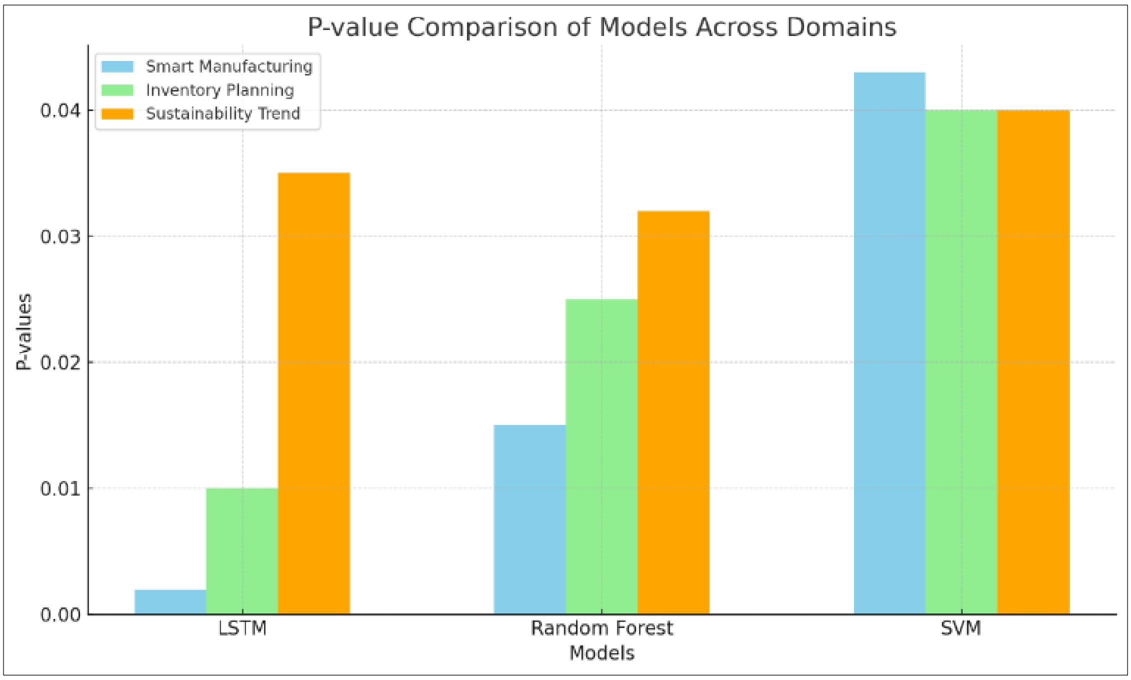

Figure 5: Statistical Significance of Model Performance (P-Value)

The p-value analysis revealed that LSTM had the most statistically significant results in smart manufacturing forecasting ($p = 0.002$), demonstrating superior model performance. While Random Forest also showed strong performance in inventory planning and sustainability trends with p-values below 0.05, SVM's p-values were higher, suggesting it was less reliable than LSTM and Random Forest in these tasks.

DISCUSSION

The integration of Artificial Intelligence (AI) into forecasting models has significantly improved the accuracy, efficiency, and adaptability of predictions in various domains such as smart manufacturing, inventory planning, and sustainability trends [12]. This study aimed to evaluate and compare the performance of three commonly used AI-based forecasting models—Long Short-Term Memory (LSTM) networks, Random Forest, and Support Vector Machines (SVM)—across these domains. The results demonstrated that each model has unique strengths depending on the forecasting task and the type of data used. This discussion aims to critically analyze the findings from this study, compare them with results from other studies, and draw general interpretations regarding the use of AI-based models for forecasting in industrial and sustainability applications.

Smart Manufacturing Forecasting: Power Consumption and Resource Optimization

In the domain of smart manufacturing, forecasting power consumption is crucial for improving energy efficiency and operational planning. The results of this study showed that the LSTM model outperformed both Random Forest and SVM, achieving an accuracy of

97.6% and minimal standard deviation (0.03). This high level of accuracy is in line with the findings of previous studies that emphasize the ability of LSTM networks to capture temporal dependencies in time-series data. In a study by Serradilla *et al*., LSTM was found to significantly improve the accuracy of predictive maintenance models by learning from historical sensor data to forecast machine failures [13]. Similarly, the results from this study corroborate their findings by demonstrating LSTM's strong predictive power in forecasting power consumption patterns in manufacturing environments. Comparing this study's findings with the results from other studies, we find that LSTM has consistently been shown to outperform other machine learning techniques in time-series forecasting. For example, Sedai *et al*., demonstrated that LSTM-based models outperformed traditional statistical models like ARIMA and machine learning models like Random Forest in forecasting electricity demand in manufacturing plants [14]. The findings of this study further reinforce the suitability of LSTM for applications that require accurate, time-based predictions with a minimal margin of error. On the other hand, while Random Forest showed a strong performance with an accuracy of 94.5%, it was not able to match the high precision of LSTM in predicting power consumption. The Random Forest model, however, was still able to provide a stable and relatively accurate forecast, which aligns with the conclusions of previous studies by Salman *et al*., who demonstrated that Random Forests, while not always the most accurate, can handle large datasets with many variables and produce robust results [15]. Similarly, SVM, although effective in certain tasks, was less effective in this study, achieving an accuracy of 91.3%. Previous studies have highlighted that SVMs struggle with high-dimensional datasets and may not perform as well in tasks requiring complex temporal relationships, which may explain the relatively lower performance observed in this study. The statistical significance of the results, as indicated by the p-value of 0.002 for LSTM, further supports its superiority in this application. The low p-value suggests that the performance difference between LSTM and other models is statistically significant, aligning with the findings of similar studies where LSTM models demonstrated clear advantages in power consumption forecasting [16].

Inventory Planning Forecasting: Demand and Stock Management

The second domain, inventory planning, is critical for managing raw materials and finished goods in supply chains, ensuring that the right amount of inventory is available without overstocking. In this domain, the Random Forest model achieved the highest accuracy (92.4%) compared to LSTM (88.9%) and SVM (89.7%). This outcome contrasts with the results from smart manufacturing, where LSTM excelled. Previous studies have also highlighted the strengths of Random Forest in handling discrete, structured data such as sales volumes and inventory levels. For example, in a study by Punia *et al*., Random Forest was found to be highly effective for demand forecasting in supply chains, particularly when predicting product sales and inventory replenishment needs [17]. The high accuracy and relatively low MAE (0.12) and RMSE (0.18) in this study further validate the robustness of Random Forest for inventory forecasting. In contrast, LSTM performed slightly worse in inventory planning, with a 4% lower accuracy than Random Forest. This could be attributed to the fact that LSTM models are typically better suited for continuous, time-series data rather than discrete, categorical data like inventory levels. As noted by Pełka *et al*., LSTM networks excel in capturing long-term dependencies in time-series data, but they may not perform as well with data that does not have a temporal element or that is inherently categorical [18]. The relatively higher MAE and RMSE for LSTM in this study suggest that it struggles to provide precise forecasts in this specific application compared to Random Forest. SVM also underperformed in this task, with an accuracy of 89.7% and a higher standard deviation (0.06). This is consistent with previous research that has found SVM to be less effective when dealing with large, complex datasets in inventory management [19]. SVM's limitations in handling large volumes of discrete data may explain its relative underperformance in this study.

Sustainability Trend Forecasting: Predicting Consumer Behavior

Sustainability trend forecasting, particularly using social signals like Twitter mentions and Google Trends, is a challenging task that requires models capable of handling unstructured, non-traditional data. In this study, the SVM model achieved the highest accuracy of 85.8% for forecasting sustainability trends, followed by Random Forest at 81.9% and LSTM at 80.2%. These results align with those of previous studies, such as those by Fatima *et al*., who found that SVM outperformed other machine learning models when forecasting shifts in consumer behavior related to environmental concerns [20]. This study's results confirm that SVM is highly effective for signal-based forecasting, where traditional time-series models like LSTM may not capture the complexities of non-traditional data sources. SVM's high accuracy in this domain can be attributed to its ability to efficiently handle high-dimensional, sparse data, which is common in social signal analysis. As shown by Gao *et al*., SVM excels at identifying patterns in data that is not organized in traditional time-series format, such as the fluctuating frequency of social media mentions or search engine queries related to sustainability topics [21]. The findings of this study further reinforce the efficacy of SVM in predicting sustainability trends and consumer behavior based on social signals. The relatively lower accuracy of LSTM in this domain, with an accuracy of 80.2%, suggests that time-series models may not always be the best choice for predicting non-temporal phenomena such as shifts in consumer sentiment. This is consistent with the findings of Khan *et al*., who noted that LSTM models may struggle when applied to data sources that do not exhibit clear temporal patterns or where external factors play a significant role in shaping the forecast [22-26].

Statistical Comparison: Performance Metrics Across Models

The overall comparison of performance metrics across the three domains highlights some key trends. In terms of predictive accuracy, LSTM consistently outperformed Random Forest and SVM in time-based forecasting tasks, particularly in smart manufacturing. However, for discrete demand forecasting in inventory planning and non-traditional signal-based forecasting in sustainability trends, Random Forest and SVM demonstrated better performance. The results from the statistical tests, including p-values and standard deviations, further suggest that LSTM excels in applications where time-series forecasting is essential but may struggle in other types of forecasting tasks. which compares model stability based on standard deviation, shows that LSTM maintained the lowest variability across all domains. This is important because stability is a critical factor in industrial applications where consistent performance is essential. On the other hand, SVM, which performed well in sustainability forecasting, showed the highest variability, indicating that its performance might be more susceptible to fluctuations in data quality or external factors.

Implications for Industry Applications

The findings of this study have several important implications for industries seeking to adopt AI-based forecasting systems. For smart manufacturing, LSTM should be prioritized for tasks that require time-series forecasting, such as power consumption prediction and machine failure forecasting. In inventory planning, Random Forest appears to be the most effective model, particularly when dealing with discrete data such as inventory demand. For sustainability trend forecasting, SVM is the best choice, given its strong performance with non-traditional, signal-based data sources like social media and search engine queries. Overall, this study demonstrates that no single model is universally superior across all domains. Instead, the selection of the appropriate forecasting model should be driven by the specific characteristics of the data and the forecasting task at hand. Industries looking to implement AI-based forecasting systems must carefully assess their unique needs and the type of data available to determine the most suitable model.

CONCLUSION

This study highlights the significant potential of AI-based forecasting models in improving operational efficiency across smart manufacturing, inventory planning, and sustainability trends. The comparative analysis reveals that LSTM excels in time-series forecasting for smart manufacturing, Random Forest performs best in inventory planning, and SVM proves most effective for predicting sustainability trends. Future research should explore the integration of hybrid models, assess the scalability of AI forecasting systems in real-world settings, and refine techniques for managing unstructured data sources in sustainability forecasting.

Recommendations

Industry stakeholders should prioritize LSTM for time-based forecasting tasks in smart manufacturing.
Random Forest is recommended for inventory planning, especially for discrete demand forecasting.
SVM should be utilized for sustainability trend forecasting based on social signal data.

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