European Institute of Knowledge & Innovation

Journal of Economics, Innovative Management, and Entrepreneurship (JEIME) ISSN: 3029-0791

Research Article

Machine Learning-Driven Export Forecasting: A Comparative Analysis for MSME Growth

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https://doi.org/10.59652/jeime.v3i1.401

Abstract: Micro, small, and medium enterprises play a fundamental role in economic devel-opment by fostering employment, innovation, and international trade. However, these enterprises face substantial challenges in volatile global trade conditions, necessitating accurate forecasting methodologies for effective strategic planning. This study aims to evaluate and compare traditional time series models and advanced machine learning techniques in predicting export trends. The research employs Double Exponential Smoothing and Autoregressive Integrated Moving Average alongside Support Vector Regression, Random Forest, and Extreme Gradient Boosting to assess forecasting accuracy. Performance metrics including Root Mean Square Error, Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and R-Square are utilized for model evaluation. Results indicate that while traditional time series models provide foundational forecasting insights, they are outperformed by machine learning techniques. Among these, Random Forest demonstrates the highest predictive accuracy and reliability. However, Extreme Gradient Boosting exhibits near-perfect met-rics, necessitating further scrutiny to address potential overfitting. The study empha-sises the necessity of integrating traditional and machine learning methodologies to enhance forecasting precision. These insights are valuable for policymakers, re-searchers, and industry practitioners seeking to strengthen export strategies and sus-tain economic growth.

Keywords: economic development; MSME exports; Autoregressive Integrated Moving Average; Double Exponential Smoothing; Random Forest; Extreme Gradient Boosting

Received: December 29, 2024
Accepted: January 19, 2025
Published: February 25, 2025

1. Introduction

Micro, small, and medium enterprises (MSMEs) are acknowledged globally as pivotal to economic stability and growth, particularly in developing countries. These enterprises, characterized by their agility and adaptability, are central to fostering innovation, generating employment, and contributing significantly to national and global economies (Gkypali et al., 2021)The essence of MSMEs transcends local markets, influencing global trade dynamics through their export activities. Their ability to export is not just a measure of business success but also reflects the competitive strength of a nation in the global marketplace (Noor Salim et al., 2021).Furthermore, MSMEs significantly contribute to poverty reduction, as evidenced in Indonesia, where their role in labor absorption and economic inclusivity has reduced inequality and poverty rates, highlighting their broader socio-economic importance (Nursini, 2020).

Despite their resilience, particularly during crises like the COVID-19 pandemic, MSMEs face dynamic challenges in maintaining robust export performance. International trade complexities – ranging from fluctuating market demands to varying economic policies and trade agreements – pose substantial hurdles (Hiremath & Deb, 2022). Traditional forecasting models, such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing, have historically been foundational in assisting MSMEs to navigate such challenges by predicting future trends using historical data (Rajput et al., 2012). However, the increasing complexity of global trade necessitates more advanced methodologies. The advent of big data and the evolution of machine learning techniques, such as Support Vector

Regression (SVR), Extreme Gradient Boosting (XG Boost), and Random Forest, have introduced sophisticated approaches capable of handling non-linear and intricate data structures, providing a strategic advantage over traditional models (Motahar Hossain & Pathak, 2023).

This research aims to assess the effectiveness of different forecasting methodologies in predicting export trends for MSMEs to enhance strategic decision-making and competitiveness in global trade

Research objectives are the following:

- To evaluate the performance of traditional time series models in forecasting MSME export trends.
- To analyze the predictive accuracy of machine learning techniques for export forecasting.
- To compare the strengths and limitations of traditional and machine learning approaches in export trend prediction.
- To provide insights into the optimal forecasting model that can support policy formulation and strategic planning for MSMEs.

This study explores the significance of MSMEs in the global economy, emphasizing their role in exports and the challenges encountered in international trade. A detailed literature review contrasts traditional time series models and machine learning techniques in forecasting export trends, evaluating their applicability and effectiveness. The research methodology details the data sources and analytical tools used for forecasting, followed by a comparative analysis of the accuracy and limitations of each forecasting approach. The study concludes by summarizing key findings, discussing their implications for improving MSME export strategies, and identifying potential future research directions to enhance forecasting methodologies for sustainable enterprise growth.

2. Materials and Methods

2.1. Research Design

This study adopts a comparative analytical research design to evaluate the effec-tiveness of traditional time series forecasting models and advanced machine learning techniques in predicting MSME export trends. A quantitative approach is employed, utilizing historical export data to com-pare the predictive accuracy of five forecasting models. The research is structured to address key questions regarding the performance of both traditional and machine learning-based forecasting models and to identify the most effective approach for MSME export forecasting. The study incorporates two traditional time series models, namely Double Exponential Smoothing (DES) and ARIMA, alongside three machine learning techniques: SVR, Random Forest, and XG Boost. These models are assessed using multiple statistical error metrics to determine their fore-casting efficacy (Ahmed et al., 2010; Hyndman & Athanasopoulos, 2018).

2.2. Data Sources

The study is based on secondary data collected from official sources, including the Ministry of MSMEs, and the Reserve Bank of India. The dataset consists of historical MSME export values spanning from 1990-2019. Given that forecasting ac-curacy depends on data completeness and reliability, the dataset undergoes rigorous pre-processing steps to ensure its integrity and applicability to the selected models (Nursini, 2020).

2.3. Data Collection Procedures

The data collection process follows a structured methodology. First, MSME export statistics are extracted from MSME data meticulously extracted from the annual reports of Ministry of MSMEs in India. Next, the collected data is structured into a time-series format to facilitate trend analysis and model training. Pre-processing techniques are applied to ensure the quality of dataset, including handling missing values through interpolation, detecting and correcting outliers using statistical methods, and applying normalization to standardize variables across different scales. The dataset is then split into training (80%) and testing (20%) subsets, following best practices in time-series forecasting (De Gooijer & Hyndman, 2005).

2.4. Data Analysis and Forecasting Models

To assess the predictive accuracy of different forecasting models, the study im-plements five forecasting techniques, categorized into traditional time-series models and machine learning models:

2.4.1. Traditional Time-Series Models

- DES model captures trends and sea-sonality in MSME export data. It is widely used for short-term forecasting where patterns in data are relatively stable (Hyndman & Athanasopoulos, 2018).
- ARIMA is employed due to its ability to handle non-stationary data and capture linear trends in MSME exports (De Gooijer & Hyndman, 2005). This model is particularly useful in scenarios where past values significantly influence future trends.

2.4.2. Machine Learning Models

- SVR is selected for its capability to identify complex, non-linear relationships in trade variables, improving predictive performance compared to linear models (Tay & Cao, 2001).
- Random Forest enhances forecasting reliability by reducing variance and mitigating overfitting, making it well-suited for large datasets with multiple influencing factors (Breiman, 2001).
- XG Boost is incorporated due to its high efficiency and scalability. It optimizes gradient boosting by re-fining feature selection and regularization, which enhances prediction accuracy (Chen & Guestrin, 2016).

2.5. Performance Evaluation Metrics

To assess the performance of these models, the study employs a set of error metrics, commonly used in forecasting evaluations:

- Root Mean Square Error (RMSE) measures overall prediction error, where lower values indicate better model performance (Ahmed et al., 2010).
- Mean Square Error (MSE) evaluates a model's ability to minimize large forecasting errors, making it a key indicator of predictive stability (Hyndman & Athanasopoulos, 2018).
- Mean Absolute Error (MAE) measures the average magnitude of errors, providing insights into the overall prediction accuracy (Iaousse et al., 2023).
- Mean Absolute Percentage Error (MAPE) evaluates the percentage de-viation of forecasts from actual values, making it a useful metric for economic forecasting (Makridakis & Hibon, 2000).
- R-Square (R^2) indicates the proportion of variance explained by the model, with values closer to 1 representing better model fit (Dave et al., 2021).

The comparative analysis is further strengthened by diagnostic assessments, in-cluding the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which validate the assumptions of time-series models and assess the presence of autocorrelation in residuals (De Gooijer & Hyndman, 2005).

2.6. Comparative Analysis of Forecasting Models

A detailed comparative evaluation is conducted to identify the most effective forecasting model for MSME exports. Machine learning models, particularly Random Forest and XG Boost, demonstrate superior forecasting accuracy, achieving lower error values across all metrics (Chen & Guestrin, 2016). However, the study also highlights concerns about potential overfitting in the XG Boost model due to its near-perfect forecasting performance, suggesting the need for further validation (Bengio, 2012; Hastie et al., 2017).

This research adopts a systematic and data-driven approach to compare the effectiveness of traditional time-series models and machine-learning techniques in MSME export forecasting. By integrating historical economic data with advanced predictive analytics, the study provides a robust framework for model evaluation. The findings contribute to enhancing the predictive capabilities of export forecasting, of-fering practical insights for policymakers, researchers, and MSME stakeholders to support strategic decision-making in a dynamic global trade environment. The com-parative analysis emphasises the potential of hybrid forecasting models, combining the statistical rigor of traditional approaches with the flexibility of machine learning techniques, to enhance forecasting precision and support sustainable MSME growth.

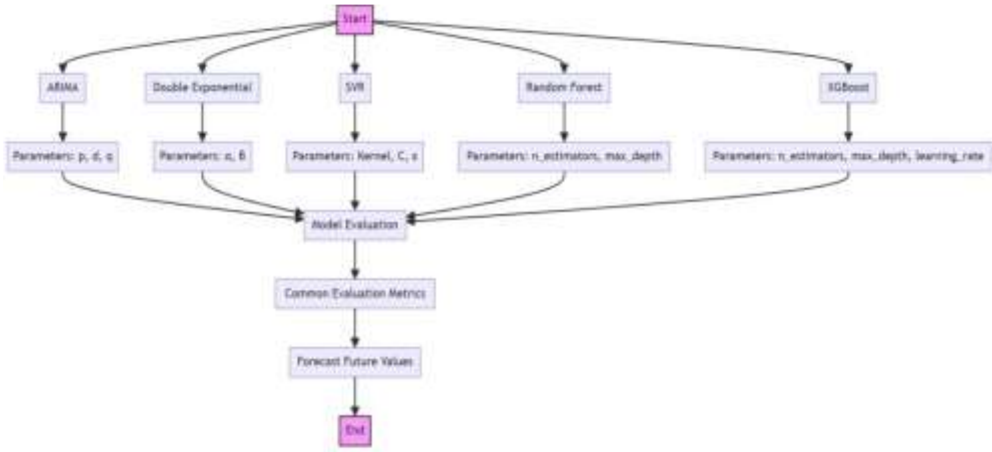


Figure 1. Process of the data analysis.
Source: Constructed by the authors using Python software.

Figure 1 illustrates the workflow for comparing forecasting models, starting with five methods (ARIMA, Double Exponential, SVR, Random Forest, and XG Boost) configured with specific parameters. The models undergo evaluation using common metrics to forecast future values, concluding the analysis.

In fine-tuning our models to forecast MSME exports, we meticulously selected parameters for each to ensure robust predictive performance. For ARIMA (1,1,1), a minimal AIC of 615.927 was achieved, suggesting an optimal balance of model simplicity and fit. The DES model was fine-tuned with a high smoothing level of 0.995 and a smoothing trend of 0.379, signifying heavy weighting on recent trends. The Random Forest model, with parameters set to a max depth of 30 and 50 estimators, was well-suited for handling the complexity of dataset. XG Boosting, with a configuration including 200 estimators, a learning rate of 0.1, and a max depth of 7, indicated a robust approach to modelling intricate patterns, thus providing a comprehensive and data-driven basis for our export forecasts.

3. Results

The performance of each forecasting model in predicting MSME export trends is detailed in Table 1, which reports various error metrics including RMSE, MSE, MAE, MAPE, and R-Square values. The analysis of these metrics provides insight into the accuracy and reliability of each model, contributing to an informed assessment of their suitability for MSME export forecasting.

Table 1: Error metrics for various models.

	RMSE	**MSE**	**MAE**	**MAPE**	**R Square**
Double Exponential	6904.00	47665177.54	4269.90	0.09	0.9854
ARIMA	6224.32	38742129.36	4429.65	14.10	0.9881
SVR	5656.00	31990291.04	3521.45	6.99	0.9894
Random Forest	2847.96	8110859.96	2048.32	3.17	0.9973
XG Boosting	0.02	0.00	0.02	0.00	0.9983

Source: Authors' computation.

The DES model, with an RMSE of 6904.00 and an R-Square of 0.9854, demonstrates a moderate level of prediction accuracy. While it captures general trends, its higher RMSE suggests it may be less effective at handling complex patterns in export data. Conversely, the ARIMA model shows improved accuracy, evidenced by a reduced RMSE of 6224.32 and a higher R-Square of 0.9881. However, the model's MAPE of 14.10 indicates higher percentage errors across different data points, reflecting certain limitations in precision.

Machine learning models show notable improvements over traditional time series methods. The SVR model reduces both RMSE and MAE values significantly compared to ARIMA, suggesting a more consistent clustering of predicted values around actual values. However, Random Forest outperforms SVR by a substantial margin, achieving an RMSE of 2847.96 and an R-Square of 0.9973, underscoring its robust predictive power.

The XG Boosting model demonstrates almost perfect forecasting capability, with minimal errors across all metrics and an R-Square close to 1. However, this remarkable precision, illustrated in Figure 5, raises the possibility of overfitting, suggesting that further validation is required to confirm its practical application in real-world scenarios.

These results are visually compared in Figures 2 through 6:

- Figure 2 illustrates the RMSE comparison across models, highlighting Ran-dom Forest and XG Boosting as superior in minimizing root mean squared errors.
- Figure 3 showcases the MSE for each model, with a noticeable reduction in error for machine learning methods.
- Figure 4 presents the MAE values, underscoring the accuracy improvements of SVR and Random Forest.
- Figure 5 provides a comparison of MAPE, with XG Boosting achieving a near-zero value, indicative of high precision.
- Figure 6 displays R-Square values, confirming the strong explanatory power of machine learning models, particularly Random Forest and XG Boosting.

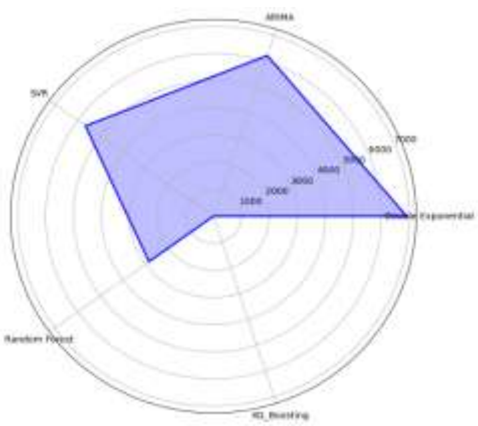


Figure 2. RMSE comparison across predictive models.

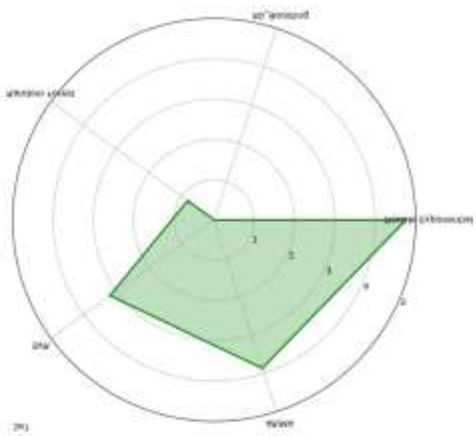


Figure 3. MSE comparison across predictive models.

Figure 4. MAE comparison across predictive models.

Figure 5. MAPE comparison across predictive models.

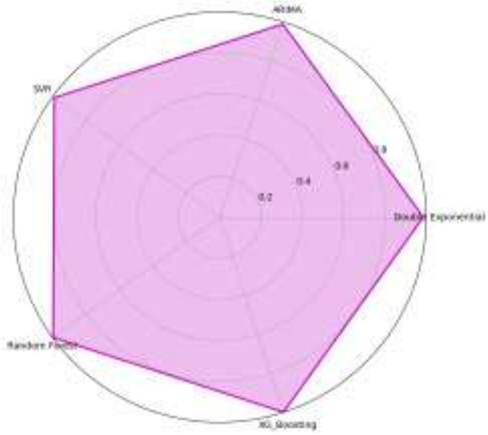


Figure 6. R-Square comparison across predictive models.

Table 1 and the associated figures emphasize the clear advantages of machine learning techniques over traditional forecasting models for MSME export prediction. While traditional models like ARIMA and DES are foundational, the machine learning models' ability to handle non-linear relationships provides en-hanced forecasting reliability, which is particularly evident in the low error metrics and high R-Square values of Random Forest and XG Boosting.

The comparison of forecasted values across different models, as illustrated in Table 2 and Figure 6, suggests a diverse range of projections for MSME exports. The XG Boosting model tends to predict higher export values for the upcoming years, consistently showing an optimistic growth pattern. In contrast, models like the Random Forest exhibit more conservative forecasts, particularly noticeable in the year 2021, where it diverges significantly from the other models. The line graph presented in Figure 6 compares the forecasted trends against the actual export data. The actual export values display a steady growth, with the forecasting models generally following this trend. However, some models, particularly XG Boosting and Double Exponential, project a sharper increase, hinting at an optimistic outlook for MSME export growth. The ARIMA and SVR models also show alignment with the growth trend but with less pronounced increases. The projections of Random Forest initially follow a similar trajectory but later predict a stabilization of export values.

Table 2. Forecasting of MSME exports.

Date	Double Exponential	ARIMA	SVR	Random Forest	XG Boosting
2020	158679	152877	155714	151146	158823
2021	161306	157490	155715	144166	150484
2022	163906	162103	155715	149588	145334
2023	166481	166717	155716	151595	158823
2024	169030	171330	155716	151595	158823
2025	171553	175944	155717	151595	158823
2026	174051	180557	155718	151595	158823
2027	176524	185171	155718	151595	158823
2028	178972	189784	155719	151595	158823
2029	181396	194398	155719	151595	158823

Source: Authors computation.

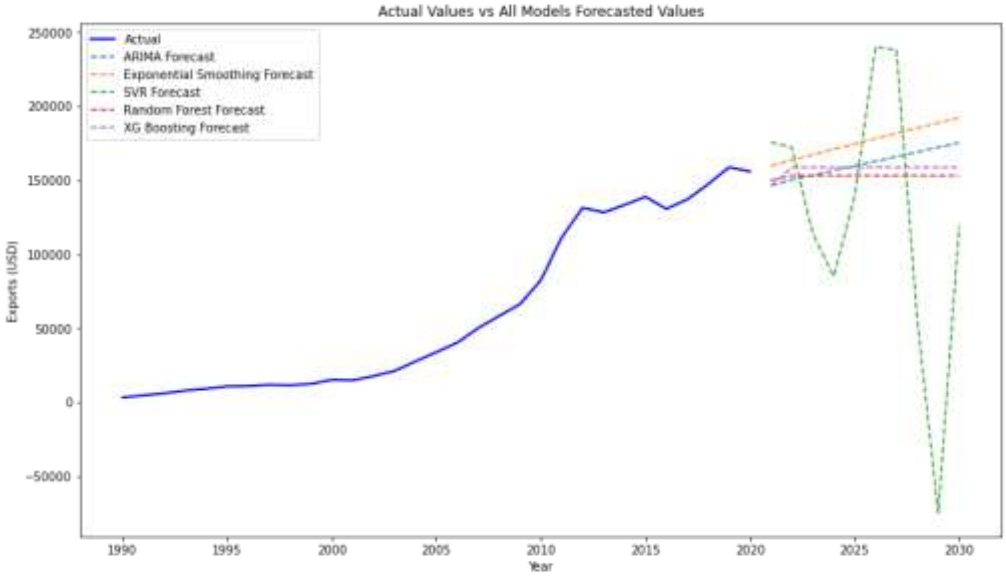


Figure 7. Forecasted MSME exports comparison of various models.
Source: Constructed by the authors using Python software.

Figure 7 compares the forecasted MSME export values across five predictive models (ARIMA, Exponential Smoothing, SVR, Random Forest, and XG Boost) against ac-tual historical data. While all models align with the historical trend, their future pro-jections vary significantly, with XG Boost and Random Forest demonstrating higher accuracy and alignment, while SVR shows more erratic behaviour, suggesting poten-tial limitations in certain scenarios.

The examination of ACF and PACF plots for residuals, as detailed in Appendix A, reflects the diagnostic checking phase in the time series analysis. The ACF plots display a decline in correlation coefficients as the lag increases, which does not indicate any significant autocorrelation in the residuals. This pattern is suggestive of an effective model that has captured the data's autocorrelations. Meanwhile, the PACF plots exhibit a significant partial autocorrelation at the first lag followed by insignificant values, which is consistent with the ARIMA (1,1,1) model's parameterization. The absence of significant spikes in higher lags supports the conclusion that the model residuals are behaving as white noise, implying that the model is appropriately specified and the forecasts are reliable. This analytical assessment confirms the models' efficacy in forecasting MSME exports, validating the choice of model parameters.

4. Discussion

This study provides a nuanced comparison of forecasting techniques, including traditional time series models (DES and ARIMA) and advanced machine learning techniques (SVR, Random Forest, and XG Boost), to evaluate their performance in predicting MSME export trends. The evaluation was based on performance metrics such as RMSE, MSE, MAE, MAPE, and R^2, which offered insights into each model's accuracy, precision, and ability to explain variance in the export data. The findings align with prior research while contributing new insights into optimal forecasting methodologies for MSME exports.

The results for DES and ARIMA demonstrate their foundational role in time series forecasting. DES effectively captures trends and seasonality but exhibits moderate accuracy in complex datasets, as reflected in its higher RMSE and MAPE values. This finding supports prior studies by Hyndman and Athanasopoulos (2018), which emphasize its utility in structured and linear data but acknowledge its limitations in handling complex, non-linear relationships. Similarly, ARIMA performs better than DES, with improved RMSE and MAPE scores, consistent with the observations of De Gooijer and Hyndman (2005). However, the reliance of ARIMA on linear assumptions and its limited ability to adapt to highly volatile export trends restrict its suitability for dynamic trade environments.

In contrast, machine learning models outperform traditional approaches, showcasing their superior ability to handle complex, non-linear relationships in export data. SVR demonstrates significant improvements over ARIMA, achieving lower RMSE and MAPE values. This aligns with prior research by Tay and Cao (2001), Chen & Wang (2007), which highlight the capability of SVR to capture intricate patterns in economic datasets. Despite these strengths, SVR is surpassed in this study by ensemble learning techniques such as Random Forest and XG Boost, consistent with the findings of Karthika, Margaret, and Balaraman (2017) who noted that the performance of SVR can plateau in datasets with high variability or complex structures.

Among the machine learning models, Random Forest emerges as the most reliable, achieving the lowest RMSE, MSE, MAE, and MAPE values. Its high R^2 value indicates exceptional explanatory power, making it particularly suitable for forecasting MSME exports. These findings are in line with Breiman (2001), Motahar Hossain and Pathak (2023), who emphasize the ability of Random Forest to handle large, multi-dimensional datasets and its robustness against overfitting. Its ensemble learning mechanism, which aggregates predictions from multiple decision trees, ensures stable and accurate forecasts even in volatile trade scenarios. This makes Random Forest an excellent choice for policymakers and practitioners aiming to strengthen MSME export strategies.

XG Boost, while exhibiting near-perfect metrics, raises concerns about potential overfitting due to its minimal error values and an R^2 value close to 1. This observation aligns with the insights of Bengio (2012), Hastie, Tibshirani, and Friedman (2017), who caution against the risks of overfitting in high-capacity machine learning models, particularly when trained on limited or highly specific datasets. Although the performance of XG Boost demonstrates its potential as a forecasting tool, its practical applicability requires further validation through techniques such as cross-validation and application in real-world scenarios. These findings are consistent with Chen and Guestrin (2016), who emphasize the importance of hyperparameter optimization and model validation to mitigate overfitting risks in gradient boosting frameworks.

The findings of this study also align with existing research advocating for hybrid forecasting approaches. Ji, Zou, He, and Zhu (2019), Dave, Leonardo, Jeanice, and Hanafiah (2021) have demonstrated the effectiveness of combining econometric models with machine learning techniques to leverage the strengths of both. For example, ARIMA-CNN-LSTM frameworks have been shown to improve accuracy by capturing both linear trends and non-linear patterns. Similarly, studies by Ray, Lama, Mishra, Biswas, Sankar Das, and Gurung (2023) highlight the potential of hybrid models like ARIMA-LSTM combined with Random Forest for addressing complex forecasting challenges in economic and trade datasets. Incorporating such hybrid approaches into MSME export forecasting could further enhance predictive precision and adaptability.

Additionally, the evaluation metrics used in this study provide comprehensive insights into model performance. Metrics like RMSE and MSE capture absolute prediction errors, while MAPE highlights percentage-based deviations, offering a multi-dimensional view of model accuracy. This multi-metric approach is consistent with recommendations by Ahmed, Atiya, Gayar, and El-Shishiny (2010), Iaousse, Jouilil, Bouincha, and Mentagui (2023), who stress the importance of diverse evaluation criteria to capture different aspects of forecasting performance.

In comparison with prior studies, this research reaffirms that traditional time series models remain relevant for scenarios with stable and linear data patterns. However, the complexity of global trade dynamics necessitates the adoption of advanced machine learning techniques, which excel in handling non-linear relationships and high-dimensional datasets. Random Forest, in particular, strikes an optimal balance between accuracy and robustness, making it the most reliable model for MSME export forecasting in this study.

Looking ahead, future research should explore hybrid approaches that combine the strengths of traditional time series models and machine learning techniques. For example, integrating ARIMA with Random Forest or XG Boost could yield models that capture both linear trends and non-linear patterns effectively. Furthermore, the potential of XG Boost should be further validated through real-world applications and cross-industry comparisons to address concerns about overfitting.

In conclusion, this study demonstrates that machine learning models outperform traditional time series models in forecasting MSME exports, with Random Forest emerging as the most reliable. However, the potential of hybrid approaches and the need for further validation of XG Boost emphasise the importance of continued research. These insights provide practical implications for policymakers, researchers, and industry stakeholders aiming to strengthen MSME export strategies in an increasingly dynamic global trade environment.

5. Conclusions

This research emphasises the significant role of MSMEs in fostering economic growth through exports, while also highlighting the challenges they encounter in an unpredictable global trade environment. By comparing traditional time series models with advanced machine learning techniques, this study provides valuable insights into optimal forecasting strategies for MSME exports. The findings reveal that traditional models like DES and ARIMA, while foundational and effective in capturing linear trends and seasonality, exhibit limitations in addressing the non-linear and complex nature of contemporary trade data. This aligns with existing literature, which acknowledges their value but also emphasises their restricted applicability in dynamic and multi-variable contexts.

The results demonstrate that machine learning models, particularly Random Forest, significantly outperform traditional models in terms of accuracy, precision, and explanatory power. Random Forest emerges as the most reliable forecasting method, with exceptionally low error metrics and a high R^2 value, corroborating prior research on its robustness and adaptability. Its ability to handle complex, high-dimensional datasets makes it particularly valuable for MSME export forecasting, providing actionable insights for policymakers and practitioners. The study also highlights the strengths of SVR in handling non-linear relationships, although its performance is surpassed by ensemble techniques like Random Forest and XG Boost.

While XG Boost exhibits near-perfect forecasting metrics, the findings caution against the risks of overfitting, which may compromise its practical utility. This aligns with existing concerns in machine learning literature, emphasizing the importance of thorough validation and cross-industry testing to ensure generalizability. Future research should prioritize hybrid approaches that combine the linear modelling strengths of traditional methods with the non-linear capabilities of machine learning, such as ARIMA-Random Forest or ARIMA-XG Boost models. These approaches can address the nuanced challenges of MSME export forecasting while enhancing precision and applicability across diverse contexts.

In conclusion, this study highlights the transformative potential of machine learning in export forecasting while advocating for continued exploration of hybrid and validated approaches to support MSME growth in an increasingly volatile global economy.

Author Contributions: Software – Dr. Vengalarao Pachava; validation – Dr. Basavaraj M.S.; writing review and editing – Dr. Shashi Kumar R.

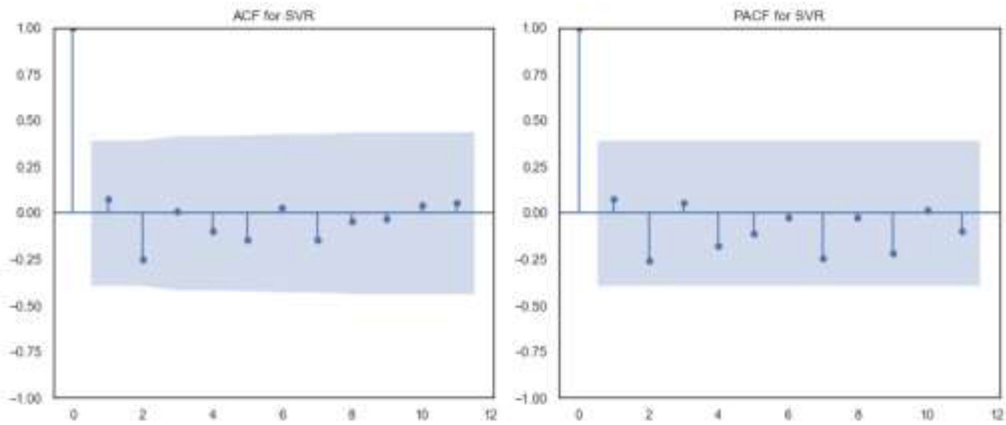
Funding: This research received no external funding.

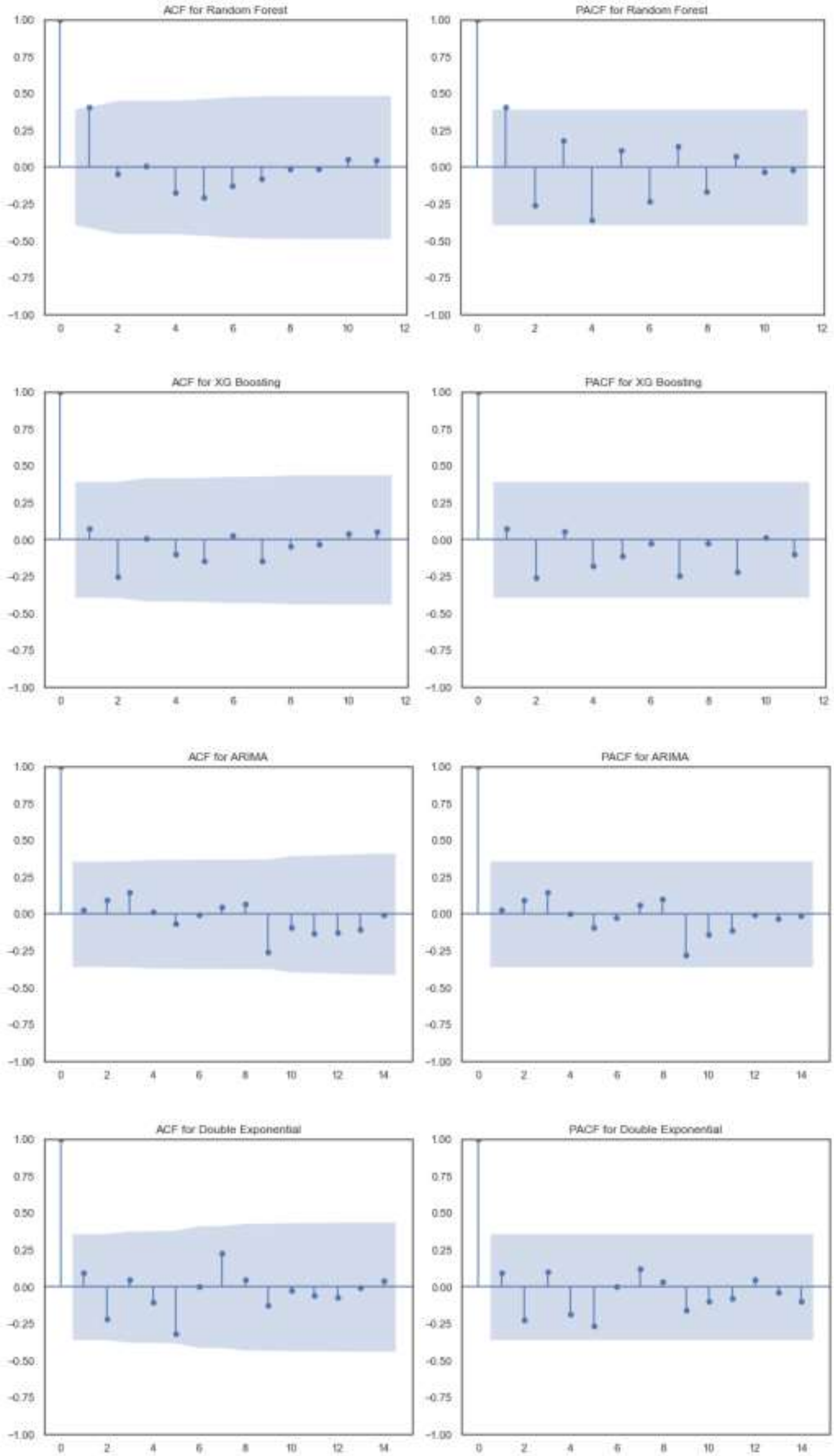
Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A.

Residual ACF plots of each model




ACF for Random Forest
PACF for Random Forest
ACF for XG Boosting
PACF for XG Boosting
ACF for ARIMA
PACF for ARIMA
ACF for Double Exponential
PACF for Double Exponential

References

Ahmed, N. K., Atiya, A. F., Gayar, N. El, & El-Shishiny, H. (2010). An Empirical Comparison of Machine Learning Models for Time Series Forecasting. *Econometric Reviews, 29*(5–6), 594–621. https://doi.org/10.1080/07474938.2010.481556

Bengio, Y. (2012). Practical Recommendations for Gradient-Based Training of Deep Architectures. In G. Montavon, G. B. Orr, K. R. Müller (eds) *Neural Networks: Tricks of the Trade. Lecture Notes in Computer Science*, vol 7700. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-35289-8_26

Breiman, L. (2001). Random Forests. *Machine Learning, 45*, 5-32. https://doi.org/10.1023/A:1010933404324

Chen, K.-Y., & Wang, C.-H. (2007). Support vector regression with genetic algorithms in forecasting tourism demand. *Tourism Management, 28*(1), 215-226. https://doi.org/10.1016/j.tourman.2005.12.018

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). https://doi.org/10.1145/2939672.2939785

Dave, E., Leonardo, A., Jeanice, M., & Hanafiah, N. (2021). Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM. *Procedia Computer Science, 179*, 480–487. https://doi.org/10.1016/j.procs.2021.01.031

De Gooijer, J. G., & Hyndman, R. J. (2005). 25 Years of Iif Time Series Forecasting: A Selective Review. Tinbergen Institute Discussion Papers No. TI 05-068/4. http://dx.doi.org/10.2139/ssrn.748904

Gkypali, A., Love, J. H., & Roper, S. (2021). Export status and SME productivity: Learning-to-export versus learn-ing-by-exporting. *Journal of Business Research, 128*, 486-498. https://doi.org/10.1016/j.jbusres.2021.02.026

Hastie, T., Tibshirani, R., & Friedman, J. (2017). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd Edition. Springer.

Hiremath, G. S., & Deb, S. (2022). Export Performance of MSMEs in India: Is Credit Constraint an Invisible Gorilla? *The Indian Economic Journal, 70*(1), 138-157. https://doi.org/10.1177/00194662211062417

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice.* OTexts

Iaousse, M., Jouilil, Y., Bouincha, M., & Mentagui, D. (2023). A Comparative Simulation Study of Classical and Machine Learning Techniques for Forecasting Time Series Data. *International Journal of Online and Biomedical Engineering, 19*(8), 56–65. https://doi.org/10.3991/ijoe.v19i08.39853

Ji, L., Zou, Y., He, K., & Zhu, B. (2019). Carbon futures price forecasting based with ARIMA-CNN-LSTM model. *Procedia Computer Science, 162*, 33–38. https://doi.org/10.1016/j.procs.2019.11.254

Karthika, S., Margaret, V., & Balaraman, K. (2017). Hybrid short term load forecasting using ARIMA-SVM. In *2017 Innovations in Power and Advanced Computing Technologies (i-PACT)* (pp. 1-7). https://doi.org/10.1109/IPACT.2017.8245060

Makridakis, S., & Hibon, M. (2000). The M3-Competition: results, conclusions and implications. *International Journal of Forecasting, 16*(4), 451-476. https://doi.org/10.1016/S0169-2070(00)00057-1

Motahar Hossain, M., & Pathak, N. (2023). Modeling the Impact of Access to Finance on MSMEs' Contribution Towards Exports of the Economy. In J. Choudrie, P. N. Mahalle, T. Perumal, A. Joshi, A. (eds) *ICT with Intelligent Applications. ICTIS 2023. Lecture Notes in Networks and Systems*, vol 719. Springer, Singapore. https://doi.org/10.1007/978-981-99-3758-5_14

Noor Salim, M., Susilastuti, D., & Astuty, P. (2021). Economics and Business Quarterly Reviews Determinants of Indonesian MSME Exports and Their Performance during the Covid-19 Pandemic. *Economics and Business Quarterly Reviews, 4*, 162–173. https://doi.org/10.31014/aior.1992.04.03.379

Nursini, N. (2020). Micro, small, and medium enterprises (MSMEs) and poverty reduction: empirical evidence from Indonesia. *Development Studies Research, 7*(1), 153–166. https://doi.org/10.1080/21665095.2020.1823238

Rajput, N., Rajput, A., Batra, G., & Oberoi, S. (2012). Relationship of exports, Forex and MSMEs in India: an econometric study. *Problems and Perspectives in Management, 10*(3). https://www.businessperspectives.org/index.php/journals/problems-and-perspectives-in-management/issue-37/relationship-of-exports-forex-and-msmes-in-india-an-econometric-study

Ray, S., Lama, A., Mishra, P., Biswas, T., Sankar Das, S., & Gurung, B. (2023). An ARIMA-LSTM model for predicting volatile agricultural price series with random forest technique. *Applied Soft Computing, 149*(A), 110939. https://doi.org/10.1016/j.asoc.2023.110939.

Tay, F. E. H., & Cao, L. (2001). Application of support vector machines in nancial time series forecasting. *Omega, 29*(4), 309-314. https://doi.org/10.1016/S0305-0483(01)00026-3