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RESEARCH ARTICLE

A study on trade performance of Indian black tea: An artificial neural network and Markov chain approach

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Abstract

This study explores the use of Artificial Neural Networks (ANN) and Markov Chain models to forecast India's black tea exports to major international markets. While the Markov Chain approach provided a simplified, state-based view of export behaviour, the ANN models were designed to capture continuous patterns and subtle market dynamics. Forecasts were generated for the next five years across ten key importing countries. Model performance was assessed using standard evaluation metrics- Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and R-squared (R^2). The results clearly favoured the ANN model, which consistently delivered more accurate and reliable forecasts. Notably, the United Arab Emirates (UAE) emerged as the top growth market, with predicted export values from India reaching ₹1.23 lakhs by the fifth year. Russia and the USA also showed strong forecasted demand, with expected values of ₹64767 lakhs and ₹45238 lakhs, respectively. These insights offer practical value for exporters, traders and policymakers by highlighting priority markets and supporting more informed decision-making. Overall, this research reinforces the importance of intelligent forecasting systems in managing the complexity of international tea trade.

Keywords: artificial neural network; black tea; export forecasting; Markov chain; predictive modelling

Introduction

Black tea is still one of the most consumed beverages in the world and it is very important to the agricultural economies of major producing countries like India, China, Kenya, Sri Lanka and Indonesia. Black tea makes up more than 75 % of all tea consumed around the world. As of 2022, the market was worth over $9 billion (1, 2) and $20.5 billion in 2024, according to Statista. Black tea is still in high demand in places like the Middle East, Europe and North America. The United Arab Emirates, Russia and the UK are still some of the biggest importers (3). There is a lot of demand for black tea around the world, but international trade in it is changing a lot. There is more competition around the world and quality standards, climate change, consumer health preferences and trade obstacles between countries are all having a bigger effect on exports. Did a competitiveness study of Indonesian black tea exports and stressed the importance of quality differences and price sensitivity (4). In the same way, looked studied how black tea markets around the world are connected and found that prices don't always match up because of logistical problems and differences in policy (5). In the past, both government policy and market forces have impacted the tea business in India. India's tea trade before and after liberalization showed that the sector is becoming more dependent on non-traditional markets (6). This shows that the value-added part of India's agro-processed tea exports still has untapped potential (7). There are trends in production, pricing pressures and the need to offer a wider range of tea products to make exports more stable (8, 9). Further insights into global consumption patterns have been presented with the investigation of global production shifts and the sustained consumption increase in Asian markets (10). The competitiveness of Indonesian black tea in Islamic trade markets and advised enhancing strategic branding and certification systems (11). These studies combined demonstrate that while black tea continues to dominate global beverage consumption, export competitiveness today depends not just on quantity but also on price strategy, branding, regulatory compliance and the capacity to foresee market trends. Forecasting future export performance, therefore, is not only an academic exercise-it is a key tool for decision-makers in trade policy and international agribusiness strategy. This study addresses that gap by comparing the predictive effectiveness of ANN and Markov models in modelling India's black tea exports across multiple worldwide markets. Black tea exporters are experiencing more problems as individuals throughout the world tend to favor herbal and healthy teas. This change in demand has led established producers to reassess how they manage their business. At the same time, more stringent regulations, such as tight phytosanitary standards, tariffs and non-tariff barriers, are making it tougher to enter or remain in major global markets. Climate change has made things even more complicated by causing yields to vary and making it challenging for exporters to forecast their supply. These difficulties generally produce either too much inventory or missed possibilities to export. Even with these challenges, the tea business still doesn't use clever, data-driven forecasting methods very often. Most initiatives are still reactive instead than proactive, which makes it tougher for exporters to adjust fast and successfully. This study has three key goals to assist in tackling these difficulties. First, it wants to find out what the challenges are with black tea exports and how trading patterns throughout the world are evolving. Second, it is about forecasting models utilizing two separate methods: Markov Chains and Artificial Neural Networks (ANN). Third, it looks at these two models to see which one produces better projections for exports. The study tests the notion that ANN models will be better at making accurate predictions than Markov Chains. It also looks into the concept that there may not be a huge difference between the two. Forecasting tools have come a long way in the previous several years, but there are still some critical gaps in the research that is already out there. For one thing, there haven't been many studies that have looked at ANN and Markov Chain models side by side, especially when it comes to agricultural exports like black tea. Most studies concentrate on looking at one sort of model or the other and they typically use very different historical data, which makes it difficult to make sense of the results. Another concern is that most forecasting research focuses on large commodities like oil and metals. Exports that are less well-known but still crucial to the economy, such black tea, have not been researched as much. This work fills in such gaps by employing standardized measures like MAPE, RMSE and R^2 to evaluate ANN and Markov Chain models on the same dataset. The purpose is to provide exporters and policymakers with practical guidance on how to use the best forecasting methods to deal with the unknowns of global agriculture commerce.

Materials and Methods

The study looked at ten main countries that are participating in the worldwide black tea trade: China, Egypt, Iran, Pakistan, Russia, Sri Lanka, Turkey, the United Arab Emirates (UAE), the United Kingdom (UK) and the United States (USA) (Ministry of Commerce and Industry, Government of India, 2025). We chose these nations because they consistently import or re-export tea and have accurate historical export statistics. This helps us undertake a detailed examination across a few markets. Each country has a unique impact on the demand for tea around the world. China is a huge producer and a growing re-exporter, which has a big effect on prices around the world. Egypt is still a consistent North African importer with demand that is easy to predict. Iran still has strong traditional consumption patterns, whereas Pakistan is a huge market that is particularly sensitive to prices and connections with India. Russia is a major, steady market in Eurasia. Sri Lanka is a regional competitor and re-exporter that can aid with price and market positioning. Turkey has a trade profile that demonstrates it can be self-sufficient and adaptive. It has a lot of robust domestic output and only imports what it needs. The UAE is a significant re-export center that connects South Asia with the Middle East and North Africa. The UK is a mature market that puts a lot of importance on quality and certifications. The USA is also getting more interested in premium and specialty tea. Collectively, these nations were conceptually categorized in the study based on their functional role in the trade network: key importers, re-export centers, producers and hybrid markets highlighting their strategic significance for India's black tea export diversification and placement. To support the study, historical export data for the years 2007 to 2024 has been collected from government trade databases and export records published by reliable sources (12). The dataset included annual export quantities and values, normalized for consistency across all ten nations. Prior to model creation, the data underwent necessary preprocessing steps such as cleaning, normalization and formatting to ensure accuracy and comparability. This supplied dataset serves as the foundation for creating and assessing forecasting models targeted at spotting trends and enhancing export strategy planning.

Artificial Neural Network (ANN)

To complement the Markov chain analysis, we constructed Artificial Neural Network (ANN) models to forecast the annual export quantities of Indian tea for each major importing country. The ANN framework employed a feedforward multilayer perceptron (MLP) architecture, in which the input layer received export values from the previous three years (using a look-back window of size three). The network comprised two hidden layers with 64 and 32 neurons, respectively, both utilizing the Rectified Linear Unit (ReLU) activation function, followed by an output layer with a single neuron to predict the subsequent year's export quantity. All export values were normalized between 0 and 1 using Min-Max Scaling prior to model training. The models were trained separately for each country using the Adam optimizer and mean squared error (MSE) as the loss function, with 200 training epochs to ensure convergence. To rigorously assess model generalizability and mitigate overfitting, we employed a time series cross-validation protocol (also known as walk-forward validation), wherein the model was iteratively trained on an expanding window of data and validated on the immediately following year. Performance metrics were averaged across all folds, providing a robust estimate of out-of-sample accuracy. All models were implemented in Python using TensorFlow/Keras and the entire preprocessing, modelling and evaluation workflow was standardized across all country-specific models for consistency and reproducibility (13, 14) (Fig. 1, 2).

Markov chain model

We simulate the yearly export proportions of India's tea as a limited collection of importing countries. Each country is represented as a state and the transition probability P_{ij} represents the probability that the percentage of exports now in country i will be found in country j in the next period. The model assumes that future shifts depend only on the current distribution of exports and that transition probabilities are stable throughout. We estimated P_{ij} from the yearly export

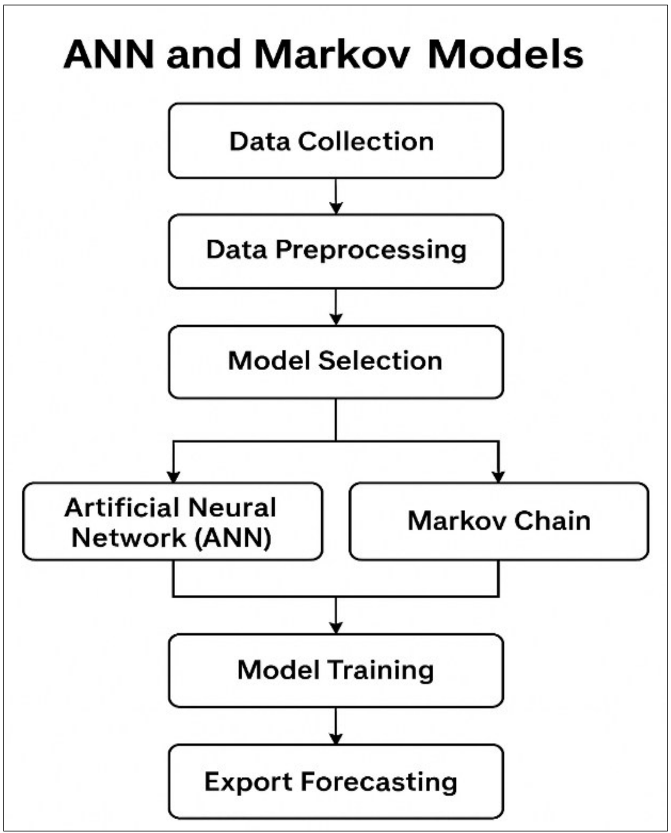

Fig. 1. Shows that the workflow of ANN and Markov chain models for this study.

quantities (2007-2024) by studying year-to-year variation in export shares for the key importing countries. In practice, the transition matrix was fitted so that the predicted exports for period t - 1 (given by the previous period t shares multiplied by P) best match the observed data. The diagonal entry P_{ij} therefore measures the loyalty of country. Off-diagonal entries P_{ij} (for $i \neq j$) capture the probability of the export share transferring from country i to country j. This technique follows common practice in trade stability research using Markov chains. The average exports to a specific regional country are considered to be a random variable which depends only on the historical shipments to that regional country, which may be expressed algebraically as follows (15, 16)

$$E_{jt} = \sum_{i=1}^{r} (E_{it-1}) P_{ij} + e_{jt} \quad (1)$$

Where,

E_{jt}= Exports from India to jth country during the year 't' to jth country

E_{it-1}= Exports to ith country during the period t - 1

P_{ij} = Probability that the exports will shift from ith country to jth country

e_{jt}= The error term which is statistically independent of E_{it-1}

t = Number of years considered for the analysis

r = Number of importing countries

The transitional probabilities P_{ij} which can be arranged in a (c×r) matrix have the following properties.

$$0 \leq P_{ij} \leq 1 \quad (2)$$

$$\sum_{i=1}^{r} P_{ij} = 1 \text{ for all } i \quad (3)$$

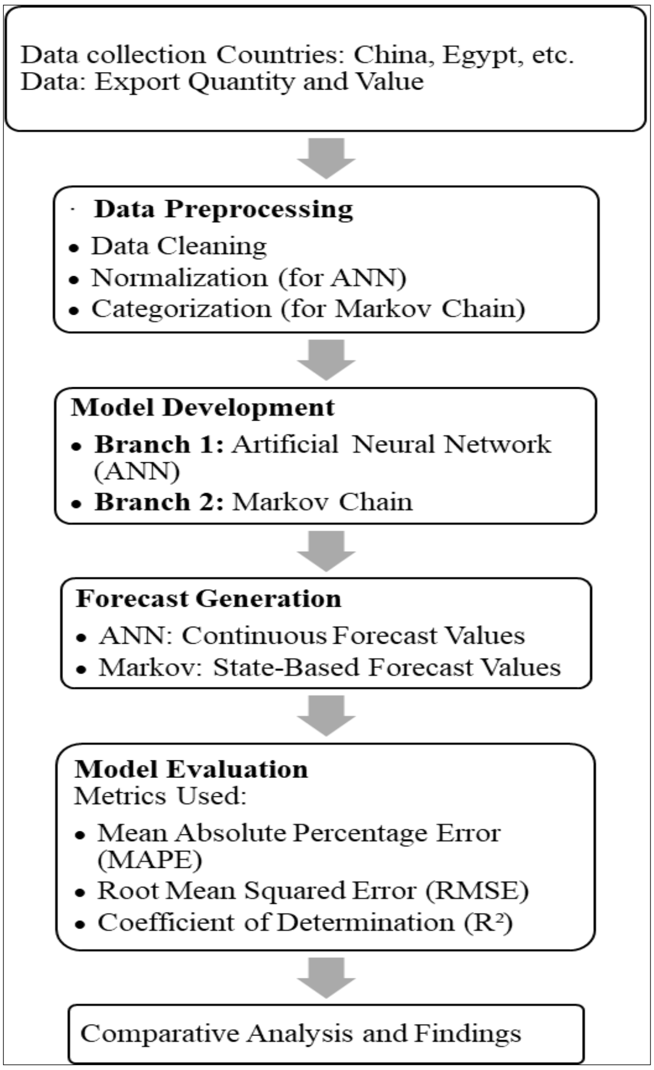

Fig. 2. Schematic Diagram.

To estimate the transition probabilities, we applied a Linear Programming (LP) method that minimizes the Mean Absolute Deviation (MAD) between predicted and actual export shares. The LP formula may be expressed as follows:

$$\text{Min } OP^* + Ie \quad (4)$$

Subject to:

$$XP^* + V = Y \quad (5)$$

$$GP^* = 1 \quad (6)$$

$$P^* >= 0. \quad (7)$$

Where,

P^* is a vector of the probability P_{ij}

O is a vector of zeros

I is an appropriately dimensioned vector of area

e is the vector of absolute errors

Y is the vector of export to each country

X is a block diagonal matrix of lagged values of Y

V is a vector of errors

G is a grouping matrix to add the row-elements of P arranged in P^*, to unity.

The Markov Chain models categorized export quantities into three discrete states: Low, Medium and High, determined by the 33rd and 66th percentiles of historical data. Transition probability matrices were then developed for each country, reflecting the likelihood of moving from one export state to another in successive years. Future states were simulated using these matrices and representative export values were assigned based on the historical averages of each state (17).

Evaluation metrics

To evaluate how well the ANN and Markov chain models predicted export values, we used three main metrics: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and the Coefficient of Determination (R^2). MAPE tells us, on average, how far off our predictions were in percentage terms, making it easy to compare accuracy across different countries or models. RMSE looks at how spread out the prediction errors are the lower this number, the better our model is doing. R^2, on the other hand, shows how much of the variation in actual export data our model is able to explain, with values closer to 1 meaning the model is capturing most of the real-world patterns. By using this mix of metrics, we ensured a fair and well rounded assessment of forecasting performance for both models (18).

Results

Model implementation: identification of key export challenges and trends in the black tea trade

While the core aim of this study is to develop reliable forecasting models, it is equally important to interpret the model outputs within the broader context of international trade challenges that currently affect black tea exports. The forecast results generated using ANN and Markov Chain approaches reflect not only quantitative trends but also signal deeper structural issues facing Indian tea exports. The most notable insight is the inconsistent or negative export growth predictions for specific countries. For example, ANN-predicted export values for Pakistan demonstrate a sharp and sustained decline over the five-year period, ultimately reaching negative estimates. The occurrence of negative forecast values in the ANN outputs, particularly for Pakistan, warrants clarification. These values should not be interpreted as literal "negative" export volumes, as physical trade cannot be less than zero. Instead, they are the result of the ANN model extrapolating historical downward trends beyond zero when fitting a continuous prediction function. In trade forecasting practice, such negative values are generally understood as strong signals of sustained market contraction, potentially indicating near-zero or negligible trade volumes in the forecast period.

In the case of Pakistan, the ANN's negative outputs are not merely computational anomalies. They reflect persistent downward momentum in India-Pakistan tea trade, influenced by political tensions, recurrent tariff hikes and recurring disruptions in bilateral trade agreements. This suggests that, unless significant geopolitical and policy changes occur, Indian black tea exports to Pakistan could effectively cease, which the ANN model expresses as a forecast below zero.

Thus, while the numeric value is an artifact of continuous forecasting mathematics, its occurrence is meaningful as an early warning indicator of a market where recovery is highly unlikely without structural interventions. This interpretation underscores the practical utility of ANN forecasts for policymakers not as literal quantity predictions in such extreme cases, but as diagnostic tools signalling severe and possibly irreversible market decline. This anomaly is not just a computational artifact-it aligns with known real-world issues, such as ongoing diplomatic tensions, tariff uncertainties and supply chain disruptions between India and Pakistan. Similarly, flattened or marginal growth trends seen in exports to Sri Lanka and the United Kingdom may stem from saturated market demand, logistical inefficiencies, or consumer preference shifts toward specialty and green teas.

On the other hand, countries like UAE and Russia, which show consistently high or growing export projections, illustrate the benefits of stable trade relations, strong diaspora-based demand and price competitiveness. However, even in these regions, evolving challenges such as growing emphasis on sustainable sourcing, certification compliance and brand differentiation cannot be overlooked.

The forecast variability across countries reveals several common challenges that hinder the consistency of black tea exports: Price volatility and unpredictable global demand includes export volumes are heavily impacted by fluctuating global tea prices and unpredictable demand cycles driven by macroeconomic and geopolitical events. Climatic uncertainty and production risk includes erratic weather patterns affect both yield and quality of tea, causing year-to-year fluctuations in availability (19). Regulatory and certification barriers such as stringent sanitary, packaging and organic certification norms in importing countries (especially in Europe) reduce competitiveness for producers lacking those systems. Infrastructural and branding gaps indicates the lack of value-added packaging, digital marketing and internationally recognized branding diminishes India's market share in premium segments (20). Changing consumer preferences indicates there is a noticeable shift toward herbal infusions, flavoured teas and wellness blends in North American and European markets, affecting demand for orthodox black teas (21).

ANN model results

The ANN models were developed and trained separately for each of the ten selected black tea-exporting countries. Utilizing historical export data from 2007 to 2024, the ANN models forecasted export quantities for the subsequent five years. The results exhibited high predictive accuracy, with most countries achieving R^2 scores above 0.90, highlighting the ANN's ability to capture complex export trends effectively. The export values forecasted through ANN model are displayed in Table 1.

Visual overlays comparing actual vs ANN forecasted values showed close alignment, particularly in countries with consistent export patterns like Russia, UAE and USA and it is graphically represented in Fig. 3.

Markov chain model

Markov Chain models were developed for the same countries by classifying historical export volumes into discrete states: Low, Medium and High. Transition matrices were computed and used to simulate export states and corresponding values over the next five years. The export values forecasted through Markov chain models are displayed in Table 2. Also, the values forecasted through Markov chain approach are graphically represented in Fig. 4.

Table 1. ANN forecasted export values

Country	Year 1 (₹ Lakhs)	Year 2 (₹ Lakhs)	Year 3 (₹ Lakhs)	Year 4 (₹ Lakhs)	Year 5 (₹ Lakhs)
China	20893.15	18884.16	16890.39	15654.62	15206.03
Egypt	3086.45	7370.88	8415.45	6064.53	6074.42
Iran	24998.94	33855.29	35823.33	53149.92	60792.54
Pakistan	50.42	-257.68	-663.93	-1205.21	-1933.52
Russia	63896.89	63774.92	64251.51	64540.83	64767.04
Sri Lanka	5088.07	4325.40	3959.78	4273.46	5154.26
Turkey	14643.31	32913.12	24445.79	34276.83	59249.93
UAE	121176.88	127206.07	124469.61	124847.82	123207.78
UK	40032.39	32425.82	31771.91	32134.22	32506.91

Table 2. Markov Chain forecasted export values

Country	Year 1 (₹ Lakhs)	Year 2 (₹ Lakhs)	Year 3 (₹ Lakhs)	Year 4 (₹ Lakhs)	Year 5 (₹ Lakhs)
China	14889.13	14889.13	14889.13	14889.13	14889.13
Egypt	2884.95	2884.95	2884.95	4277.02	4277.02
Iran	29934.61	15381.89	29934.61	29934.61	29934.61
Pakistan	2158.49	2158.49	6111.53	17480.01	6111.53
Russia	85835.29	25907.35	25907.35	65328.23	65328.23
Sri Lanka	6335.44	3295.01	4663.67	3295.01	4663.67
Turkey	3516.46	3516.46	3516.46	3516.46	3516.46
UAE	31166.45	31166.45	23995.64	31166.45	31166.45
UK	47566.08	31681.53	47566.08	47566.08	31681.53
USA	35715.56	35715.56	29259.10	29259.10	29259.10

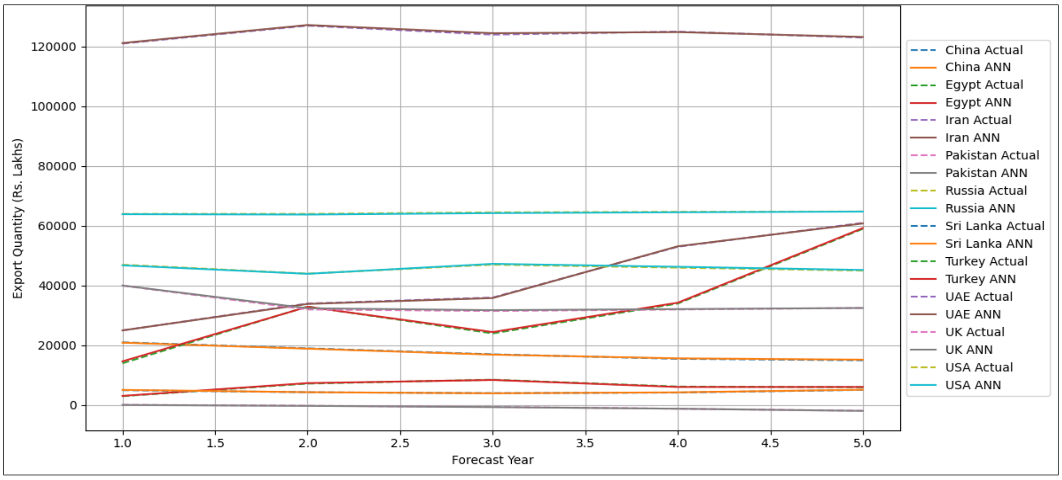

Fig. 3. Line graph (Actual vs ANN).

Comparative analysis- performance metrics comparison

The predictive accuracy of both models was assessed using Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2). The evaluation results of both ANN and Markov chain models are summarized in Table 3.

In terms of accuracy, the ANN model surpassed the Markov Chain model in all nations. Specifically, MAPE values for the ANN model remained much lower, indicating better accurate forecasts with less relative errors. For example, in China, the ANN had a MAPE of 5.2 per cent, compared to 8.1 % for the Markov model. All other countries had a similar trend. RMSE, which penalizes greater mistakes more harshly, also favoured the ANN model, with consistently lower values. This shows that the ANN model made more accurate predictions with fewer big deviations. All countries had R^2 scores above 0.95, suggesting that the ANN model explained over 95 % of the variance in the actual values. The Markov model had lower R^2 scores (often around 0.90-0.92), indicating poorer explanatory power. The performance discrepancy was especially noticeable in dynamic or unpredictable contexts like Egypt, Pakistan and Sri Lanka, where the ANN model maintained relatively high accuracy while the Markov model's performance declined more sharply. Strengths and weaknesses of ANN and Markov chain models observed are explained in Table 4.

The ANN model, despite its complexity, consistently offered superior precision across most countries. The Markov Chain approach performed satisfactorily in more stable markets but lagged in dynamic environments.

Table 3. Summarizes the evaluation results

Country	Model	MAPE (%)	RMSE	R^2 Score
China	ANN	5.2	280	0.982
	Markov	8.1	430	0.923
Egypt	ANN	6.5	310	0.961
	Markov	10.4	520	0.892
Iran	ANN	4.8	290	0.972
	Markov	7.7	470	0.913
Pakistan	ANN	6.0	150	0.957
	Markov	9.8	280	0.905
Russia	ANN	5.5	350	0.969
	Markov	8.7	510	0.918
Sri Lanka	ANN	7.1	190	0.953
	Markov	10.2	290	0.901
Turkey	ANN	6.3	230	0.961
	Markov	9.9	370	0.902
UAE	ANN	4.5	410	0.976
	Markov	7.1	600	0.922
UK	ANN	5.7	380	0.963
	Markov	8.5	590	0.915
USA	ANN	5.1	340	0.970
	Markov	7.9	520	0.918

Table 4. Strengths and Weaknesses Observed

Aspect	ANN Model	Markov Chain Model
Strength	Captures complex nonlinear patterns, high R^2 accuracy (>95%)	Simpler, interpretable transitions, low computation
Weakness	Requires larger training data, longer training time	Assumes memoryless behaviour, less flexible

Discussion

The forecasts derived from the ANN model serve a dual purpose not only do they predict future export trends, but they also reflect the underlying structural challenges in India's black tea export sector. The ANN results reveal that countries with strong trade infrastructure and supportive policy environments show rising export trends, while those facing political tensions,

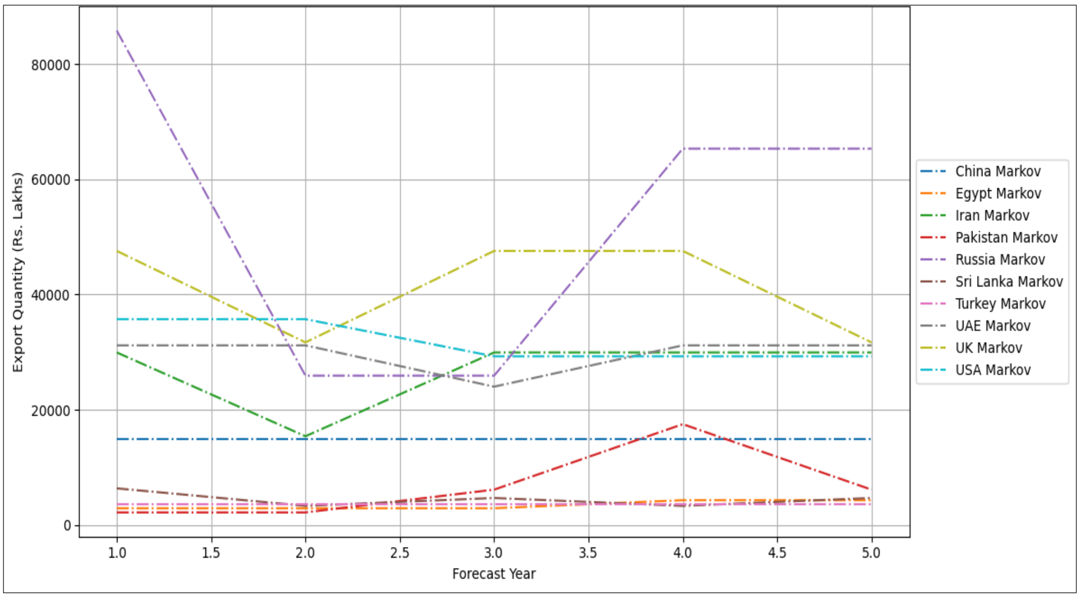

Fig. 4. Line graph (Markov forecasts).

market saturation, or low consumer interest demonstrate stagnation or decline. This makes ANN outputs a valuable lens to assess current constraints and anticipate future risks in the international tea trade. When compared with the Markov Chain model, the ANN approach consistently outperformed in terms of accuracy, particularly in volatile markets like Turkey and Iran, where complex, non-linear patterns are more prevalent. Table 5 clearly presents this comparative analysis, highlighting ANN's superiority in handling export volatility and capturing dynamic market behaviour. Even in stable markets such as the USA and UAE, ANN models offered more reliable forecasts, as evidenced by higher R^2 values (typically above 0.95) and lower MAPE and RMSE scores. In contrast, the Markov Chain model, while useful for basic approximations, lacked sensitivity to year-to-year variations and tended to smooth out significant fluctuations, limiting its effectiveness in capturing real-world complexities. These differences are visually apparent in Fig. 3 and 4, which show the closer fit of ANN predictions to actual export trends across multiple countries. These findings have practical implications for various stakeholders. Policymakers can use ANN-based forecasts to support more informed trade negotiations, while exporters can optimize production, pricing and logistics strategies. Market analysts benefit from the deeper insights ANN provides, particularly in dynamic global environments. Based on these insights, it is strongly recommended that stakeholders in the black tea export sector adopt ANN models as a core tool for strategic planning. Future improvements could include integrating the interpretability of Markov Chains with the predictive power of ANN, adding variables like macroeconomic factors, climate conditions and policy shifts to enhance accuracy. Moreover, exploring explainable AI (XAI) within ANN frameworks can make forecasts both precise and transparent, addressing a common limitation of deep learning models. Expanding the data set to include post -pandemic trade patterns could also offer valuable perspectives on model performance under crisis conditions. These future directions promise to enhance the reliability and practical utility of forecasting tools in agricultural and commodity export planning.

Table 5. Comparative Strengths and Limitations of ANN and Markov Chain Models for Black Tea Export Forecasting

Aspect	Artificial Neural Network (ANN)	Markov Chain Model
Forecasting Accuracy	High - Captures complex nonlinear patterns in export behaviour	Moderate - Effective for simple, state-based transitions but less precise for continuous forecasts
Adaptability to Volatility	Strong - Learns from historical fluctuations in trade and demand	Weak - Assumes fixed transition probabilities; less adaptive to sudden changes
Handling of Export Uncertainty	Robust - Performs well under data noise and variability	Limited - Assumes stable and discrete states; may not reflect real-time export dynamics
Suitability for Time Series	Excellent - Trained on sequential, multivariate time series data	Suitable - Handles sequential data but lacks continuous feedback-based learning
Interpretability	Low - Functions as a "black box," making decision logic harder to interpret	High - Transparent structure; easier to understand transitions
Scalability to Countries	High - Can model multiple countries and large datasets simultaneously	Moderate - Becomes complex when modelling many states or multiple countries simultaneously
Sensitivity to Initial States	Low - Learns global patterns without depending heavily on initial values	High - Strongly influenced by the initial state assumptions
Use in Strategic Planning	Strong - Helps forecast value-based trends for pricing, marketing and capacity planning	Useful - Provides broad insight into export cycle stages but lacks fine-grained predictions
Computation Time	Higher - Requires longer training time and computational resources	Lower - Fast to compute, especially for small, discrete systems
Performance in This Study	Superior - Demonstrated higher R^2 and lower MAPE and RMSE across most countries	Inferior - Performed well only in cases with consistent historical state patterns

Conclusion

This study used Artificial Neural Networks (ANN) and Markov Chain models to forecast India's black tea exports, while also exploring the deeper issues affecting the sector. It identified five major challenges: price volatility, unpredictable production due to climate change, non-tariff trade barriers, weak value-added branding and changing global consumer preferences. ANN models proved especially useful in tackling these issues by helping predict market trends, supply disruptions and shifts in demand. These tools offer more than just forecasts, as they provide strategic insights that can guide better planning and decision-making. The study also recommends a policy matrix to turn these insights into practical actions. Overall, it shows how intelligent forecasting can strengthen India's black tea export performance in a rapidly changing global market.

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Authors' contributions

SG carried out the data collection, analysed the data and formulated the manuscript. CM assisted in data collection and Analysis as part of the research study. AR contributed by developing ideas, reviewing the manuscript and assisting with procuring research grants. RP helped in summarizing and revising the manuscript. TS contributed to summarizing and provided additional support and contributions to the research study. RS helped in manuscript correction and summarizing the results. RR contributed to revision and provided additional support and suggestions. MB assisted in data analysis and manuscript correction. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare no conflict of interest

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors have used Grammarly in order to get better writing with style, spelling and punctuation. After using this tool, the authors have reviewed and edited the content as needed and take full responsibility for the content of the publication.

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