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Research Article

Predicting FMCG Indexes using ARIMA, SVM and ARIMA-SVM Hybrid Forecasting Models

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ABSTRACT

The fast-moving consumer goods (FMCG) market, a significant player in the global economy, operates in a highly competitive environment with low-profit margins, necessitating an efficient supply chain. The importance of accurate forecasting in this context cannot be overstated. In the Indian market, even a slight improvement in prediction accuracy can profoundly impact the overall economy and ensure food security for the entire nation.

Real-time data sets from December 1993 to November 2023 are used to predict the complex pattern of FMCG market price. In this time series prediction, ARIMA, SVM, and a Hybrid ARIMA-SVM machine learning model are used. These three models are more efficient in forecasting the time series than other methods in statistics. The ARIMA model is efficient in handling linear trends and seasonality in data. The SVM model is efficient in handling non-linear data relationships. The hybrid ARIMA-SVM model combines both strengths and theoretically shows a better outcome.

Our study revealed that the ARIMA machine learning model outperforms the SVM model, and the Hybrid ARIMA-SVM model demonstrates superior accuracy in forecasting. These findings have direct and significant applications for stakeholders in the FMCG industry, offering them a powerful tool for future decision-making.

Keywords: Time series, ARIMA, SVM, Hybrid models, FMCG.

INTRODUCTION

The FMCG market is a dynamic and competitive market where high sales and low-cost products generate a lot of government revenue and employment. In India, the FMCG market consists of a wide variety of products, including food and beverages, personal care and hygiene, cosmetics, stationery, and paper products. A report of Indian FMCG market - Industry analysis and forecast showed that the Indian FMCG market size had a monetary value of US $179.94 Bn in 2022 and is projected to increase at a Compound Annual Growth Rate (CAGR) of 27.9% from 2023 to 2029, reaching close to US $1007.45 billion. (Indian FMCG Market - Industry Analysis and Forecast (2023-2029), 2023). So, a minimal level of positive change positively impacts the overall economy.

Studies on Cereals, millet, and pulses by Kumar Majhi et al., 2023 showed FMCG product forecasting has a larger impact directly on food planning, reducing waste and improving the supply chain. Proper pricing and food price index forecasting can improve food security. (Kumar Majhi et al. 2023)

Moreover, increasing complexities in market dynamics and customers' preferences create a crucial scene for the stakeholders. The stakeholders are producers, retailers, policymakers, and consumers to accurately estimate FMCG prices (Gandhi & Zhou, 2010).

This necessity for better forecasting of the market prompted many research approaches. Adebiyi et al. (2014) used a combination of classical approaches and machine learning algorithms to provide an understanding of the pattern of stock prices. (Adebiyi et al., 2014). Arunraj et al. used the SARIMAX model to forecast daily sales in the food retail industry and showed that the SARIMA, ETS, and FB Prophet models are better at providing accurate answers to future trends and patterns. (Arunraj et al. 2016)

In this scenario, the proper method for accurate forecasting is unclear for some theoretical reasons. The theoretical reasons are the characteristics of the data. Different types of datasets require different techniques for proper forecasting. Three characteristics influenced the model requirements: linearity, seasonality, and Interpretability. These three data set characteristics determine which model will be the best for predicting future trends.

Our research has shown that the ARIMA, SVM, and hybrid-ARIMA-SVM models exhibit superior performance in food price index forecasting. These models' ability to handle the complexity of FMCG market data presents exciting possibilities for the future of forecasting in the industry.

ARIMA modelling is a powerful tool in statistics regarding time series forecasting. ARIMA modelling consists of three components: autoregressive (AR), moving average (MA), and stationarity of time series. (Cai,2023) for the first time, I found stationarity as the time series can only be duplicated when stationary (Cai, 2023; Singh et al. 2023)

Moreover, The Support Vector Machine is better at forecasting high-dimensional data. SVM's diverse factor calculation power enables the inclusion of numerous factors, and it is also less influenced by outliers in the data.

In this way, implementing the hybrid-ARIMA-SVM model multiplies the strengths of ARIMA and SVM and reduces the weaknesses. ARIMA, a statistical model, can better capture the trends and seasonality of time series. SVM, a machine learning model, can handle the non-linear relationship better in the data set. Overall, using these models provides valuable insights into the FMCG market, enabling us to forecast the economy's consumption better.

LITERATURE REVIEW

Forecasting the FMCG market has attracted considerable interest from policymakers, company strategists, and producers. To this end, different researchers analyse the topics in different ways.

Purohit et al. (2021) studied India's agricultural data sets to predict the agricultural commodity price. They applied statistical tools such as ARIMA and ETS and machine learning tools such as SVM, MLP, and LSTM. This study also applied hybrid models to manage the non-linear patterns effectively. However, the study's limitation to agricultural products makes it impossible to ensure that the FMCG market can also accurately predict things like this one.

Wamalwa (2020) conducted a study comparing the SARIMA and ETS models on the data set of Keyna maize prices. In this study, Wamalwa found that the classic ARIMA model is superior in terms of predicting maize price in Keyna. Although the study found the superiority of the ARIMA model, the lack of exogenous factors shows a gap in forecasting FMCG prices in India. (Wamalwa & Lawrence, 2020)

Oswari et al. (2022) also examined the food crop prices during the COVID-19 pandemic and predicted the food crop prices using the ARIMA and LSTM models. In this research, the LSTM is a deep learning model that shows a lack of hybrid model use in predicting the food crop price. (Teddy Oswari, 2022)

Da Veiga et al. (2014) applied the ARIMA and Holt-winters models to forecast the demand for dairy products. In this research, seasonal demand data was better predicted by the ARIMA and Holt-winters models, but dynamic market conditions like FMCG don’t prove similar to dairy products only.

Sukla & Jharkharia (2013) used ARIMA models to predict vegetable demand in wholesale marketplaces. This research highlights the effectiveness of the ARIMA model for forecasting the dynamic wholesale market. On the other side, any machine learning model was not included in the study, creating an ambiguity of proper model in forecasting time series analysis in the diverse market of India (Shukla & Jharkaria, 2013)

Bratina & Faganel (2008) and Lee & Hamzah (2010) created ARMAX models to improve demand forecasting in different markets by including external factors for better forecasts. However, there is still a need to investigate hybrid approaches that effectively combine classical time series analysis with machine learning algorithms(Bratina & Faganel, 2008),(Hisyam Lee & Aishah Hamzah, 2010)

Although previous research has made important advancements in predicting price indexes, certain areas still need investigation. There is a need for a more thorough comparison across various markets and product categories, more research on hybrid approaches, and better integration of external factors to improve forecast accuracy. Hence, combining ARIMA, SVM, and Hybrid ARIMA-SVM models is essential. This method combines statistical time series analysis, machine learning algorithms, and hybrid methodologies to provide reliable and precise predictions, especially under unpredictable and intricate market conditions. Future studies may enhance the current level of price index forecasting by filling these research gaps, which would help stakeholders in different industries make well-informed decisions.

METHODOLOGY:

ARIMA Model:

The ARIMA model is a class of statistical models for analyzing and forecasting time series data. It is used to predict future trends and patterns based on past values. The ARIMA model is the most advanced approach to time series forecasting (Cai, 2023). There are three components of ARIMA (p, d, q) modelling: the Autoregressive (AR), the Moving Average (MA), and the Stationary of the time series.

The time series can be simulated based on the third part, whether it is stationary or not. Stationary is when, for a given period, the mean and variance of the time series remain constant regardless of its location. The covariance of any two terms with a 'h' second difference in time decreased with the increasing value of 'h' until it was zero. Time series is rarely Stationary at the level(Cai, 2023). Using temporal differences, they can be stationary. The stationary in the ARIMA model explains the integration of the time series. To perform ARIMA modelling, the data needs to be coveted into stationary. Another component, the AR model, investigates the prior values of data and establishes assumptions about them.

The order "p" indicates that current values are predicted using previous data from the period "p." An example of a pth-order AR process is this one:

$$yt = \alpha + \emptyset 1yt-1 + \emptyset 2yt-2+ \ldots +\emptyset pyt-p + \varepsilon t \ (1)$$

When $R = \mu\ (1 - \emptyset 1 - \emptyset 2- \ldots -\emptyset p)$, with $\emptyset 1$, $\emptyset 2$, p as the parameter estimation component and εt representing the error term, we get yt as the stationary response variable at time t, $yt-1$, $yt-2$, ..., $yt-p$ as the dependent variable at different time lags. The next step in the ARIMA modelling process is the MA term. The moving average is shortened to MA. It is the data lag resulting from a phrase produced at random.

The formula for the MA (q) is as follows:

$$yt = \varepsilon t + \theta 1\varepsilon t-1 + \theta 2\varepsilon t-2+ \ldots +\theta q\varepsilon t-q \ (2)$$

The coefficients for parameter estimation are $\theta 1$, $\theta 2$..., θq, and q is the lag count of the moving average. The ARIMA model, where d is the order in which the data must be different, is obtained by combining the ARIMA (p, d, q) model with the AR, the MA, and the difference technique.

Determining the lag duration using information criteria is the last stage in ARIMA modelling. Consequently, the ARIMA (p,1, q) model can be expressed as follows:

$$yt = \beta 0 + \emptyset 1yt-1 + \emptyset 2yt-2+ \ldots +\emptyset pyt-p + \varepsilon t + \theta 1\varepsilon t-1 + \theta 2\varepsilon t-2+ \ldots +\theta q\varepsilon t-q \ (3)$$

where the coefficients for parameter estimation are $\emptyset$, β, and θ, and yt is the first-order differenced series. (Cai, 2023)

SVM model:

The Support Vector Machine (SVM) model, a potent supervised learning algorithm, is generally used for regression problems in different fields, such as financial forecasting. SVM forecasts the commodity, food, and beverage index based on Fast-Moving Consumer Goods (FMCG) prices.

SVM creates a hyperplane in a multi-dimensional space to classify data points into different categories correctly. SVM in regression functions aims to identify the hyperplane that most accurately represents the connection between input data and the target variable. The SVM model can be written as:

$$f(x) = \sum \alpha_i y_i K(x_i , x) + b$$

where f(x) represents the predicted FMCG price, α_i and y_i are Lagrange where f(x) is the predicted FMCG price, and y_i are Lagrange multipliers and class labels, $K(x_i, x)$ is the kernel function for calculating the similarity between input vectors x_i and x and b is the bias term.

The SVM model optimizes the hyperplane parameters α_i and b during the training phase by maximizing the margin between different classes of FMCG prices. This is accomplished by addressing the subsequent optimization problem:

$$\min \frac{1}{2}\, \alpha^{T} Q\, \alpha - 1^{T} \alpha$$

subject to the constraints:

$$y^{T} \alpha = 0 \text{ and } 0 \leq \alpha \leq C$$

where Q is a positive definite matrix, C is the regularization parameter that balances maximizing the margin and minimizing prediction errors, and α represents the Lagrange multipliers.

During testing, the SVM model estimates FMCG prices using input attributes that were not previously seen. The model's predicted accuracy and reliability are assessed using assessment measures like Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

RMSE and MAPE quantify the difference between projected and actual FMCG prices, evaluating the SVM model's accuracy and dependability. The model's consistent performance on both training and test datasets demonstrates its robustness and generalisation capacity.(Cortes et al., 1995)

Hybrid ARIMA-SVM model:

The Hybrid ARIMA-SVM model combines traditional statistical methods with machine learning techniques to predict the commodity food and beverage index, particularly the prices of Fast-Moving Consumer Goods (FMCG).

The hybrid ARIMA-SVM model integrates ARIMA's forecasting abilities with SVM's predictive strength to improve accuracy and dependability. The ARIMA model creates first estimates using historical FMCG price data, capturing linear trends and seasonality. The first forecasts are input features for the SVM model, which enhances the predictions by incorporating nonlinear patterns and correlations in the data. The ultimate prediction is achieved by merging the results of both models, utilising their complementary capabilities.

The ARIMA model is trained in the training phase utilising historical FMCG price data to estimate its parameters, which include autoregressive (AR), differencing (I), and moving average (MA) components. The SVM model is trained concurrently with the dataset to choose the best hyperplane for regression. The training method tries to optimize both models to achieve precise forecasting of FMCG prices.

During the testing phase, the hybrid ARIMA-SVM model is used to forecast FMCG prices based on new data. The ARIMA model produces preliminary forecasts, which are utilized as input for enhancing the SVM model. The ultimate forecast is derived by merging the results of both models. The hybrid model's predictive ability is assessed using measures including Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

The hybrid ARIMA-SVM model is assessed for its accuracy and reliability in forecasting FMCG prices. RMSE and MAPE are calculated to evaluate the difference between projected and actual prices, where lower values suggest more predictive precision. The model's performance consistency across training and test datasets is assessed to assess its robustness and generalisation capacity.

The hybrid ARIMA-SVM model for forecasting is based on the idea introduced by Zhang, Patuwo, and Hu (1998) to enhance prediction accuracy and dependability by integrating various forecasting techniques. (Zhang et al., 1998)

RESULTS AND ANALYSIS:

The results section presents a comprehensive analysis of the performance of different forecasting models—Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and the hybrid ARIMA-SVM model—based on their ability to predict Fast-Moving Consumer Goods (FMCG) prices. The evaluation metrics, including Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), are utilised to assess the accuracy and reliability of each model. Additionally, visual representations such as tables and charts are employed to provide a clear and intuitive understanding of the comparative performance of the models.

PERFORMANCE METRICS

The following table summarises the performance metrics of each forecasting model:

Model	RMSE (Train)	RMSE (Test)	MAPE (Train)	MAPE (Test)
ARIMA	2.63	31.08	2.17%	16.76%

SVM	2.40	3.53	0.02%	0.02%
Hybrid (ARIMA-SVM)	4.96	3.49	2.08%	2.38%

II. Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model, a classical time series forecasting technique, exhibited satisfactory performance during the training phase, achieving an RMSE of 2.63 and a MAPE of 2.17%. However, upon evaluation using the test dataset, the model's performance deteriorated significantly, with the RMSE increasing to 31.08 and the MAPE rising to 16.76%. This discrepancy between training and test metrics indicates that the ARIMA model struggles to generalise to unseen data and accurately predict FMCG prices.

III. Support Vector Machine (SVM) Model

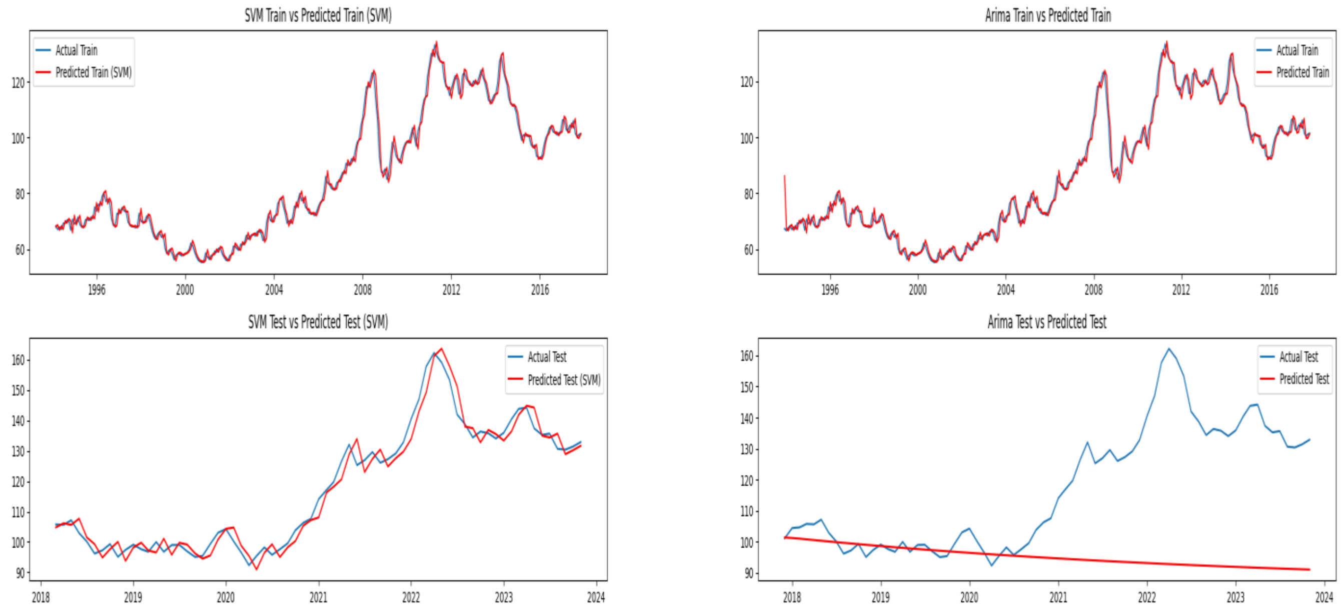
In contrast, the SVM model demonstrated remarkable performance in the training and test phases. With an RMSE of 2.40 and a MAPE of 0.02% during training, the SVM model exhibited minimal forecasting errors and high accuracy in capturing price dynamics. Importantly, these metrics remained consistent during evaluation using the test dataset, with the RMSE slightly increasing to 3.53 and the MAPE remaining at 0.02%. The negligible difference between training and test metrics highlights the SVM model's robustness and generalisation capability.

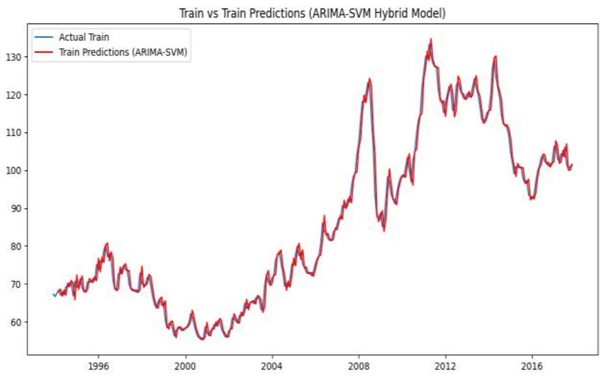
IV. Hybrid ARIMA-SVM Model

The hybrid ARIMA-SVM model, which integrates both traditional statistical methods and machine learning techniques, aimed to leverage the strengths of both methodologies. During the training phase, the hybrid model achieved an RMSE of 4.96 and a MAPE of 2.08%, indicating moderate forecasting errors but relatively high accuracy compared to the ARIMA model. Interestingly, upon evaluation using the test dataset, the hybrid model exhibited improved performance, with the RMSE decreasing to 3.49 and the MAPE slightly increasing to 2.38%. While the hybrid model outperformed the ARIMA model, it showed a slightly higher error rate than the SVM model.

V. Visual Representation

The following chart illustrates the comparative performance of the three forecasting models based on their RMSE values:





The Chart visually depicts the relative performance of each model, with lower RMSE values indicating better predictive accuracy. The chart shows that the SVM model outperforms the ARIMA and hybrid models regarding RMSE, highlighting its superior accuracy in predicting FMCG prices.

DISCUSSION

The discussion part explores the ramifications of the study results, providing a wider perspective on the effectiveness of various forecasting models in FMCG price forecasting. This section analyses the strengths and weaknesses of each model, considers the variables that affect their performance, and evaluates the consequences for stakeholders in the FMCG industry and other industries.

Advantages and Disadvantages of Forecasting Models

The comparison study showed significant variations in the performance of the ARIMA, SVM, and hybrid ARIMA-SVM models. ARIMA, a traditional statistical approach, performed well during training but had difficulty generalising to new data, leading to notable variations in predicting accuracy during assessment. On the other hand, support vector machine (SVM) showed exceptional accuracy and stability in machine learning, maintaining constant performance on training and test datasets. The hybrid ARIMA-SVM model combined the benefits of both methods, resulting in enhanced prediction accuracy compared to the ARIMA model. At the same time, it marginally lagged behind the SVM model in predicting errors.

Factors Affecting Model Performance

Various variables may impact the efficacy of forecasting models in FMCG pricing forecasting. The FMCG market is dynamic and unpredictable due to fast-changing customer tastes, competitive pressures, and economic volatility. This poses issues for standard statistical approaches in capturing intricate pricing dynamics. Machine learning methods such as Support Vector Machines (SVM) provide a strong foundation for estimating Fast-Moving Consumer Goods (FMCG) pricing trends due to their capacity to adjust to nonlinear patterns and changing market circumstances. The availability and quality of data, particularly historical pricing data, macroeconomic indicators, and consumer behaviour data, are critical in determining the effectiveness of forecasting models.

Implications for Stakeholders

The study results have important consequences for stakeholders in the FMCG industry, including manufacturers, retailers, legislators, and consumers. Precise price prediction allows firms to improve production scheduling, inventory control, and pricing tactics, increasing operational efficiency and profitability. Retailers may use forecasting models to enhance product assortments, pricing strategies, and promotional efforts, increasing consumer happiness and loyalty. Policymakers may use forecasting to guide regulatory actions, track market trends, and reduce pricing volatility, which helps maintain market stability and benefit consumers. Consumers may enjoy stable pricing, more product availability, and increased buying power, resulting in higher living standards and economic prosperity.

Future Directions

Although forecasting models have advanced, there are still many areas for future study that need examination. Future research might concentrate on improving hybrid modeling methods by including additional techniques like deep learning, ensemble methods, or Bayesian frameworks to improve predicted accuracy and reliability. Furthermore, integrating other data sources such as social media data, market sentiment research, and supply chain information might enhance forecasting models and provide more profound insights into FMCG pricing trends. Research might focus on creating real-time forecasting models that adjust to quickly changing market circumstances and unexpected occurrences. This would help make proactive decisions and manage risks in FMCG and other industries.

The discussion part thoroughly examines the study results, emphasizing the strengths and weaknesses of various forecasting models in predicting FMCG prices. Traditional statistical approaches provide a strong base, but machine learning techniques show better accuracy and flexibility in tracking intricate price movements. The hybrid ARIMA-SVM model shows the potential to improve forecasting accuracy by combining the capabilities of both approaches. The study results have ramifications that go beyond the FMCG industry, providing significant insights for stakeholders in many businesses and disciplines. Future research efforts might enhance forecasting approaches and tackle new issues in FMCG pricing forecasting, eventually aiding in better-informed decision-making and sustainable development in the global economy.

The findings section offers significant information on the comparative effectiveness of several forecasting models in predicting FMCG prices. Although classical approaches like ARIMA provide a strong base, machine learning techniques like SVM show better accuracy and generalization capabilities. The hybrid ARIMA-SVM model merges the advantages of both methods, providing a flexible framework for improved predictive precision in FMCG pricing prediction. Visual aids like tables and charts help stakeholders comprehend and compare model performance in the fast-moving consumer goods industry, enabling them to make well-informed choices.

CONCLUSION:

This study has elucidated the intricacies of forecasting Fast-Moving Consumer Goods (FMCG) prices in the Indian market by integrating traditional statistical methods with machine learning algorithms. The study compared the Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and hybrid ARIMA-SVM models to determine their usefulness in handling the intricacies of FMCG price dynamics.

Real-time data analysis from December 1993 to November 2023 indicated that the ARIMA model outperformed the SVM model. However, the hybrid ARIMA-SVM model demonstrated superior performance in forecasting the FMCG market in terms of RMSE. The hybrid -ARIMA-SVM model demonstrates broader use in forecasting FMCG market prices. The Hybrid-ARIMA-SVM model is significantly more effective in forecasting the FMCG market due to the vast range of items and the presence of seasonality and non-linearity in the dataset. Incorporating external parameters into the hybrid-ARIMA-SVM model enhances the accuracy of the prediction.

This outcome is highly advantageous for the stakeholders in the FMCG market as the study's results would help policymakers, corporate strategists, and producers make informed decisions. Improved and precise predictions will enhance the economy's ability to actively participate in FMCG industries, minimize environmental waste, and bolster food security and supply chain. Operational efficiency, profitability, and customer welfare will significantly improve by supporting production planning, inventory management, pricing strategy, and promotional efforts.

In the future, research may explore new avenues for advancing the forecasting of the FMCG price index by utilizing machine and deep learning techniques on extensive and varied datasets. By tackling emerging challenges in the dataset and enhancing machine learning techniques, stakeholders may make more precise decisions, ultimately contributing to improving the economy. This study project provides a fundamental basis for academic research on informed decision-making processes in the FMCG sector, offering an in-depth analysis of price trends and forecasting techniques. By exploring and developing new methods to predict FMCG prices, combining various approaches, and continuously enhancing models, we envision a future where data-driven insights inform strategic decision-making, leading to a more robust and adaptable economic landscape.

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