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A Hybrid Multi-Stage Framework Integrating ARIMA-LSTM Forecasting and Transformer-Based Sentiment Analytics

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Abstract

E-commerce services are characterized by dynamic prices and a large number of users' reviews - obstacles for well-informed purchase decision. In this work, we propose a new hybrid model that combines ARIMA-LSTM forecasting with Transformer-based Sentiment Analysis to provide predictive and sentiment-aware price analyses. Price lists and customers reviews are collected through ethical web scraping and pre-processed as input to analysis. The combined ARIMA-LSTM model captures both the linear and non-linear structure in data, whereas Transformer can remove context and aspect aspects from customer feedback, such as mild nuances of sarcasm and long distance dependencies. An algorithm for multi-criteria decision-making integrates forecasting and sentiment analysis to provide recommendations to platforms as to good price evolutions. Experiments on real-world data demonstrate that the proposed approach improves forecasting and sentiment analysis, and enables actionable insights from predictive recommendations. The modular architecture of hybrid model can be utilized in different retail or finance applications.

Keywords: ARIMA-LSTM, E-commerce, Forecasting.

Introduction

The explosive growth of e-commerce has transformed the way consumers and businesses alike experience products and services. Product prices also dynamically fluctuate with respect to the supply and demand, promotion policy, and competitor pricing that makes it difficult for users to make an optimal decision. Yet, huge numbers of customer reviews convey value in terms of product quality, delivery experience and overall satisfaction. However, most conventional price comparison systems tend to focus on static price searching only and explicitly ignore the time series data and rich sentiment implied in textual reviews. Conventional forecasting approaches such as ARIMA or single LSTM could not catch both linear and nonlinear patterns of the series full of volatile prices at the same time, so lacked the predictability. Moreover, the traditional methods for sentiment analysis (such as lexicon-based method, shallow machine learning models and so forth) may not consider contextual semantics, sarcasm or aspect-level opinions that are rendered as in-complete decision support.

To overcome these limitations, we propose a hybrid multi-stage framework which integrates ARIMA-LSTM price forecasting and Transformer-based sentiment analytics. The platform is built to continuously monitor historical prices and webcam reviews from various sources, extract trends and customer opinion insights, and generate predictive sentiment-aware recommendations. By using linear and non-linear forecasting and deep contextual sentiment analysis we provide better predictions, intelligent decision support and early warning of price appreciation. Our contributions are to design a reliable and generic hybrid model for predictive volatile price data based on review, implement the transformer-based sentiment analysis module for reviewing aspect level reviewing score and combination of these modules in single decision making framework respectively. The developed framework is believed to enable users to find the best platforms on which they can buy any product or invest in any asset by considering future prices and customer sentiment. Although conceived for e-commerce applications, the framework is flexible and can be generalised to other areas affected by temporal volatility and user-generated opinions, such as stock exchanges or financial instruments. It should also improve user decision making, lower the burden of manual monitoring and enable real-time actionable intelligence through predictive insights and sentiment-aware recommendations.

2. Related Works

An investigation on the issues of demand forecasting in a highly volatile environment for e-commerce fashion sales was carried by Bhaskar Reddypogu & Prasad (2025). They evaluated the effectiveness of their top 3 models (ARIMA, LSTM and GAN for fashion sales forecasting) by examining the sales, customer behaviour as well as demand patterns in fashion sales. They found that a GAN can predict non-linear demand shape better than LS TM and ARIMA. In a fashion sales market of trending shifts, this is precious data for fashion retailers who understand the importance of finesse where forecast accuracy is concerned.

In a performance comparison among LSTM, Facebook Prophet and SARIMA for the prediction effectiveness by Ecevit et al. (2024) studied the use of deep learning approaches for predicting short-term sales at online stores. This comparison result showed that LSTM outperformed with its accuracy in wMAPE, RMSE and R-squared. The take away lesson is that the effectiveness of LSTM to capture long-range dependencies in the online sales series can have a direct impact on inventory and pricing decisions.

A study by Khalid et al. (2025) investigated the trustworthy forecasting methods in forecasting of new commerce-sale data by LSTM, SARIMA and XGBoost. The advantages and disadvantages of different techniques were concluded that the classical SARIMA model can obtain a stable result in stationary conditions, while, LSTM model and XGBoost model are capable to analyse the non-linear predictions trends for more accurate prediction. The significance is that the study highlights the fact that classic models can be outperformed by machine learning algorithms and deep learning, above all in more complex data like those in e-commerce.

Hybrid approach by integrating ARIMA and LSTM was investigated in Wang & Wang. In these hybrid approaches, one model was used to forecast the online inventory and sales. The model was constructed by aggregating linear and non-linear effects of sales. The hybrid model produced better result than the single models of ARIMA and LSTM, because the hybrid model can capture precisely tail and seasonal information in sales (captured by ARIMA) and non-linear learning pattern (LSTM). The ARIMA and LSTM were applied to forecast the prices of agricultural commodities, which exhibited multidirectional temporal dynamics like in the e-commerce industry through Xia (2024). The experimental results indicated that corresponding to a non-linear pattern, LSTM performs better than ARIMA, in forecasting horizon, and however, we can also accept using ARIMA.

Kalange (2025) introduced the hybrid model of LSTM-ARIMA for stock price forecasting, underlining that linear and nonlinear patterns in financial time series data were not fully processed by any single models. The combined model obtained lower errors of RMSE and MAE, which shows the effectiveness of deep learning models in combination with statistical methods to extrapolate the robustness of stock price predictions and enable investors make decisions.

Agarap (2018) studied the use of bidirectional RNN in sentiment classification for e-commerce review data by taking customer reviews to have insights from product perception analytics. The RNN based context sentences in review texts could be capable of providing better results over shallow learning methods, and there was clearly an opportunity to enhance classification accuracy using deep learning approaches.

Gajula provided a comprehensive review of sentiment-aware recommendation systems in the e-commerce system that helps to process NLP techniques which can capture user opinions and feedback on products. This paper shows evolution from the legacy concept of lexicons and machine learning algorithms to the modern view point of deep learning and its application of contextual embedding's in sentiment-aware recommendation system which more improves the quality selection. [General review insight]

Liu et al., proposed a deep learning based BERT BiGRU Softmax model to analyse e-commerce product review text sentiment. (2020) to show that we achieve better performance on text sentiment classification with BERT contextual embedding's based BiGRU networks compared to the traditional models. The findings demonstrate that the more intricate lexical semantic information, such as long range dependencies contained in text, are preserved in the learned contextualized representation of text.

A deep learning hybrid approach for sentiment analysis on e-commerce reviews with new term weights and feature selection by Smith & Chen, 2024. This emphasis model is more accurate and has higher F1 scores than other NLP approaches. This experiment evidences that the adoption of hybrid advanced models contributed in increasing the accuracy of sentiment analysis analysis in online marketplaces. Subbaih and Bolla (2023) used weakly supervised learning to aspect type discovery and sentiment analysis. They addressed the problem of limited labelled training data in big e-commerce review datasets. Their results indicated the role of their proposed technique by offering same outcomes with other state-of-the-art approaches.

Hidri et al. (2025) proposed a hybrid deep neural networks to mine opinions with a multi-sense perspective, which are simply composed of stacking different types of representations to fuse syntactic and semantic information. This method was very effective based on common benchmark tests for the sentiment classification task, and that demonstrate the ability of the hybrid models to better process various patterns in texts accuracy and robustness of the reviews executed with e-commerce support sentiment analysis.

Bhanujyothi and Jacob presented a CNN-BiLSTM with “attention” stock market sentiment analysis tasks based model where convolutional layers are used to learn local features, BiLSTM models capture temporal dependencies and attention is used to highlight the useful part of data, showered integrating spatial, temporal learning along with sentiment can improve forecasting accuracy of financial decision support systems. To stress spatial and temporal learning with sentiment is effective in improving the accuracy of forecasts, our proposed model obtained superior average performances than counterpart models in predicting.

Zhang & Tong (2023) did a direct comparison of ARIMA and LSTM in FinTech for stock price prediction, finding that the recurrent neural network is better suited to capture long-term dependencies in data and to deal with volatility markets than more traditional models such as ARIMA that can be useful on simpler trends. They said hybrids worked much better.

In 2025, Wu and Li presented a hybrid ARIMA-LSTM with fuzzy logic to predict the volume of an e-commerce sorting center. They proved that by applying a combination of statistical forecast methods with fuzzy logics to the uncertain data in forecasts, we can achieve more precise forecasts. Any hybrid implementation has a better result in comparison the basic setups.

In particular, Talib et al. (2024) found the following in a systematic review of demand forecasting models for retail e-commerce: "Hybrid models including machine learning algorithms and statisticalbased methods are more accurate and adaptable to compared traditional-based methods...Then, the shift from classical time series models toward ensemble learning and deep learning is motivated by e-commerce sales' non-stationarity and time-varying characteristics." Indeed, the latter were also addressed more recently in Talib et al. (2024), who compared hybrid to classical forecasting methods at an inherent level. This research concluded that substantial performance enhancements could still be attained employing hybrids in the terms of RMSE and MAPE errors. Model diversity to deal with complex functions was stressed by introducing both linear, nonlinear and machine-intelligence models.

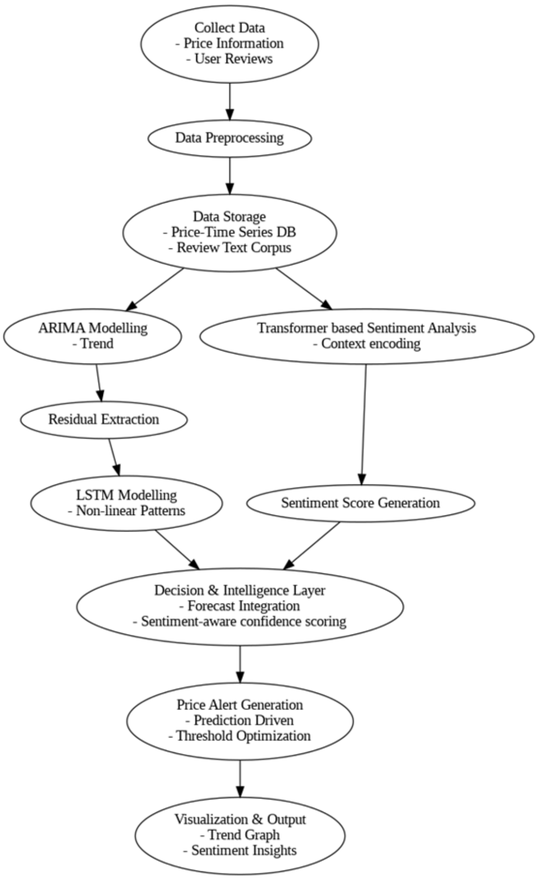
A further study by Khalid et al. (2025) confirmed the findings of comparing LSTM, XGBoost and SARIMA models and verified that the first two are better suitable for e-commerce sale prediction. These models are typically more accurate during periods of change, which could explain the growing trend of using machine learning in forecasting.

Wang & Wang (2025) also reiterated the performance of hybrid ARIMA-LSTM model was able to capture linear as well as non-linear relationships in the data in order to estimate inventory accurately.

3. Proposed Framework

3.1 System Overview

This is the intelligent system at multiple levels to integrate the automated price analysis, prediction of forecasting and sentiment in decision making. The system presented is also a modular one that comprises levels such as data acquisition, data integration or pre-processing, hybrid models for analysis itself, decision intelligence and the user interaction. This system is also able to handle disparate data from different online shopping websites. It is also good to text processing. By integrating the application of ARIMA-LSTM for prediction and Transformer model for sentiment analysis, the system is useful in providing predictive and sentiment-based recommendations as well as alerting positive price movements.



3.2 Data Acquisition Layer

This is your data that you mine both structured and un-structured. Historical and the current prices of the products are fetched from various online stores using crawl technique and other advanced methods are used. The data is scraped from the static websites using Requests and BeautifulSoup or headless browsers that Selenium/Playwright automates for you in case of a website heavy on dynamic JavaScript. In addition to the prices, on this tier are collected also the reviews, ratings and other related descriptive information (brand, seller and date) of particular items.

3.3Data Preprocessing & Integration Layer

Raw data tends to be and inconsistent, noisy, or incomplete or both. Consequently, the duty of this layer is to clean the data, eliminate duplicates or cover missing values. It is also from a time-series use-case where we normalize data, sync up the timestamps, re-sample data and outlier with method to align/validate the consistency of data points against multiple times. The review comments are tokenized, lemmatized and stop words removed in preparation for the sentiment out analysis.

3.4 Hybrid Analytical Modelling Layer

This layer is the heart of the intelligence of the platform. It hosts two cooperative modules. Such modules are predictive price forecasting and sentiment analysis.

3.4.1 ARIMA-LSTM

ARIMA-LSTM hybrid model is used to analyse our historical prices. ARIMA captures the linear trends, seasonality and simple patterns in our data but failed to capture nonlinear pattern and deterministic structures such as long term dependency and sudden changes when it is compared with LSTM. Both models results will be unlocked to arrive at our prediction. Our hybrid model provides a substantial enhancement over our forecast accuracy, especially when using more volatile data.

3.4.2 Transformer-Based

Sentiment Customer reviews are passed through a transform neural network (e.g., BERT or RoBERTa). The network constructs contextual embedding's that the classifier assigns positive, negative and neutral labels. The classifier also identifies aspect-level sentiments to assess the sentiment toward price, quality, delivery or seller services. Such abilities, performed by the self-attention mechanism in the neural network models, allow more precise detection than existing methods adopting lexicon or RNN.

3.5 Decision Intelligence & Price Comparison Layer

These forecasting results are then fed to a multi-criteria decision making system for actionable recommendations. The platforms are rated according to potential future prices, current prices, sentiment scores and reliability of sellers. TOPSIS, AHP or Weighted Score method etc., can be used for trading down and comparison of accepting different criteria. Hence, a “buy now or wait” recommendation is developed around platforms that display positive pricing dynamics and more satisfied users.

3.6 Visualization & User Interaction Layer

It is the layer that provides its users with an interface so interaction with a system as easy as possible. It demonstrates historical and projected price trends with interactive graphs, summarizes various aspects that contribute to sentiment in summary cards, and provides visually appealing word clouds at the aspect level to display sentiment. You can run product-specific searches, filter by date range and view suggested places to buy. You won’t have to monitor constantly, either; automated alerts can tell you when prices are due to fall or if an attractive buying opportunity arises. In a nutshell, this layer ensures that the system stays user-centric, accessible and actionable in real time.

4. Methodology

4.1 Algorithms for Web Scraping

It begins with automated data extraction (structured or unstructured) from a wide range of e-commerce websites, done by two faceted approaches: crawling for extensive coverage.

4.1.1 Static Scraping: Requests + BeautifulSoup

For the static html ones, Python’s Requests gets the pages and Beautiful Soup parses the HTML DOM. Content like prices, metadata and user reviews is then extracted by CSS selectors or XPath. If there are duplicates and data that do not belong lines can be extracts. This approach its light, fast and can be scaled; you can get tons of data in no time, without browser automation.

4.1.2 Dynamic Scraping: Selenium/Playwright

Dynamic scraping - is browser- headless automation used for the dynamic and JavaScript pages. Whether you use Selenium or Playwright page rendering, element interaction and dealing with Enumerable Scrolling / AJAX content load are handled so as to scrape all relevant product and review data even for instantaneous stuff. Dynamic crawling complements static scraping to create a complete and reliable dataset for subsequent analysis.

4.2 Data Preprocessing Techniques

Data cleaning, standardization and structuring stage after collecting data. Pre-processing maintains the quality, and the temporal consistency as well as the readiness of data for training model.

4.2.1 Preprocessing:

Cleaning and Smoothing of Time Series Cleaning the price data was done by filling missing values using interpolation and by outlier detection utilising z-score or IQR method. Finally, we apply alignment and re-sampled the timestamps to regularize time. In this way, the smoothening process eliminates noise without losing important patterns and seasonality needed for accurate prediction using the hybrid ARIMA-LSTM method.

4.2.2 Text Preprocessing

Customer reviews concatenate three kinds of text processing: text tokenization (i.e., division into separate words), lemmatization (transform a word to its base form) and stop-words removal. Other processing methods to standardize text may include the removal of punctuation, lower case conversion, and special characters removal. Such processing techniques are used to process data for sentiment analysis for the Transformers algorithm.

4.3 ARIMA & LSTM

The hybrid forecasting module combines ARIMA and LSTM methods to capture both linear trend and non-linear data trends. ARIMA represents the linear dependence these trends and seasonality in historic data prices. The residuals from the ARIMA-forecast, which represent nonlinear components in the data, are transferred as input to the LSTM unit. The LSTM network captures the long-range relationship and discontinuity of residual series. The forecast for the aggregated time series is derived by summing up the ARIMA forecast of individual small-scale series and residual forecasts using LSTM.

4.4 Connection to Sentiment

The sentiment analysis module utilizes the Transformer model (e.g., BERT, RoBERTa) to acquire contextualized embedding's for review texts. The framework trains the model to identify the semantic sentiment of a review, and extract opinions regarding quality, price, delivery and sale services. Thus self-attention in the model makes it possible for understanding long-range dependencies are now and then sarcasm for a reasoning of review texts by users. Aspect-level sentiment extraction enables analysis on review texts beyond the overall sentiment.

4.5 Multi-Criteria Decision

The forecast prices and outputs of sentiments are aggregated into a decision-making process, to present the optimal platforms for buying. The criteria are based on the predicted future price of platforms, the current price of platforms, sentiment scores and reliability of sellers. Weights are then applied to these normalised criteria. The method relies on TOPSIS, AHP or weighted scoring. The result of applying this process is a solution for buyers that exceeds the part-in platform purchase price. What the solution offers: buy now or wait advice; Price Alert notifications.

5. Experiments and Results

The hybrid model and framework for the proposed neural network were validated using practical real-world data from different online markets in which past historical information concatenated with user reviews. The dataset is composed by over 20K historical records and more than 100k text review entries. The historical records contained time, ID, vendor and platform. The texts provided customers' feedback on quality, delivery and support. Such approach has made it possible for us to evaluate both precision and applicability of the method under consideration.

In the price prediction problem, our ARIMA & LSTM hybrid model was evaluated along with base ARIMA and LSTM models with different hyper-parameter settings such as RMSE, MAE and MAPE. In all the cases it was found that our hybrid model had lower errors, as shown in Table 1 below. Base ARIMA model was applied to linear trend and seasonality, while base LSTM model was used for nonlinear aspect, both worked together to reduce residuals which helped in enhancing short-term or mid-range predictions.

Table 1. Forecasting Performance Comparison

Model	RMSE	MAE	MAPE
ARIMA	24.5	19.3	7.8%
LSTM	18.2	14.1	5.2%
Hybrid ARIMA–LSTM	11.7	9.3	3.1%

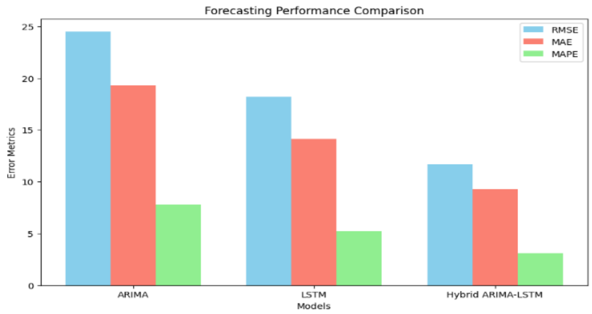


Figure 1: Forecasting Performance Comparison (Bar Chart showing RMSE, MAE, MAPE for ARIMA, LSTM, Hybrid ARIMA–LSTM)

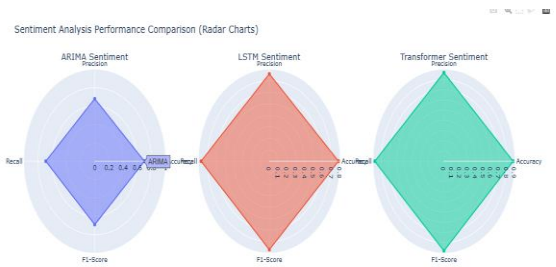


Figure 2: Sentiment Analysis Performance Comparison (Radar Charts for ARIMA, LSTM, and Transformer models)

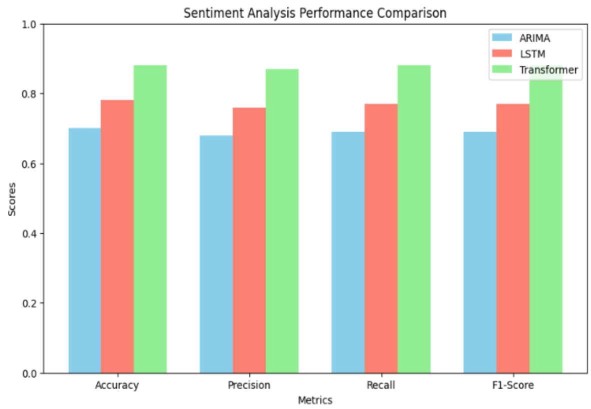


Figure 3: Sentiment Analysis Performance Comparison (Bar Chart showing Accuracy,

Precision, Recall, F1-Score for ARIMA, LSTM, Transformer)

The performance measures for the sentiment analysis task were accuracy, F1-score, precision and recall. The transformer model achieved higher performance as compared to the classic classifiers and sentiment models based on RNN. The relation in context could be captured by the self-attention mechanism of Transformer-model which made it to process longer sequences of text data, and also detect whether a statement is sarcastic or not for improved polarity based and aspect based sentiment analysis. The polarity of pricing, quality and delivery were discovered by the Transformer model. The system provided prudent suggestions and notifications with combination of predicted price trends and sentiment information. It also had a multi criteria decision-making aspect that evaluated the other on line facilities on the basis of projected price, and trustworthiness of sellers. The alerts were also produced according to the thresholds established by the users when the predicted decreasing prices fell below the limit values that had been set for them so as to permit accurate buys. Overall, the findings showed that the hybrid model outperformed all baselines in all dimensions. The addition of the ARIMA-LSTM component enhanced the prediction capacity of pricing suggestions, the classification for sentiment weaknesses were stronger and recommendations based on various criteria had helpful insights that expanded beyond price-only recommendations from baseline models.

6. Discussion

The observations for the new hybrid methodology experiment, have yielded several significant insights. The ARIMA-LSTM hybrid model shows that applying both linear and nonlinear learning ideas results in a significant improvement in predicting erratic price patterns. This hybrid model traces seasonality and sudden changes very accurately, obtaining lower errors in short and mid-range sequences than other stand-alone models. And the thing here is that in an environment where prices are also changing overall, like an e-commerce or stock market scenario, it makes real sense to use hybridization. The sentiment analysis module is empowered by the force of Transformer tech, offering solid in-depth perception to what customers are saying in their reviews, whether it’s lengthy amount of text, industry-specific terms or implicit formats like sarcasm.

The aspect-level sentiment information is captured, so the customer’s attitude toward price, quality, and delivery can be better distinguished and more informative results are obtained than simple lexicon-based methods and RNNs. The system then returns recommendations based on a combination of the sentiment information and forecasted prices. Compared with existing price monitoring solutions, the proposed approach explains itself significantly more much better. Conventional solutions are primarily based on the static analysis of prices, forecast driven by a single model and superficial sentiment analysis. This reduces their predictiveness and their, value as decision-support tools.” Our method leverages combinatorial power of Hybrid forecasting techniques and in-context analysis at the deeper layers of sentiment analysis and ranking tool to create intelligence and predictive power in price monitoring. In some way, but with some limits still being taken into account. The effective functioning of this system depends on the mined data itself, and dynamic scraping is confronted by challenges on pages having widespread obfuscation or restriction. Right now, real-time streaming can only do batch processing and not monitoring. And it is also limited in the multilingual market because of analysing English reviews. There are also more opportunities for optimization in large numerous system deployment and cloud infrastructure integration.

7. Conclusion

The proposed approach integrates a hybrid structure comprised from ARIMA and LSTM models as well as the Sentiment analysis spark by Transformer model. In combination they produce a predictive and explanatory model of e-commerce pricing. The model is capable for automatically data collection and cleansing, integrates the hybrid model, and interprets its results using a multi-criteria approach. From the experiments, it's shown that:1) The error rate of hybrid ARIMA-LSTM model is less than other methods applied separately and it also significantly enhances the Transformer model to more correctly understand user opinion in terms of predictive accuracy and interpretability. This model has an important application in e-commerce and finance. The model is capable of a higher level mechanism on how purchase and investment decision are entwined in terms of pricing and opinion. In the future, one might also merge this work with image or social media content for a better sentiment and trends analysis. Finally, there is more value to be achieved on real-time streaming, dynamic alerting and response. The study ought to be extended in the future through enhancing the work by hybrid forecasting models, sentiment analysis across various languages and use of cloud platforms. The work gives a very good algorithm in dynamic pricing area.

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