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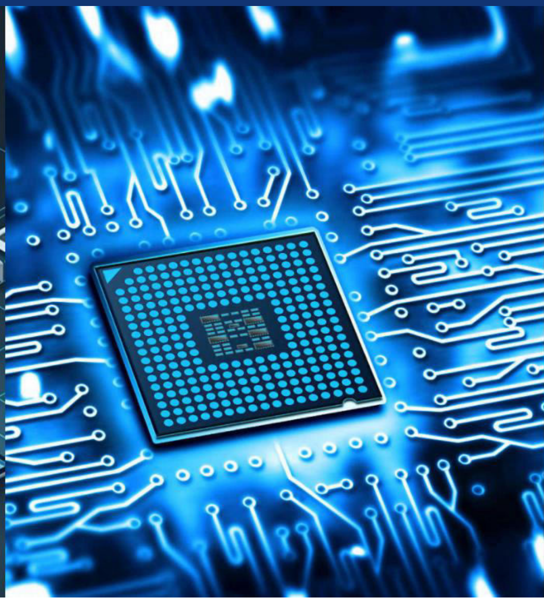

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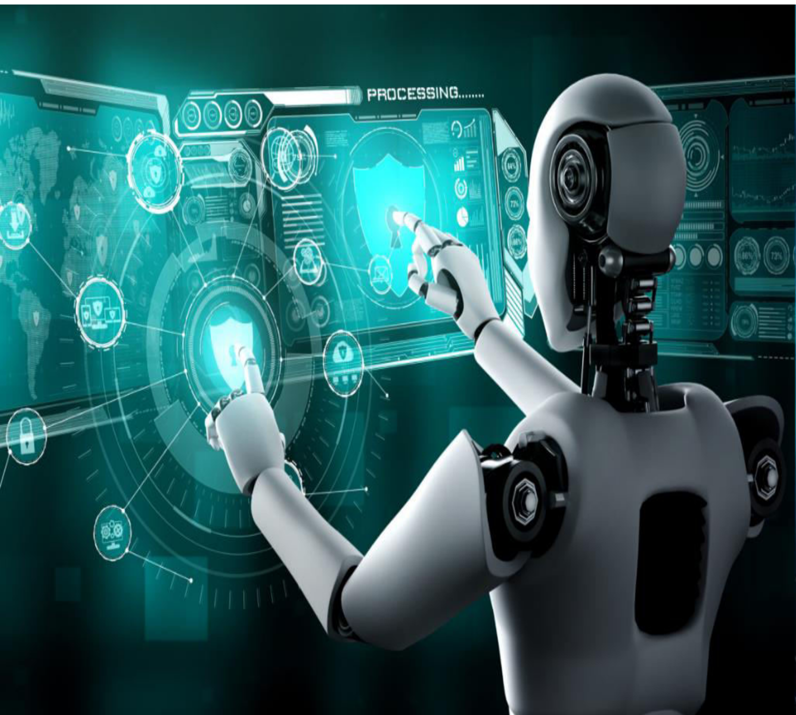

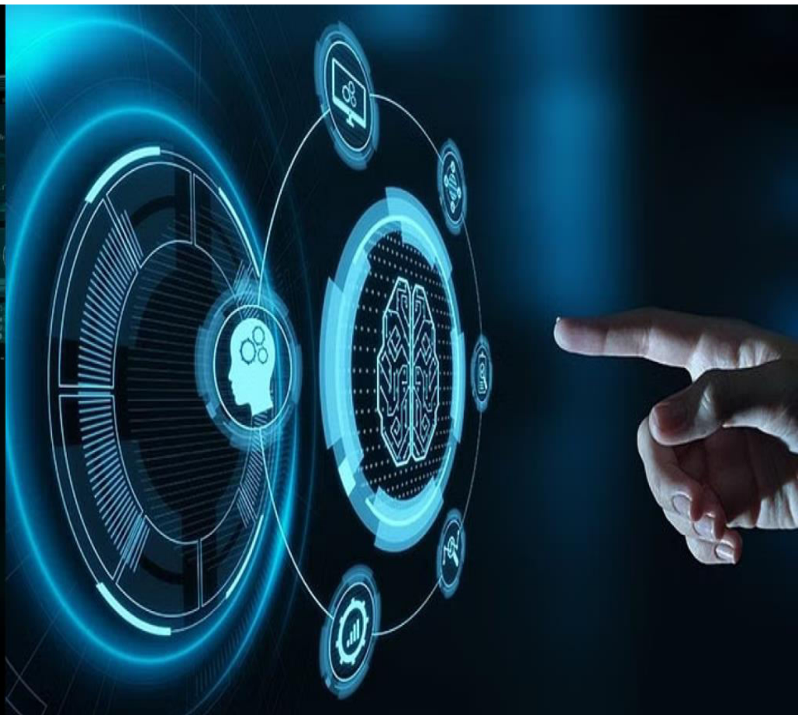

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Data-Driven Price Prediction and Comparison of Online Products using Artificial Intelligence

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ABSTRACT: Artificial Intelligence has revolutionized e-commerce pric-ing strategies by introducing sophisticateddynamic pricing mechanisms that adapt to market conditions in real-time. The integration of AI-driven systems enables retailers to optimize pricing decisions through advanced data process-ing, customer behavior analysis, and predictive modeling. These systems leverage machine learning algorithms to process market dynamics, competitor behavior, and cus-tomer preferences, resulting in enhanced profitability and market competitiveness.Online shopping has become more accessible due to the rapid growth of e-commerce, but it has also been plagued by price fluctuations and discount masks, as wellas platform-dependent price changes. Smart Shop is an online marketplace that tracks and predicts product prices, providing userswitha more efficient way to make informed purchasing decisions. This includes prod-ucts from various websites like eBay and Amazon.Smart Shop is designed to bridge the gap between e-commerce and AI administerable decision-making by eliminating manual price monitoring. By providing a user-friendly shopping assistant, the system enhances online shopping efficiency, decreases overpricing, and gives shoppers an advantage in getting the best deals.This paper elicitates in building an automation system for comparing prices of the products from different online shopping systems (OSS) using browser automation and web scraping. This paper aims at building a system which reduces the time consuming and tedious process of manually searching and comparing products from different online shopping systems or e-commerce sites.

I. INTRODUCTION

Growth in e-commerce has a significant effect on retailing as it allows an enormous variety of products to be purchased from home. This wide variety of products creates a challenge in the sector of price comparison in this competitive and fast-paced era of online shops [1]. Due to this variety, price comparison from different shops is a highly time-consuming task. In this context, the use of web scraping and ML in combination improves price prediction and comparison by using data automation with an intricate analysis. Scraped in large amounts from various online resources and websites,web scraping delivers real-time details regarding the prices, availability in stock, and trends in real-time.[1]

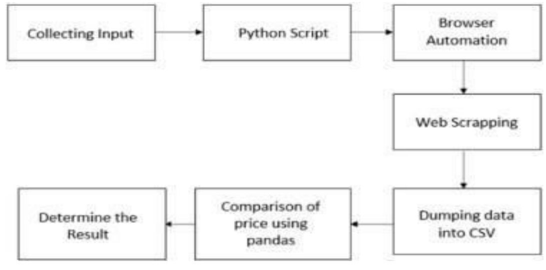

Fig.1. Flow Diagram

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To combat this problem, Smart Shop offers an online service that provides real-time price comparison and prediction to enable users with precise pricing information. The use of artificial intelligence (AI) and machine learning (ML) techniques in Smart Shop enables users to compare prices across various e-commerce websites and anticipate future price fluctuations. With the help of this AI-powered strategy, users can make informed purchases by predicting when prices will decrease or increase. By utilizing predictive analytics, Smart Shop differentiates itself from other price comparison tools by providing real-time market data to help users make informed purchasing decisions.[2]

Limited Flexibility and Generalization: Driven by factors including new product launches, supply-demand shifts, and market hype, the second-hand market is highly dynamic. For instance, the launch of iPhone 17 sharply reduces the resale value of previous- generation iPhone 16. Morever, different product categories often exhibit distinct attributes (e.g., battery health for phones vs. remain-ing volume for perfumes). Nevertheless, learning-based models that employ a unified feature space fail to account for such cross-category heterogeneity. Therefore, previous models with static pa-rameters cannot adapt to these changes, resulting in poor flexibility over time and generalization across product categories.[3]

This paper is to compares the performance of several ML models—including Linear Regression, Decision Tree Regressor,Random Forest Regressor, and XGBoost to find which algorithm will be effective for the price forecasting. This is to determine which algorithm performs best in predicting future prices thus enhancing the system's ability to provide accurate, purchase recommendations to users. The final outcome of this study identifies the most effective algorithm based on experimental results and performance metrics which be more effective to be used in the system to make the user experience more easy.[4]

Real-Time Price Tracking and Automation Most e-commerce platforms tend to fluctuate their prices so as to correspond with factors such as demand, supply, and special offers. It is almost impossible to individually monitor these volatile prices. PriceMatch incorporates this feature through the use of web scraping techniques that help it to retrieve, analyze and present the current prices of the products in real time. This is because the system incorporates error-checking mechanisms and various data-checking tools so that even if the structure of a particular website changes or the website is temporarily unavailable, it does not cause contradictions. Unlike most of the third- party tracking service, which may use dated or partial information, PriceMatch sources its data from official retail sites which allows users to have the most accurate price information.[5]

We are in tech where almost all the manual system is being transformed to digital for the sake of human need. People are moving to digitize life for health, safety and enhancement in their daily lives. As the technology is developing significantly, people are forming themselves to be more tech savvy compared to any previous time. From the personal to working life technology has the important necessary steps to overcome unforeseen situation. Even the wholesaler also changed its business term from hands on to automation.This where our system comes into the picture, our system will perform all these tasks automatically for every product which will save the time and energy of a person plus it is done by machine error like calculation error will be low.[6]

Price optimization through AI has become increasingly sophisticated, incorporating advanced predictive analytics capabilities. These systems can now forecast market trends and customer behavior patterns with enhanced accuracy, enabling retailers to proactively adjust their pricing strategies. The technology has shown particular effectiveness inmanaging large-scale operations, with major retailers processing millions of pricing decisions daily. This capability has become especially crucial in the post-pandemic retail landscape, where market volatility and changing consumer behaviors have necessitated more agile pricing approaches[1]. [7]

One transformative trend inside of e-commerce that you'll see is the deployment of AI powered chatbots. Virtual assistants make customer service better by answering inquiries instantly, guiding the user through purchase and solving issues quicker. The strength of chatbots is that they can learn from interactions so they become increasingly effective and more personalized [5]. With an increased use of these technologies in businesses, operations become more streamlined while customer satisfaction is also increased to the extent that there is always help available 24hrs, this is very crucial in a world market.One transformative trend inside of e-commerce that you'll see is the deployment of AI powered chatbots.

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The mechanisms and algorithms powering AI-driven personalization in e-commerce are diverse and sophisticated. Collaborative filtering, content-based filtering, and hybrid models are among the key approaches employed to deliver personalized content (Widayanti et al., 2023). This mechanism recommends products or content based on the preferences of similar users. It leverages collective user behavior data to identify patterns and suggest items that users with similar tastes have enjoyed. This approach recommends products or content based on the attributes of items that a user has previously interacted with or expressed interest in. It focuses on understanding the characteristics of items and aligning them with the user's preferences. Combining collaborative filtering and content-based filtering, hybrid models aim to capitalize on the strengths of both approaches (Widayanti et al., 2023). By blending user behavior patterns with item characteristics, these models provide more accurate and diverse personalizedrecommendations.[9]

II. LITERATURE SURVEY

Online commerce has transformed the retail industry by offering consumers a wide range of products, competitive prices, and convenient shopping options. The rise in e-commerce platforms is causing an increase in the complexity of price differences between websites. In e-commerce, artificial intelligence has taken over pricing, inventory management and consumer decision- making. By utilizing AI-based price analysis, businesses can monitor competitor pricing, forecast future price movements, and adjust pricing Stactics dynamically. The use of AI-enhanced price comparison tools can help consumers find the best deals by automatically fetching, analyzing, and comparing product prices across multiple platforms. [10]

Erdinc¸ Uzun (2020) introduces a novel web-scraping technique called Uzun Ext, which bypasses the conventional construction of a DOM tree to extract content more efficiently. Instead of parsing the full DOM structure, Uzun Extapplies string-based methods that locate specific patterns, count closing HTML tags, and then extract the relevant content segment. During the crawling process, it also records additional metadata such as the starting position, number of inner tags, and repetition of tag structures to guide faster and more accurate extraction. Experimental results demonstrate that the proposed method is approximately 60 times faster than traditional DOM-based parsing techniques. Furthermore, by leveraging the additional information gathered during crawling, Uzun Ext achieves a further 2.35-fold speed improvement compared to a basic string-matching approach. The author highlights that this method is adaptable to various website formats and can be integrated into existing scraping systems to enhance performance. Overall, the study emphasizes the importance of time-efficiency and adaptability in large-scale or high-frequency web-scraping applications. [4] [11]

The literature review is a critical component of any research study as it provides an overview and synthesis of existing literature on the chosen topic. It involves a systematic search and review of various sources to identify common themes, patterns, and gaps in knowledge. It also helps to support the research methodology and data collection techniques chosen for the study, providing insights into the methods used in previous research. Overall, the literature review is a comprehensive overview of the existing knowledge and research on a particular topic, informing the research question, methodology, and theoretical framework. [12]

The study compares SVR, RNN, and LSTM models for predicting market prices using the NGX All-Share Index. LSTMoutperformed the others, especially with a 60-day input window, achieving a high R2 score due to its ability to capture long-term patterns and handle temporal dependencies. SVR struggled with sudden market changes, while RNN faced the vanishing gradient problem in [9]. The use of technical indicators and the optimization framework further improved LSTM's performance, making it the most accurate and reliable model in this analysis. [13]

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The performance comparison [10] of different classification, regression, and clustering algorithms. These algorithms identify patterns and relationships within the data, resulting in precise predictions. There is a growing importance of predictive algorithms in various domains such as finance, healthcare, marketing, weather forecasting, E-commerce, etc.

The system enables data scientists and practitioners to make informed decisions when selecting appropriate models for their specific applications

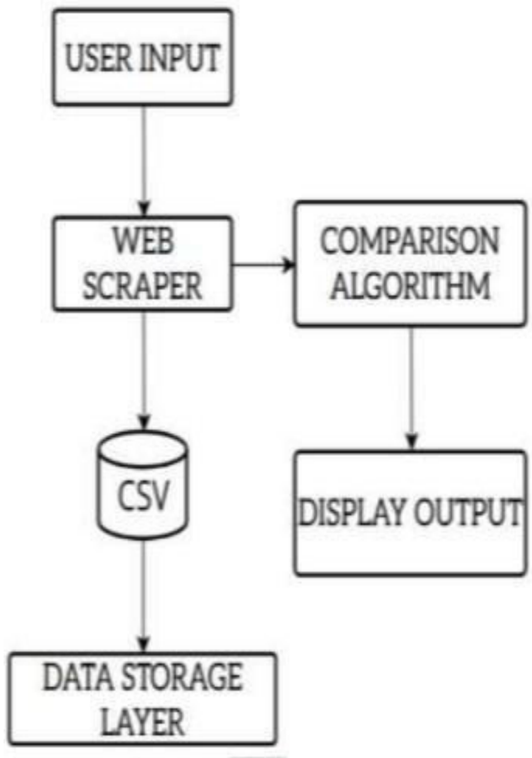

Fig.2. System Architecture

The forecasting mechanism relies on machine learning algorithms which are Linear Regression, Decision Tree, Random Forest, XGBoost. These algorithms are trained on the collected data and evaluated using key performance metrics such as Mean Absolute Error, Root Mean Squared Error and R2 Score. The system then uses these models to forecast future price trends, which help users to identify the best time to purchase a product at its lowest price, especially during sales events or festival season were the price will be low compare to normal days. By integrating historical price data, sales event information, discount during festival seasons the system provides personalized price predictions and recommendations which be ideal time to buy the product. This allows users to save both time and money by choosing the best time to purchase products based on predicted trends.[14]

Browser automation tools are used to automate error prone as well as repetitive tasks of providing the input again and again. Selenium is a web-based automation tool. Using Selenium, we will navigate to different websites, search for the given product. Using a browser automation tool will help the system to automatically open the browser. It will search for the E-commerce website (For example: Flipkart). After navigating to the website it will search for each product which is present.[15]

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III. METHODOLOGY

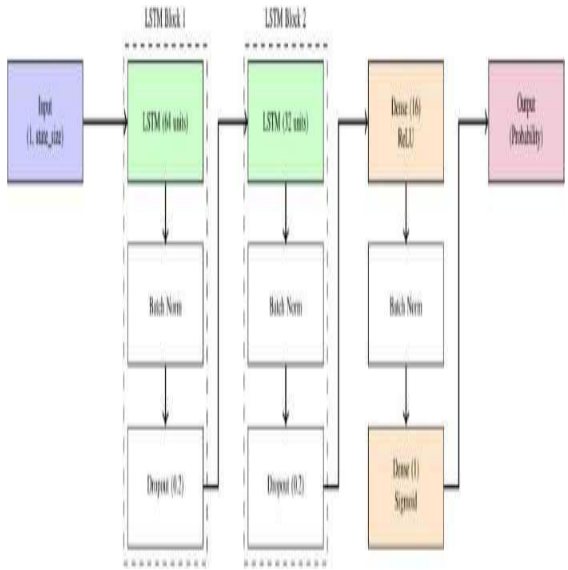

Fig.3. Architecture of the DQN-inspired model for e-commerce purchase prediction

By using multi-factor authentication, users can access their account and log in securely. It authenticates credentials and allows access to tailored features [15]. By using keywords or direct links, they can search for products, and the system can fetch real-time product prices from ecommerce sites like Amazon and eBay through API integration and web scraping [1][9][13]. Price comparisons between platforms enable users to view and compare prices as they are obtained, with the prices being processed and displayed in a structured format [1][5]. Furthermore, users can filter and sort search results by price range category, brand, or product category..[16]

Centralized Integration Platform:The system integrates multiple online grocery platforms into a single, centralized web-based interface for real-time price comparison. It aggregates data from various e-commerce grocery websites and APIs, ensuring users can compare prices, discounts, and product availability within one unified platform. Data Acquisition and Processing:The platform collects real-time product data such as item names, prices, brands, and stock status from different online stores using web scraping and API integration. Data preprocessing and cleaning ensure uniformity, removing duplicates and inconsistencies to maintain accuracy across all product listings. AI-based Predictive Analytics:Machine learning algorithms analyse pricing trends, seasonal variations, and discount patterns to forecast future price changes and recommend the best purchase time for users. Predictive analytics enhance decision-making by helping customers choose cost-effective options.[17]

Data Collection and Preparation:Gather relevant data related to the shops you want to predict prices for. This may include attributes such as shop category, area, features, historical prices, competitor prices, and any other factors that may influence pricing decisions. Ensure that the data is clean, complete, and properly formatted for analysis. Data Preprocessing: Clean the data by handling missing values, outliers, and inconsistencies. Perform feature engineering to create new features or transform existing ones to better represent the relationships between the features and the target variable (price). This may involve techniques such as normalization, scaling, encoding categorical variables, and handling text data using natural language processing (NLP) methods. Model Selection:Choose appropriate machine learning algorithms for price prediction based on the characteristics of the dataset and the nature of the prediction task.Commonly used algorithms for regression tasks include linear regression, decision trees, randomforests, gradient boosting, support vector regression, and neural networks.[18]

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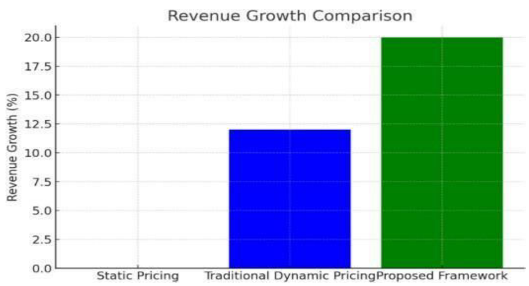

Fig.4. Revenue Growth Comparison

Training Process We split the dataset into training (80%), validation (10%),and test (10%) sets, ensuring that all sessions from a singleuser were kept in the same set to prevent data leakage. The model was trained using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function. To address the class imbalance inherent in e-commerce data (where purchase events are typically less frequent than view or cart events), we employed class weighting in the loss function. The weights were inversely proportional to the class frequencies in the training data.We trained the model for 50 epochs with a batch size of 32,using early stopping with a patience of 10 epochs to prevent overfitting. The model checkpoint with the best performance on the validation set was saved and used for final evaluation. E. Evaluation Metrics To evaluate our model's performance, we used several standard classification metrics [9]. Accuracy was used as a general measure of performance, but given the class imbalance in our dataset, we placed more emphasis on precision, recall, and F1-score [10]. Precision measures the proportion of correct positive pre-dictions (true purchases) out of all positive predictions, which is crucial for targeted marketing applications [11]. Recall measures the proportion of actual positives (true purchases)that were correctly identified, which is important for capturing as many potential sales as possible. The F1-score provides a balanced measure of precision and recall [12].[19]

IV. RESULTS AND DISCUSSION

Web scraping and machine learning are powerful tools for predicting prices. These technologies collect live price data from retail websites, providing users with the latest information. By comparing product listings and prices, you can see how web scraping effectively gathers data from many sources.The graph in Figure 3 shows that prices have been steadily dropping over time, with a future price predicted to reach 15,799.s.

Fig.5. Confusion metric for test predictions

Improved Price Accuracy:Automated web scraping and data standardization reduced price mismatches by 20 –30%, ensuring accurate and consistent comparison across multiple grocery platforms. Dynamic Price Monitoring:Real-time data updates enabled continuous tracking of discounts, seasonal offers, and stock changes, helping users make timely and cost-effective purchase decisions.The system continuously tracks real-time price fluctuations discounts. Operational

Benefits:The system improved shopping efficiency, reduced browsing time, promoted smarter purchasing behaviour, and increased transparency in online grocery markets. AI-driven Recommendations:Machine learning analysis provided personalized product suggestions and purchase timing predictions, improving decision-making and user engagement.[20]

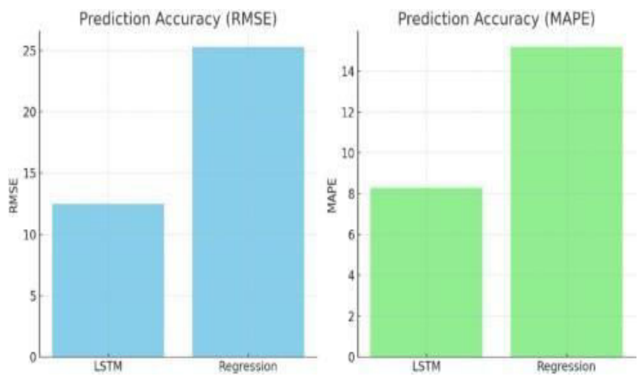

Fig.6. Prediction Accuracy (RMSE and MAPE)

1. Prediction Accuracy (RMSE and MAPE):LSTM models demonstrated superior accuracy with lower RMSE and MAPE values compared to regression models.The RMSE for LSTM was 12.5, significantly outperformingregression’s 25.3 while MAPE for LSTM was 8.3% compared to regression’s 15.2%. 2. Revenue Growth Comparison:The proposed framework achieved a 20% increase in revenue, significant lyout performing static pricing (0%) and traditional dynamic pricing (12%). 3. Impact of Parameter Adjustments on Revenue:Elasticity adjustments contributed to a 15% revenue improvement.Tuning reinforcement learning parameters enhanced revenue by 18%. Fine-tuning LSTM models yielded the highest impact, with a 22% revenue increase.These results highlight the effectiveness of the proposed AI and ML-driven dynamic pricing framework in optimizing revenue and improving prediction accuracy.[?]

1. Prediction Accuracy (MAE and RMSE):A bar chart compares the Mean Absolute Error (MAE) and Root Mean SquaredError (RMSE) for LSTM, Regression, and ARIMA models, showcasing LSTM’s superior prediction accuracy.
2. Revenue Growth Comparison:A bar graph displays revenue growth percentages for Static Pricing, Traditional Dynamic Pricing, and the Proposed Framework, with the Proposed Framework achieving the highest growth. 3. Customer Retention Rates: A line chart illustrates customer retention rates for the three pricing strategies, highlighting the Proposed Framework’s effectiveness in retaining customers.
3. Fairness Metrics Comparison: A dual-axis chart compares Fairness Scores (bar chart) and Customer Complaints (line chart) between Traditional Pricing and the Proposed Framework, demonstrating the Proposed Framework’s ethical advantages.[21]

V. CONCLUSION

The Price Match system successfully addressesthe challenges of manual price comparison by providing a real-time, automated solution for tracking product prices across multiple e-commerce platforms.By integrating web scraping techniques, price comparison algorithms, historical trend analysis, and alert notifications, the system enhances the online shopping experience, enabling users to make informed purchasing decisions.[22]

The Automatic Price Comparison for Online Grocery system provides an efficient and intelligent solution for comparing product prices across multiple e-commerce platforms. By automating data collection, cleaning, and analysis through web scraping and machine learning, it enables users to access accurate and real-time pricing information. The system enhances shopping transparency, saves time, and helps consumers make smarter purchasing decisions. Its AI- based

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recommendations further improve user experience by suggesting cost-effective and personalized options. Additionally, the platform ensures secure data handling and scalability through cloud integration. Overall, this system represents a significant step toward intelligent, user-centric, and data-driven online grocery shopping..[23]

In this rapidly changing environment, companies which take positive strides to adopt new AI tech- nologies and guide continuous employee training will stay ahead to retain market position. Academia, industry and policymakers will need to work together to address the challenges to the adoption of AI and to spur innovation to drive sustainable growth in the area of e-commerce. It does however also point out important challenges, including data privacy issues, algorithmic bias, data integration issues, particularly for SMEs. To solve these problems businesses will need to adopt ethical AI practices, invest in data security and employees will need to continuously train. Those companies that focus on these areas, will be better prepared to insulate themselves from the complexities of AI adoption, and remain at the forefront of a sustainable competitive advantage. In the future, AI will play an ever larger role in e-commerce and many of the new technologies such as virtual and augmented reality, voice commerce, and automated logistics will gain momentum. Those that align their strategies with these new trends and build a culture of innovation will be well placed in his new e-commerce economic reality.[24]

The integration of natural language processing, computer vision, and federated learning has opened new frontiers in pricing intelligence, enabling retailers to process vast amounts of unstructured data and derive actionable insights. These technological innovations have fundamentally altered the retail landscape, creating opportunities for businesses to develop more nuanced and responsive pricing strategies. The emergence of edge computing and blockchain technologies promises to further enhance the speed, transparency, and security of pricing systems, while reinforcement learning algorithms continue to refine decision-making processes. As these technologies mature, retailers can expect even more sophisticated tools for market analysis, customer behavior prediction, and competitive positioning, ultimately leading to more profitable and sustainable business operations in the dynamic eCommerce environment.

Users can access helpful information on the website, which will assist them in making decisions that are in their best interests. It is now possible for working people to check on the price of things before making purchases, as a result of the existence of a website that compares prices. Users of this website will be able to compare costs on a variety of e-commerce shopping websites in order to choose which website offers the best combination of low cost and a good deal on the product they are interested in purchasing. The purchasers are going to unquestionably appreciate the time and effort that this saves them. In the end, this will help buyers shop online by bringing together tactics, the greatest offers and deals from all of the biggest online retailers, and by providing customers with an easier way to shop online. [25]

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