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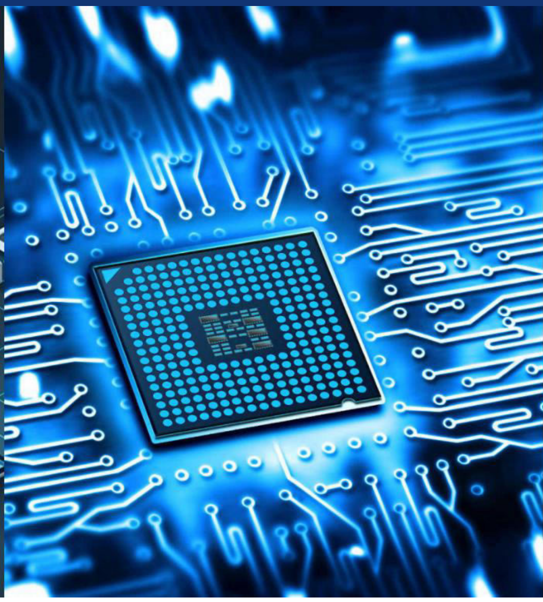

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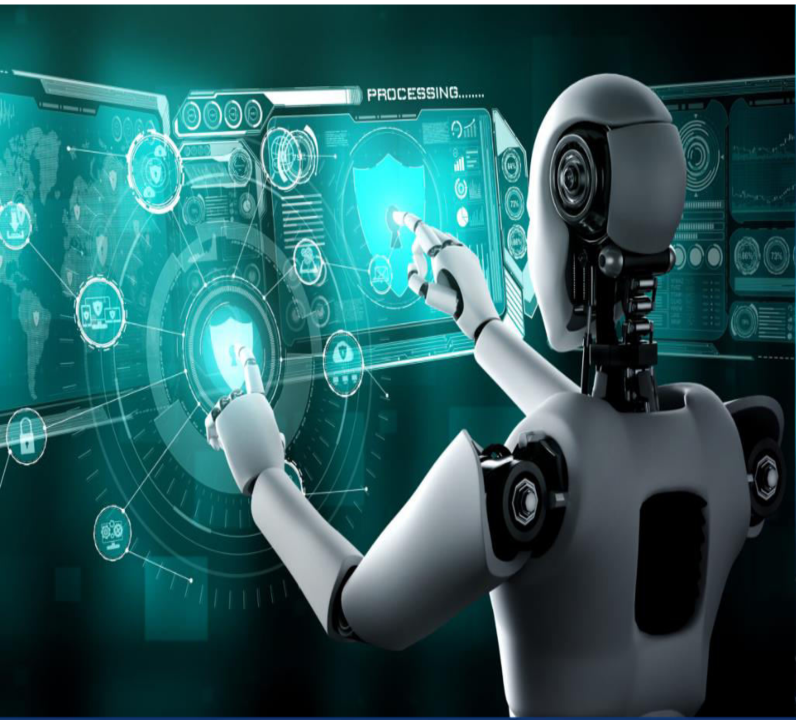

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An Effective Approach for Dynamic Pricing using DL-Optimizer

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ABSTRACT: Dynamic pricing enables companies to instantly modify prices in response to consumer behaviour, demand, and market trends. The goal of this research is to optimise dynamic pricing strategies through the use of deep learning (DL). It analyzes big datasets, including purchasing history, rival prices, and market demand. DL models recognise trends and recommend the ideal rates to maximize revenue. Dynamic pricing has become a key tactic in the travel sector, helping businesses to increase revenue, improve operational effectiveness, and react quickly to changes in the market. Airlines, hotels, ride-sharing platforms, and other travel service companies use real-time data and sophisticated machine learning algorithms to modify prices according to factors like demand trends, booking times, rival rates, customer behaviour, and inventory quantities. The technology and processes that support dynamic pricing are examined in this article, including big data integration, AI-driven models, and predictive, analytics.

KEYWORDS: Deep-Learning, Dynamic Pricing, Linear Regression, Bidirectional GRU

I.INTRODUCTION

Fixed prices are no longer effective because markets are changing quickly. Deep Learning (DL) Optimization combined with dynamic pricing enables companies to instantly modify prices in response to consumer demand and behavior. Our suggested deep learning-based model, DL-Optimizer, leverages sophisticated algorithms including Linear Regression, Temporal Convolutional Networks (TCN), Bidirectional GRU, and Iterated Dilated CNN (ID-CNN) to forecast optimal prices in real time through dynamic pricing. In contrast to conventional static pricing systems, which use fixed rates regardless of market conditions, DL-Optimizer dynamically modifies prices by continuously analysing demand patterns, historical data, and outside factors. By adjusting prices to reflect changes in the market and customer behaviour, this flexible strategy helps businesses optimise profits. DL-Optimizer improves price agility and forecast accuracy by combining many deep learning architectures, guaranteeing that companies stay profitable and competitive in quickly evolving markets. The difference between static and dynamic pricing is shown in fig 1.1.

In the paper, we explained the related works in section II, Background of which algorithms used and implemented in our Dynamic pricing is explained in section III in detail. Our Proposed methodology in section IV, our model uses an ensemble method of classifiers where Linear Regression concepts are the base for our algorithm and in section V the comparative results are shown using graphical representations and we concluded, and future works focused on section VI.

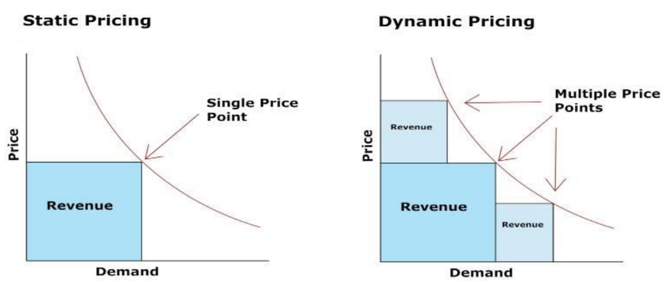

Fig: 1.1 This figure explains static and dynamic pricing

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II.RELATED WORKS

According to the research, AI-driven dynamic pricing strategies are replacing conventional static pricing models. Although ML and DL techniques like regression, RNNs, and Transformers increase the accuracy of price predictions, they have drawbacks like scalability and data quality. Real-time market adaption is made possible by deep learning. To improve dynamic pricing and increase organisational revenue, we have presented a **DL-Optimizer** that combines Linear Regression, TCN, Bi-GRU, and ID-CNN.

S.no	Paper _information	Description	Limitations / Inference
1.	Hofmann, Martin, Florian Neukart, and Thomas Bäck (2017) Artificial intelligence and data science in the automotive industry [1]	Explores how AI and data science transform the automotive industry with applications in smart manufacturing and autonomous systems.	Highlights need for clean, structured data; organizational challenges in upskilling workforce and integrating AI tools.
2	Das,Sumit,etal.(2015) Applications of AI in ML: Review and Prospect [2]	Reviews ML and AI applications across industries, especially in demand forecasting and decision automation.	Emphasizes importance of data quality and suggests that more domain-specific applications are needed.
3	Bakakeu,Jupiter,etal.(2018) AI for Online Optimization of Flexible Manufacturing Systems [3]	Focuses on AI-based optimization in manufacturing systems to increase flexibility and efficiency.	Applicable to manufacturing but lacks direct extension to pricing strategies in retail or e-commerce.
4	Nagle,ThomasT.,etal.(2023) The Strategy and Tactics of Pricing [4]	Discusses foundational pricing strategies including cost-plus, value-based, and competitive pricing.	Not AI-focused; mainly useful as a theoretical backdrop for dynamic pricing frameworks.
5	Davis, Ernest, and Gary Marcus (2016) Scope and Limits of Simulation in Automated Reasoning [5]	Analyzes limits of simulation techniques in AI decision-making, especially in complex environments.	Suggests AI decisions may lack human-like reasoning and context understanding..
6	Calvano,Emilio,etal.(2019) Algorithmic Pricing and Competition Policy [6]	Investigates the risks of algorithmic collusion and its implications on competition and antitrust policies	Raises concerns about unintended price fixing due to independent AI agents.
7	Stamatopoulos,Ioannis,etal.(2021) Effects of Menu Costs via Electronic Shelf Labels [7]	Studies how adopting ESL technology reduces pricing friction and boosts retail efficiency.	Focus is more on tech-driven operational gains than on ethical/strategic aspects of pricing

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8	Gerlick, Joshua A., and Stephan M. Liozu (2020) Ethical & Legal Considerations in AI Pricing [8]	Evaluates the ethical and legal concerns of personalized pricing via AI (e.g., fairness, transparency, bias).	Strong emphasis on legal risks; calls for regulatory frameworks and clearer consumer disclosures.

III.BACKGROUND

3.1Machine Learning and Deep Learning Models

3.1.1 Linear Regression

In pricing strategies, static pricing employs a single price point, assuming a stable, linear relationship between price and demand. However, this assumption often fails in real-world scenarios where demand curves are typically non-linear, making linear regression models inadequate for accurate demand prediction. Dynamic pricing, which adjusts prices in response to fluctuating demand, requires more complex modelling techniques. Advanced models such as Temporal Convolutional Networks (TCN), Bidirectional Gated Recurrent Units (Bi-GRU), and Iterated Dilated Convolutional Neural Networks (ID-CNN) are better suited to capture these intricate demand-price patterns, thereby enhancing revenue optimization.

3.1.2Temporal Convolutional Network (TCN)

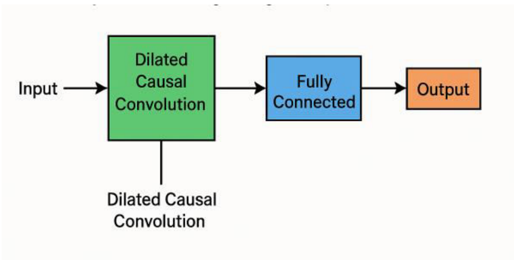

Fig3.1.2: TCN

In Fig 3.1.2 The Temporal Convolutional Network (TCN) architecture utilised in DL-Optimizer for dynamic pricing is depicted in the diagram. In order to capture historical demand trends without leaking information from future data, TCN uses 1D causal convolutions to handle sequential pricing data. By enlarging the receptive field, dilated convolutions facilitate the model's effective learning of long-range relationships. TCN is faster and more stable for price prediction than typical RNNs since it supports parallel processing. By precisely predicting changes in demand, this improves real-time dynamic pricing.

3.1.3 Bidirectional GRU(Bi-GRU)

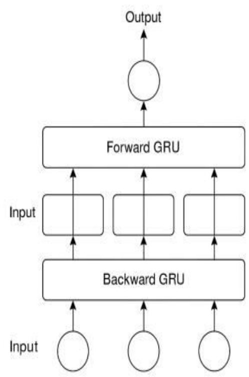

Fig 3.1.3: Bi-GRU

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The DL-Optimizer for dynamic pricing uses a Bidirectional GRU architecture, as shown in the diagram, in which input data passes through both forward and backward GRU layers. This configuration improves the model's capacity to precisely predict price changes by concurrently capturing patterns from historical and prospective settings. Real-time pricing decisions are then optimised using the combined outputs.

3.2. Dataset

A Supermarket(shopping) dataset with the following attributes are taken for analysis to perform the prediction as shown in Table 1.

Data	Attributes	Description
Shopping	Invoice ID	A unique identifier for each transaction or purchase.
Shopping	Branch	The branch location of the supermarket (e.g., A, B, or C).
Shopping	City	The city where the transaction took place (e.g., Yangon, Naypyitaw, Mandalay).
Shopping	Customer type	Type of customer – either **Member** (loyalty program) or **Normal**.
Shopping	Gender	Gender of the customer – **Male** or **Female**.
Shopping	Product line	Category of the purchased item (e.g., Health & beauty, Food & beverages).
Shopping	unit price	Price of a single unit of product before tax
Shopping	Quantity	Number of units purchased in the transaction
Shopping	Tax 5%	The 5% tax applied to the total price before tax.
Shopping	Total	Total amount paid by the customer
Shopping	Date	Date when the transaction occurred
Shopping	Time	Time of the transaction during the day
Shopping	Payment	Mode of payment used
Shopping	Cogs	Cost of goods sold
Shopping	Gross Margin percentage	Fixed gross margin percentage
Shopping	Gross income	Profit made on the transaction
Shopping	Rating	Customer rating of the transaction experience

Table1. Dataset key attributes and its description

Table1 presents a dataset focused on the collection that includes comprehensive transactional data from a supermarket that records many facets of consumer purchases. Invoice ID, branch location, city, product line, quantity, unit pricing, customer type, gender, and payment method are among its features. It also keeps track of financial information such as tax, total, gross income, cost of items sold, and customer ratings. This dataset is useful for examining sales patterns, customer behavior, and overall company performance.

IV. PROPOSED METHODOLOGY

4.1. Architecture

Fig4.1 illustrates the architecture of the dynamic pricing architecture presented in the diagram uses an ensemble model technique employing supermarket sales data. Three distinct deep learning models—the Bidirectional Gated Recurrent Unit (Bi-GRU), the Iterated Dilated Convolutional Neural Network (ID CNN), and the Temporal Convolutional Network (TCN)—process the input dataset. Before being combined, the outputs from these models go through both high and low pooling processes. To ensure optimal pricing based on patterns found in the sales data, the combined data

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is then used to generate dynamically priced data. By utilising several deep learning techniques for precise price optimisation, this architecture improves pricing strategies.

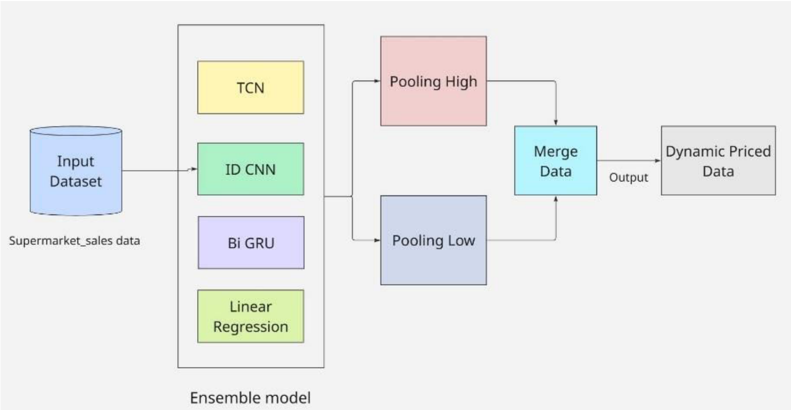

Fig4.1: Ensemble-Based Dynamic Pricing Architecture

The system can identify a variety of patterns, such as short-term trends, long-term dependencies, and sequential behaviours in consumer interactions, by integrating the advantages of several models. The pricing forecasts are more accurate and robust when ensemble learning is used. By enabling data-driven, customised pricing strategies that optimise revenue and customer pleasure, this architecture gives merchants a competitive edge by instantly adapting to shifting market conditions

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4.2. Workflow

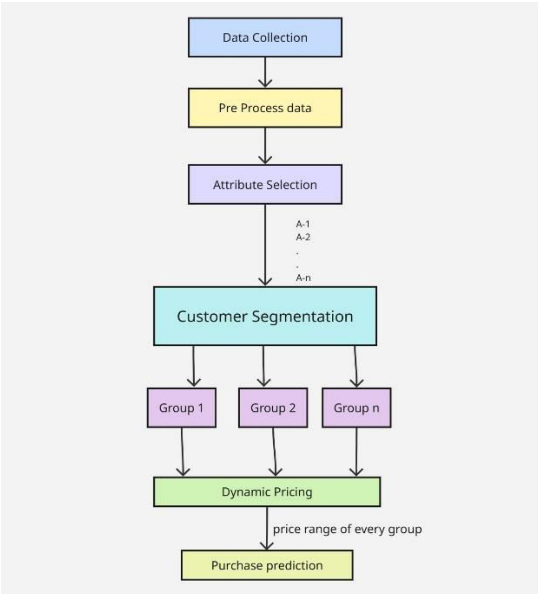

Fig 4.2: Customer-Based Dynamic Pricing Workflow

Fig. 4.2 illustrates a comprehensive workflow for Short-term trends, long-term interdependence, and sequential behaviour in client interactions are just a few of the many patterns that the system may identify by combining the advantages of several models. When ensemble learning is used, the pricing forecasts become more accurate and robust. With its ability to instantly adjust to shifting market conditions, this architecture gives merchants a competitive edge by facilitating data-driven, personalised pricing strategies that optimise sales and consumer happiness.

V. COMPARATIVE ANALYSIS AND RESULTS

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5.1. Comparative Analytic table

MODEL	**Sum of Accuracy**	**Sum of Mean Relative Error**	**Sum of Root Mean Square Error**	**SUM OF ROOT MEAN SQUARE ERROR**
Bi-Directional GRU	805.7	1.375	27.5	20.5
Gradient Boosting	851.8	0.975	23.5	16.5
Linear Regression	919.6	0.575	16.6	11.8
TCN	769.9	1.575	31.5	23.5

Fig5.1: Different model evaluations

Four machine learning models are compared in Fig.5.1, The most accurate and dependable of these is Linear Regression, which achieves the highest accuracy (919.6%) and the lowest error rates. Four machine learning models are compared in Fig.5.1,—The most accurate and dependable of these is Linear Regression, which achieves the highest accuracy (919.6%) and the lowest error rates. Although it makes somewhat more mistakes, gradient boosting is still a serious contender. TCN has the lowest ranking, with the largest errors and lowest accuracy, whereas Bi-Directional GRU performs moderately. This implies that the best model is linear regression, but TCN needs major enhancements to perform better in terms of prediction.

5.2. Results:

5.2.1 Accuracy

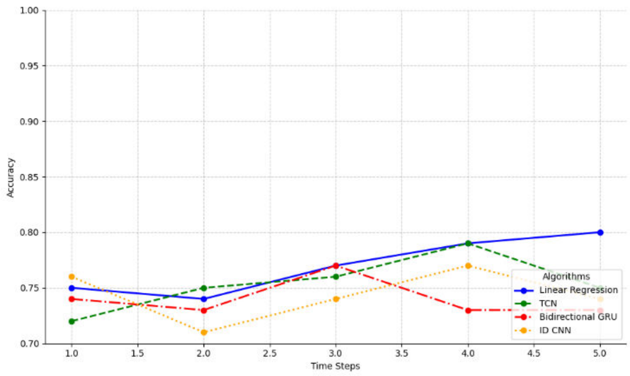

Fig5.2.1(a): Accuracy % for various Classifiers

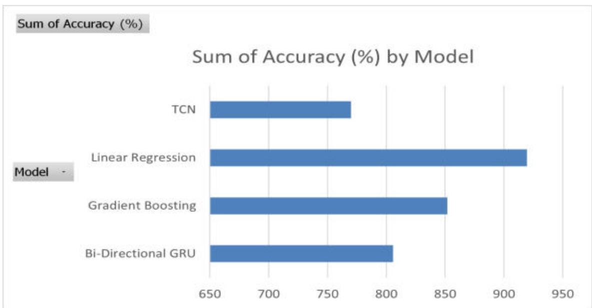

Fig5.2.1(b): Sum of Accuracy

According to the results, the most accurate model is linear regression, which is followed by gradient boosting and bi-

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directional GRU, both of which perform well. TCN maintained its competitiveness despite having somewhat reduced accuracy. Whereas TCN and Bidirectional GRU displayed erratic but improving patterns over time, Linear Search demonstrated the greatest accuracy growth. In general, the most dependable models were found to be Linear Regression and Linear Search.

5.2.2 Optimizer.py

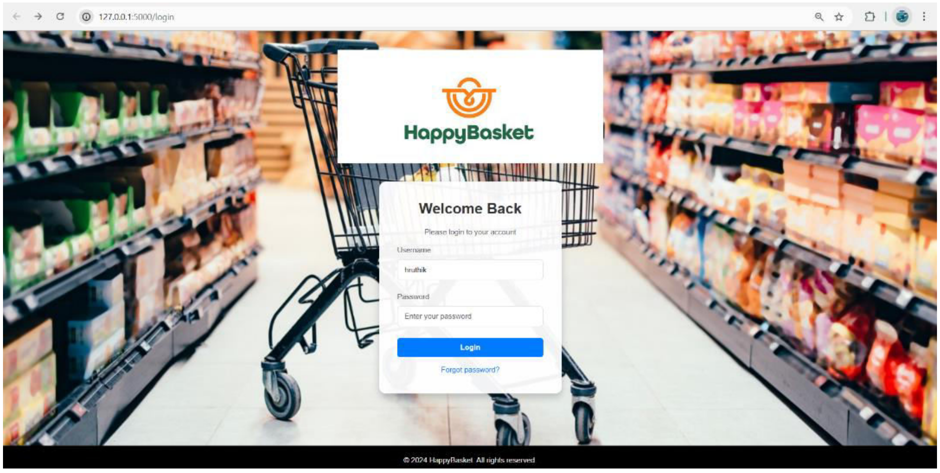

Fig1: Input page

Fig1 shows the login credentials.

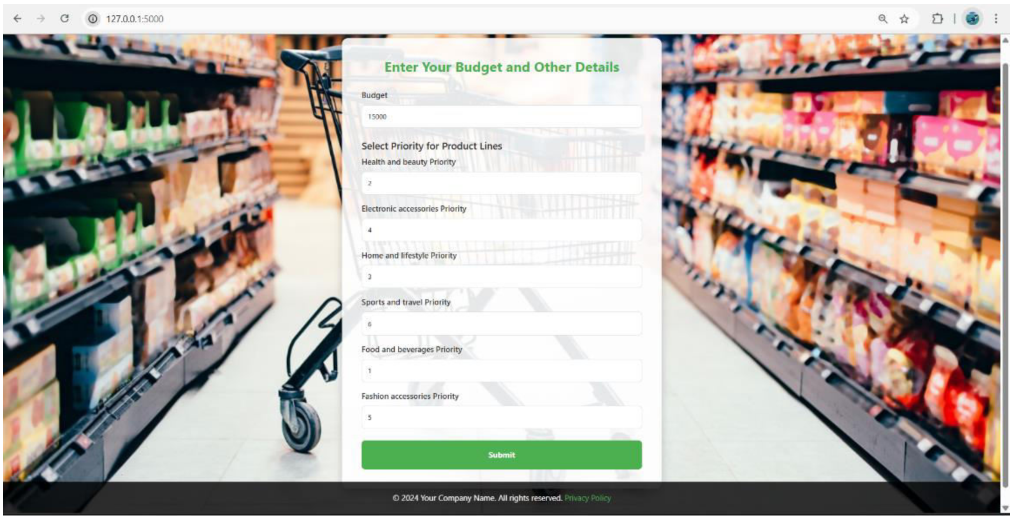

Fig2: Prediction Result

Fig 2 shows the priority order and the budget.

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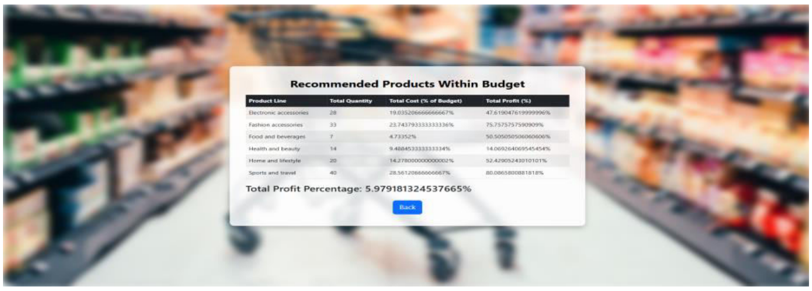

Fig 3: Recommended products within budget

VI. CONCLUSION

To increase revenue and competitiveness, this project uses deep learning optimisation for dynamic pricing. By using historical sales data to estimate optimal prices, our Flask-based web application facilitates data-driven decision-making. Future enhancements will include multi-product optimisation, sophisticated deep learning models for increased accuracy, and real-time pricing adjustments. Pricing plans can be further improved by using real-time market data and using AI to analyse consumer behaviour. The overall effectiveness and competitiveness of the system will be improved by integration with e-commerce platforms and algorithmic bots to monitor competitor pricing.

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