



Expert System to Determine Camera Price Using VIKOR Method

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Abstract

This study presents the design and implementation of an expert system for determining the best camera recommendations for beginners, utilizing a web-based platform to deliver tailored results based on user input. The VIKOR method is employed to evaluate and rank camera products, ensuring optimal recommendations by balancing multiple criteria such as technical specifications, usability, and cost-effectiveness. Analysis of five camera products revealed that the Fujifilm X-A5 achieved the lowest VIKOR value of 0, indicating it as the top recommendation for beginners. The system's calculations were validated against manual computations, achieving a 100% accuracy rate, thereby confirming the reliability of the expert system. The proposed system not only enhances decision-making efficiency but also significantly reduces the time required for experts to rank and evaluate multiple camera products. This approach demonstrates the potential of integrating multi-criteria decision-making methods into expert systems to provide accurate, user-centric recommendations in real-time.

Keywords:

Expert System, Camera, Vikor Method

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1. Introduction

Nowadays the market is very complex and competitive. The price of the Product plays a major role in the success of the product. Due to this Determining the price of the Product is very important. Price is the only element that affects revenues, and the business's profits. An Expert system is proposed to make decisions considering the uncertainties in the market environment to determine the price of a product [1]. An expert system is being developed to help assure the quality of data in the consumer price index (CPI). The system replicates the reasoning of commodity analysis, determining if a substitute product is comparable to a product priced in the previous month. If comparable, its price can be considered in producing the CPI. The system reasons with expertise directly entered by commodity analysts. To help the commodity analysts serve as their knowledge engineers, they are provided with a skeletal system to which they add their knowledge of particular product categories. The system was tested on six months of CPI data [2].

Predicting product prices using traditional methods often faces several challenges that can be effectively addressed by expert systems. Traditional methods, such as statistical models or simple regression techniques, rely heavily on historical data and predefined relationships between variables. These methods struggle to capture the complex, nonlinear interactions between various factors that influence product prices, such as market demand, supply chain disruptions, competitor pricing, and consumer behavior. Additionally, traditional approaches may not adapt well to rapidly changing market conditions, leading to inaccurate predictions. For instance, sudden economic shifts or global events (e.g., pandemics or geopolitical conflicts) can render historical data less relevant, making it

difficult for traditional models to provide reliable forecasts. This limitation highlights the need for more adaptive and intelligent systems that can incorporate real-time data and dynamic market trends [3][4].

Expert systems, which leverage artificial intelligence (AI) and machine learning (ML), offer a robust solution to these challenges. Unlike traditional methods, expert systems can process vast amounts of data from diverse sources, including social media, news, and real-time market feeds, to identify patterns and correlations that may not be apparent through conventional analysis. By incorporating advanced algorithms such as neural networks, decision trees, or ensemble methods, expert systems can model complex relationships and make more accurate predictions. Furthermore, these systems can continuously learn and adapt to new data, ensuring that predictions remain relevant even in volatile markets. For example, an expert system could analyze competitor pricing strategies, consumer sentiment, and supply chain data to predict price fluctuations with greater precision [5].

Another significant advantage of expert systems is their ability to incorporate domain-specific knowledge and rules, which can enhance the accuracy and reliability of price predictions. Traditional methods often lack the flexibility to integrate expert insights or business rules, limiting their effectiveness in specialized markets. In contrast, expert systems can be designed to include heuristic rules and expert knowledge, allowing them to account for unique market dynamics or industry-specific factors. For instance, in the fashion industry, an expert system could consider seasonal trends, brand reputation, and influencer impact when predicting product prices. By combining data-driven insights with expert knowledge, these systems can provide more nuanced and actionable predictions, helping businesses optimize pricing strategies and improve profitability. Expert systems represent a powerful alternative to traditional methods, addressing their limitations and enabling more accurate, adaptive, and context-aware product price predictions [6].

In this paper, we construct an expert system to predict the camera price in the market. The novelty of using the VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) method for camera price prediction lies in its ability to handle multi-criteria decision-making (MCDM) problems [16][17]. Unlike traditional price prediction methods that rely solely on historical data or single-variable analysis, the VIKOR method incorporates multiple factors such as camera specifications (e.g., resolution, sensor size, zoom capabilities), brand reputation, market trends, and consumer reviews. This approach allows for a more holistic and nuanced prediction model that considers both quantitative and qualitative aspects. By ranking and weighting these criteria, the VIKOR method can identify the optimal price range that balances technical performance, market demand, and competitive positioning. This makes it particularly useful for predicting prices in dynamic markets like consumer electronics, where multiple factors influence pricing decisions. The use of VIKOR introduces a structured and systematic framework for price prediction, offering a unique and innovative alternative to conventional methods.

2. Related Works

Various communities explored product price prediction as one of the most important aspects that affect a company's pricing system tends to affect its profits and losses. Currently, many manufacturing companies fix product prices manually by members of an organization's management team. Many papers proposed various methods for predicting product prices utilizing past information on attributes, sales trends, and market trends. The suggested methodology may identify patterns and generate accurate price forecasts for new products by examining big datasets that include details about pricing trends, consumer behavior, and comparable products. Precise systems can predict prices accurately and

can assist businesses in determining fair prices so they may increase revenue and satisfy clients [11][12][13][14].

A paper proposed the development of a fuzzy-based price expert system (Expert Fuzzy Price (EFP)) for manufacturing companies. This system will be able to recommend appropriate prices for products in manufacturing companies based on four major pricing strategic goals [7]. Another article presented a fuzzy multi-criteria evaluation system that operates based on a non-fuzzy neural approach that is capable of implementing a learning paradigm and working with vague concepts. Within this context, the necessary elements of fuzzy logic are identified, and the algebraic formulation of the fuzzy system using the Tesla share dataset. The functioning of a fuzzy system and fuzzy neural network in the field of time series value prediction is discussed. By using a fuzzy system, can produce a higher speed of convergence in the learning process than a fuzzy neural network using the minimum range of input data carrying the necessary information [8].

An article introduced an adaptive neuro-fuzzy inference system (ANFIS), trained by the particle swarm optimization (PSO) algorithm for stock price prediction. In the proposed fuzzy rule-based system some technical and fundamental indexes are applied as input variables. They generate a robust noise rejection clustering algorithm to generate membership functions (MFs). The proposed neuro-fuzzy model is applied to an automotive part-making manufactory in an Asia stock market. According to the experimental result, the proposed model is superior in comparison with the available models in terms of error minimization, robustness, and flexibility [9].

Current research focuses on the process that operates effectively in the context of resale price prediction of jewelry. The study constructed the pricing procedure of an expert using iterative co-attention networks in which the appearance and attributes of the product are carefully and iteratively observed. The proposed model can demonstrate its effectiveness of the model using a large dataset of secondhand no-brand jewelry items received from a collaborating fashion retailer. Thus, it can show that the iterative co-attention process operates effectively in the context of resale price prediction [10].

3. Proposed Method

In this study, there were methodological stages which can be seen in Fig. 1.

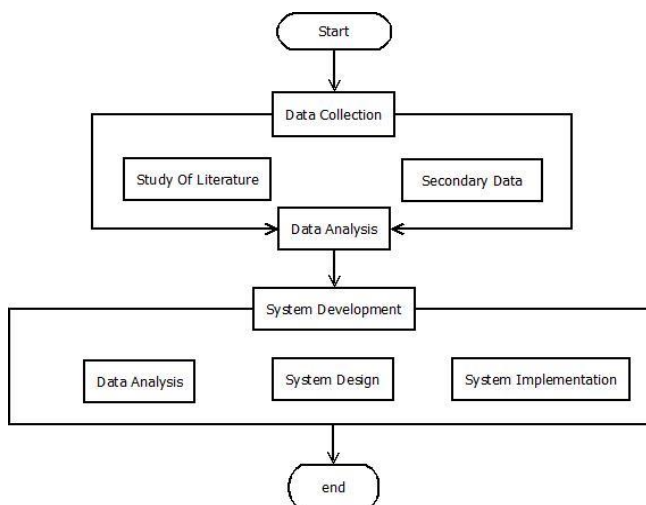


Fig. 1 Research Stages

Collecting data is carried out to obtain the data needed for research and for this research, the data collection process has two stages as shown in Figure 1, namely:

1. Literary Studies

This research was carried out to provide an overview of a research object or theory that supports the research being carried out. For the literature study that the authors use this time are online journals, as well as theses related to the research that the authors need.

2. Secondary Data

Is data that has a source from primary data, secondary data usually has the advantage that it takes a shorter time, this secondary data aims to find out alternatives to research that has been carried out. The secondary data needed to carry out this research is detailed data on each camera such as price, brand, and specifications as well as weight data which will be used as calculation material.

In this study, data analysis is to process data into information as needed in finding the best camera recommendations. In this process, the data that has been obtained will enter the calculation process using the VIKOR method. The system performs calculations using the VIKOR method to find the most ideal recommendations with the lowest results. The initial stage in developing the system in this research is that the author processes all the data that has been obtained. After the data processing is complete, the author will then carry out a literature study and learn about decision support systems using the VIKOR method from various references. The design for the system in this study is in the form of an illustration used in designing the main menu page of a decision support system, namely by making a flowchart design, UML, database design, and interface design.

The system flowchart is used to find the best camera recommendations with the VIKOR method, where the VIKOR method is a method that focuses on sorting and retrieving data from a sample set with opposing criteria, to help users make more effective decisions. This method is useful when the decision-maker is unable to make a choice when a system is started.[15]

The following are the solution steps, among others. [16]

1) Making a Decision Matrix.

Step 1 : Compilation of criteria and alternatives in a matrix.

$$F = \begin{matrix} x_{AC} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{matrix} \begin{bmatrix} C_1 & C_2 & \dots & C_j \\ x_{11} & x_{12} & \dots & x_{1j} \\ x_{21} & x_{22} & \dots & x_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} \end{bmatrix} \dots\dots\dots(2.1)$$

Information

- x_{ij} : Value of alternative i and criterion j
- i : Sequence of the ith numbers
- j : Sequence of the jth number
- A_i : Alternative Sequence i
- C_j : Sequence of the jth Criteria
- F : Decision Matrix

Determination of Weight on Criteria.

Step 2 : Determination of the weight for each existing criterion

$$\sum_{j=1}^n w_j = 1 \dots\dots\dots(2.2)$$

Information

- w_j : Criterion weight j
- j : Sequence of the jth number

Creating a Matrix for Normalization.

Step 3: Making a normalization matrix to determine the value of each criterion

$$N_{ij} = \frac{f^+ - f_{ij}}{f_j^+ - f_j^-} \dots \dots \dots (2.3)$$

Information

- f_{ij} : The value of the i-th alternative and the j-th criterion
- f_j^+ : The highest score in criterion j
- f_j^- : The lowest score in criterion j
- i : Alternative order to-i
- j : Order of the jth criteria
- N : Matrix that has been normalized

To determine the highest (f_j^+) and lowest (f_j^-) values, the following statements can be determined:

$$f_j^+ = \max (f_{1j}, f_{2j}, f_{3j} \dots, f_{ij}) \dots \dots \dots (2.4)$$

$$f_j^- = \min (f_{1j}, f_{2j}, f_{3j} \dots, f_{ij}) \dots \dots \dots (2.5)$$

Information

- f_j^+ : The highest score in criterion j
- f_j^- : The lowest score in criterion j
- i : Alternative order to-i
- j : Order of the jth alternative

Determination of Normalized Weight Values.

Step 4 : Determine the value of the data that has been normalized for each alternative and criteria

$$f_{ij}^* = w_j \cdot N_{ij} \dots \dots \dots (2.6)$$

Information

- f_{ij}^* : The value that has been normalized
- w_j : Value on criterion j
- N_{ij} : Normalized value
- i : Alternative order to-i
- j : Order of the jth alternative

Look up the Utility Measures value and look up the Regret Measures value.

Step 5: Calculate the value of the Utility Measure and look for the highest value of the Regret Measure

$$S_i = \sum_{j=1}^n w_j \frac{(f_j^+ - f_{ij})}{(f_j^+ - f_j^-)} \dots \dots \dots (2.7)$$

Information

- s_i : Collection of the number of each alternative and criteria

$$R_i = \max_j \left[w_j \frac{(f_j^+ - f_{ij})}{(f_j^+ - f_j^-)} \right] \dots \dots \dots (2.8)$$

Information

- R_i : A collection of the highest scores of each alternative and criteria

Calculations to determine the VIKOR index value.

Step 6: Find the VIKOR index value from the existing R and S values

$$Q_i = v \left[\frac{S_i - S^-}{S^+ - S^-} \right] + (1 - v) \left[\frac{R_i - R^-}{R^+ - R^-} \right] \dots \dots \dots (2.9)$$

Where

- $S^- = \text{terendah dari}_i(S_i)$
- $S^+ = \text{tertinggi dari}_i(S_i)$
- $R^- = \text{terendah dari}_i(R_i)$

- $R^+ = \text{tertinggi dari}_i(R_i)$

The v value is a value that ranges between 0-1. In general, other studies use a value of 0.5. The value v is the value of the strategy of the maximum group utility, and the value $1-v$ is the value of individual regret. The lowest Q value is the best solution from the existing alternatives.

4. Experimental Setup

The process of inputting the criteria and sub-criteria and weights that have been determined in this study, for the criteria and sub-criteria data will be described in Table 1. and Table 2.

Table 1 Criteria

Alternative Code	Name Kriteria	Criteria Weight
C01	Price	5
C02	Touch screen	3
C03	Year	4
C04	Connectivity	2
C05	Brand	4

After that, the following is a table of sub-criteria used in this study.

Table 2 Sub-Criteria

Name of Sub-Criteria	Sub Criteria Weight
Very good	50
Good	40
Enough	30
Bad	20
Very bad	10

The sub-criteria data will be used when assessing so that it will produce a matrix for the VIKOR method in this study. Assessment Data can be seen in Table 3.

Table 3 Assessment Data

NO	ALTERNATIVE	CRITERIA				
		C1	C2	C3	C4	C5
1	Nikon D7000	30	40	30	30	50
2	Olympus OM-D E-M10	40	40	30	30	30
3	Fujifilm X-T30	30	40	40	20	50
4	Olympus OM-D E-M1	30	40	30	30	30
5	Fujifilm X-A5	40	40	40	20	30

From the results of research on decision support systems to determine the best low-cost camera for new users using the VIKOR method, this calculation can be applied to the process of decision-making systems to determine the best low-cost camera using the VIKOR method. Then the final result obtained from this research is to find a product with the highest satisfaction accuracy value to determine the best cheap camera for new users

based on the data they already have. The following is an example of a decision support system using the VIKOR method:

A. Input the weight of each product based on the criteria in Table 3.

With Table 3, a decision matrix can be made using the formula that has been written in section 2.1, the results are as follows:

1. C01

$$N_{11} = \frac{40-30}{40-30} = 1$$

$$N_{21} = \frac{40-40}{40-30} = 0$$

$$N_{31} = \frac{40-30}{40-30} = 1$$

$$N_{41} = \frac{40-30}{40-30} = 1$$

$$N_{51} = \frac{40-40}{40-30} = 0$$

2. C02

$$N_{12} = \frac{40-40}{40-40} = 0$$

$$N_{22} = \frac{40-40}{40-40} = 0$$

$$N_{32} = \frac{40-40}{40-40} = 0$$

$$N_{42} = \frac{40-40}{40-40} = 0$$

$$N_{52} = \frac{40-40}{40-40} = 0$$

3. C03

$$N_{13} = \frac{40-30}{40-30} = 1$$

$$N_{23} = \frac{40-30}{40-40} = 1$$

$$N_{33} = \frac{40-30}{40-40} = 0$$

$$N_{43} = \frac{40-30}{40-30} = 1$$

$$N_{53} = \frac{40-40}{40-30} = 0$$

4. C04

$$N_{14} = \frac{30-30}{30-20} = 0$$

$$N_{24} = \frac{30-30}{30-20} = 0$$

$$N_{34} = \frac{30-20}{30-20} = 0$$

$$N_{44} = \frac{30-20}{30-30} = 0$$

$$N_{54} = \frac{30-20}{30-20} = 0$$

5. C05

$$N_{15} = \frac{50-50}{50-30} = 0$$

$$N_{25} = \frac{50-30}{50-30} = 1$$

$$N_{35} = \frac{50-50}{50-50} = 0$$

$$N_{45} = \frac{50-30}{50-30} = 1$$

$$N_{55} = \frac{50-50}{50-30} = 1$$

From the results of the above calculations, the matrix results will be obtained with the following table:

Table 4. Calculation Results Table

C1	C2	C3	C4	C5
1	0	1	0	0
0	0	1	0	1
1	0	0	0	0
1	0	1	0	1
0	0	0	0	0

- B. From the data that is already available, the criteria will be normalized and produce a value of w which can be seen in Table 5.

Weight of each criterion:

$$W = 1 / (5 + 3 + 4 + 2 + 4) = 1 / 18$$

$$W = 0.056$$

Weighting:

$$W1 = 0.056 * 5 = 0.278$$

$$W2 = 0.056 * 3 = 0.168$$

$$W3 = 0.056 * 4 = 0.224$$

$$W4 = 0.056 * 2 = 0.112$$

$$W5 = 0.056 * 4 = 0.224$$

The results of this weighting can be used as a w matrix:

$$W = [0.278 \quad 0.168 \quad 0.224 \quad 0.112 \quad 0.224]$$

- C. We then use the results of the W weighting obtained to find the criterion weighting values by multiplying the N matrix and the w matrix weighting results, so we get the results with the following table:

Table 5. Multiplication Results Table

C1	C2	C3	C4	C5
0.278	0	0.224	0	0
0	0	0.224	0	0.224
0.278	0	0	0	0
0.278	0	0.224	0	0.224
0	0	0	0	0

- D. The results of the multiplication above will be used to find which S and R as the explanation mentioned in equation 2.1.

Weighting:

$$S1 = \text{SUM}\{M1\} = 0.502$$

$$S2 = \text{SUM}\{M2\} = 0.448$$

$$S3 = \text{SUM}\{M3\} = 0.278$$

$$S4 = \text{SUM}\{M4\} = 0.726$$

$$S5 = \text{SUM}\{M4\} = 0$$

$$R1 = \text{MAX}\{M1\} = 0.278$$

$$R2 = \text{MAX}\{M2\} = 0.224$$

$$R3 = \text{MAX}\{M3\} = 0.278$$

$$R4 = \text{MAX}\{M2\} = 0.278$$

$$R5 = \text{MAX}\{M3\} = 0$$

E. After the S and R values are obtained, we get the results with the following table:

Table 6. Table of S Values and R Values

Alternative	S	R
Nikon D7000	0.502	0.278
Olympus OM-D E-M10	0.448	0.224
Fujifilm X-T30	0.278	0.278
Olympus OM-D E-M1	0.726	0.278
Fujifilm X-A5	0	0
MAX	0.726	0.278
MIN	0	0

F. With the above results, then we look for the VIKOR index using formula 2.9.

$$Q_1 = 0.5 \left[\frac{0.502-0}{0.726-0} \right] + (1 - 0.5) \left[\frac{0.278-0}{0.278-0} \right] = 0.845$$

$$Q_2 = 0.5 \left[\frac{0.448-0}{0.726-0} \right] + (1 - 0.5) \left[\frac{0.224-0}{0.278-0} \right] = 0.705$$

$$Q_3 = 0.5 \left[\frac{0.278-0}{0.726-0} \right] + (1 - 0.5) \left[\frac{0.278-0}{0.278-0} \right] = 0.69$$

$$Q_4 = 0.5 \left[\frac{0.726-0}{0.726-0} \right] + (1 - 0.5) \left[\frac{0.278-0}{0.278-0} \right] = 1$$

$$Q_5 = 0.5 \left[\frac{0-0}{0.726-0} \right] + (1 - 0.5) \left[\frac{0-0}{0.278-0} \right] = 0$$

From the results above, the results are obtained in the form of Table 7.

Table 7. Calculation Results Table

No	Alternative	Q
1	Nikon D7000	0.845
2	Olympus OM-D E-M10	0.705
3	Fujifilm X-T30	0.69
4	Olympus OM-D E-M1	1
5	Fujifilm X-A5	0

Table 7 presents a ranking of five camera models based on their assigned Q values, which likely represent a performance metric, quality score, or another evaluation criterion. The Olympus OM-D E-M1 achieves the highest score (1.0), indicating its superior performance compared to the other alternatives. The Nikon D7000 follows with a score of 0.845, demonstrating strong capabilities, making it a competitive option. The Olympus OM-D E-M10 (0.705) and Fujifilm X-T30 (0.69) have relatively close scores, suggesting comparable performance levels with only a slight difference between them.

However, the Fujifilm X-A5 receives a score of 0, which implies it lacks key features or significantly underperforms in comparison to the other cameras. Notably, the ranking of the Olympus OM-D E-M1 at the top aligns with its reputation for advanced features, whereas the Nikon D7000's high score highlights its reliability. The ranking suggests that the cameras were evaluated based on criteria where professional-grade or feature-rich models outperformed entry-level or mid-range alternatives.

5. Results and Analysis

This study uses 5 product data, 5 criteria, 5 sub-criteria, and weights based on criteria. The following is the ranking obtained after sorting the Q values from the calculations that have been carried out, following the provisions of the Vikor method that the smallest value is the best result and can be seen in the following table.

Table 8. Rank Validation

Rank	Alternative	Mark
1	Fujifilm X-A5	0
2	Fujifilm X-T30	0.69
3	Olympus OM-D E-M10	0.705
4	Nikon D7000	0.845
5	Olympus OM-D E-M1	1

Based on the calculated data, Table 8 presents a ranking of five camera models based on their assigned marks. The ranking is structured from the highest to the lowest mark, with Olympus OM-D E-M1 securing the top position (1.0), followed by Nikon D7000 (0.845), Olympus OM-D E-M10 (0.705), Fujifilm X-T30 (0.69), and Fujifilm X-A5 (0.0). From the analysis, the Olympus OM-D E-M1 is the most preferred option, likely due to its superior features, image quality, or performance in comparison to the alternatives. The Nikon D7000 also scores well, indicating it as a strong contender with reliable capabilities. Interestingly, the Fujifilm X-A5 scores the lowest with a mark of 0, suggesting that it may lack certain essential features or performance aspects that other cameras in the list provide. The relatively close scores of the Fujifilm X-T30 and Olympus OM-D E-M10 indicate similar performance levels, but the latter slightly outperforms the former. The ranking suggests a preference for more advanced cameras, possibly with better image sensors, superior autofocus, or enhanced usability.

6. Conclusion

The development of an expert system designed to identify the most suitable camera for beginners can be effectively implemented within a web-based platform, providing optimal camera recommendations based on user inputs. The VIKOR (method is employed to evaluate and rank camera options, ensuring a systematic and multi-criteria decision-making approach. In this study, five camera products were analyzed, with the Fujifilm X-A5 achieving the lowest VIKOR value of 0, indicating it as the top recommendation for beginners. The results of the VIKOR-based calculations were validated against manual computations, demonstrating a 100% accuracy rate, thereby confirming the reliability of the expert system. This system significantly reduces the time required for experts to rank and evaluate numerous camera products, streamlining the decision-making process while maintaining high precision and consistency. The integration of the VIKOR method into the expert system not only enhances its effectiveness but also provides a robust framework for future applications in product recommendation systems.

Reference

- [1] P. Manchikatla, "Expert System for Price Determination," *International Journal of Computer Applications*, 2019.
- [2] F. Conrad, R. F. Kamalich, J. A. Longacre, and D. Barry, "An expert system for reviewing commodity substitutions in the consumer price index," in *Proceedings of 9th IEEE Conference on Artificial Intelligence for Applications*, 1993, pp. 299–305.
- [3] S. Kumar and M. Singh, "A review on applications of expert systems in price prediction," *International Journal of Computer Applications*, vol. 164, no. 7, pp. 1–6, 2017, DOI: 10.5120/ijca2017913667.
- [4] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, 2009, DOI: 10.1007/978-0-387-84858-7.
- [5] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 785–794, DOI: 10.1145/2939672.2939785.
- [6] V. Kotu and B. Deshpande, *Predictive Analytics and Data Mining: Concepts and Practice with RapidMiner*. Morgan Kaufmann, 2014.
- [7] C. C. Obijiaku and K. Y. Kim, "Price estimation based on business model pricing strategy and fuzzy logic," *Korean Institute of Smart Media*, 2023.
- [8] S. Hašková, P. Šuleř, and R. Kuchár, "A fuzzy multi-criteria evaluation system for share price prediction: A Tesla case study," *Mathematics*, 2023.
- [9] M. H. Zarandi, M. Avazbeigi, and M. Alizadeh, "A neuro-fuzzy expert system trained by particle swarm optimization for stock price prediction," 2012.
- [10] Y. Yamaura, N. Kanemaki, and Y. Tsuboshita, "The resale price prediction of secondhand jewelry items using a multi-modal deep model with iterative co-attention," *ArXiv*, abs/1907.00661, 2019.
- [11] V. Prakash, H. Sahil, P. Rayi, B. Reddy, and B. Maridu, "Product price prediction using ensemble learning techniques," in *2024 8th International Conference on Inventive Systems and Control (ICISC)*, 2024, pp. 73–78.
- [12] Y. Gong and P. Zhang, "Commodity price analysis and prediction based on ensemble learning," in *2022 2nd International Conference on Networking Systems of AI (INSAI)*, 2022, pp. 199–204.
- [13] B. Thupakula, S. A. Shiney, S. B. Rani, K. Maheswari, S. Ray, and V. Mohanavel, "Usage of ensemble regression technique for product price prediction," in *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2022, pp. 1439–1445.
- [14] R. El Youbi, F. Messaoudi, and M. Loukili, "Machine learning-driven dynamic pricing strategies in e-commerce," in *2023 14th International Conference on Information and Communication Systems (ICICS)*, 2023, pp. 1–5.
- [15] M. A. Mohamed, I. M. El-Henawy, and A. Salah, "Price prediction of seasonal items using machine learning and statistical methods," *Computers, Materials & Continua*, 2022.
- [16] S. Huang, J. J. Liou, H. Chuang, and G. Tzeng, "Using a modified VIKOR technique for evaluating and improving the national healthcare system quality," *Mathematics*, 2021.