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GRA-Based Methodology for Ranking Machine Learning AI and Data Type Effectiveness

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Abstract: *This study examines the comparative performance of different data types in machine learning and artificial intelligence applications using gray relational analysis (GRA). The research evaluates five distinct data types across four key machine learning tasks—image, spectrogram, photometry, light curve, and time series—for classification, regression, clustering, and prediction. By systematically applying the GRA method, the study transforms multi-objective optimization problems into single-objective evaluations to identify the most versatile data types for AI applications. Photometry performs best overall, achieving the highest gray relational grade (GRG) of 0.7876, with particularly strong results in classification (98.60) and regression (80.00). Image data comes in second with a GRG of 0.7684, excels in clustering (23.00), and provides solid prediction results (40.00). Spectroscopy data ranks third (GRG: 0.6602), while light bending and time series data rank fourth and fifth, respectively. While the overall GRG (0.3864) is very low, time series data shows significant strengths in forecasting (70.67) and clustering (65.00) tasks. This research advances the knowledge of data-driven decision-making in AI applications across a variety of domains that require optimization across multiple performance metrics.*

Keywords*: Machine Learning; Artificial Intelligence; Gray Relational Analysis (GRA); Data Types; Multi-objective Optimization; Clustering;*

1. INTRODUCTION

Machine learning (ML) and AI can help uncover hidden properties of wireless networks, detect interactions and anomalies that are not immediately apparent through manual inspection, and propose innovative methods to optimize network deployments and operations. [1] Machine learning, a field within AI, provides techniques for building mathematical models (precise sets of computer instructions aimed at solving specific problems) based on sample data. These models, also known as functions, connect input data with corresponding outputs. Inputs can be images or any set of numerical or categorical data, referred to as input features. [2] Machine learning, a subset of artificial intelligence (AI), is playing an increasingly important role due to its ability to process vast datasets and extract meaningful insights, transforming a variety of industries (Sestina & De Mauro, 2021). Previous research has described AI as "programs, algorithms, systems, and machines that demonstrate intelligent behaviour" and "technology designed to emulate human cognitive functions, particularly problem-solving and learning." [3] Machine learning (ML) has emerged as a central focus in the field of artificial intelligence (AI). While previous AI systems typically lacked this feature, a system without learning capabilities is often not considered truly intelligent. ML now plays a key role in a wide range of AI domains, including expert systems, automated reasoning, natural language processing, pattern recognition, computer vision, and intelligent robotics. [4] Machine learning – automated processes that learn from examples to classify, predict, detect, or generate data – and artificial intelligence – techniques that help computers make decisions or discoveries that would normally require human intelligence – have become essential tools in astronomy. New applications are emerging weekly, continually expanding the field's growing body of research and innovation. [5] Thanks to major advances in processor availability, speed, connectivity, and cost-effective data storage, machine learning (ML) and artificial intelligence (AI) are playing an increasingly influential role in everyday life.AI is driving progress in areas such as healthcare, transportation, internet connectivity, food delivery systems, and improving security in evolving geopolitical environments. [6] Machine learning is the process of acquiring knowledge. Humans naturally learn from everyday experiences, due to their ability to reason and understand. Although machines do not have this innate ability, they can learn "artificially" through algorithms and procedures, which gave rise to the term artificial intelligence (AI). In contrast, machine learning (ML) is a subset of AI that uses statistical methods to automate the processes of learning, discovery, and prediction without the need for explicit programming. [7] Machine learning, a branch of artificial intelligence, uses mathematical methods to help systems or machines learn independently and gain knowledge through experience. It focuses on building algorithms based on experience and training data, aiming to improve outcomes and make better predictions through learning processes. [8] Machine learning (ML) provides powerful capabilities for building artificial intelligence (AI) software tools that can automatically identify patterns within large datasets. This technology forms the foundation of many major software products, such as Google Translate, Alexi, and Face book. Researchers have also successfully applied ML in the medical field, in areas such as diagnosing diabetic retinopathy, detecting malignant melanomas, and detecting large blood vessel blockages in stroke patients. [9] Artificial intelligence (AI) plays a key role in advancing the principles of the circular economy. A growing number of studies have integrated AI and machine learning (ML) into circular economy frameworks, which often emphasizes zero-waste production. For example, Alive et al. introduced a nonlinear decision support system that uses machine learning to evaluate and incorporate supplier benchmarking scores into circular economy strategies. Similarly, Rackham et al. developed sophisticated tools to assess the potential for reuse of building materials once buildings have reached the end of their operational life. [10] AI/ML and data analytics present both opportunities and challenges for situation and decision fusion (SDF). The challenges stem from the overlap in the problems they seek to solve – while SDF is concerned with methods for assessing situations and their potential impacts, AI/ML is primarily focused on big data analytics that support object evaluation and classification. [11] There are many legitimate reasons behind the rapid growth of this field – although some are less promising. This surge in popularity has also led to the frequent misuse of certain terms. As the field has expanded rapidly, it has also become difficult to clearly define its boundaries. As a result, the definitions of key terms like AI and ML have become increasingly blurred and ambiguous. [12] Machine learning (ML) and artificial intelligence (AI) have become widely used tools in many research and industrial fields, driven by recent technological advances. However, the portrayal of these technologies in the media, blogs, and news organizations often overstates their capabilities. While both fields are based on the idea that intelligent behaviour can be replicated through computational systems, the challenge goes beyond choosing the right programming or computational method. These models encompass a wide range of strategies, such as search algorithms, logic-based systems, probabilistic techniques, and various learning methods - including supervised, unsupervised, deep, and reinforcement learning.. [13] Machine learning (ML), a branch of artificial intelligence (AI), demonstrates the experience-based "learning" characteristic of human intelligence, while improving its performance over time through computational algorithms. These algorithms analyze a wide range of input and output data to detect patterns, allowing the system to "learn" and make independent recommendations or decisions. [14] In recent years, advances in artificial intelligence (AI) technologies have led to a rapid increase in machine learning (ML) research in the medical field. In particular, the emergence of innovative ML applications holds significant promise for transforming emergency medicine. These tools aim to address key challenges in emergency departments, including patient classification and disposition, early diagnosis and outcome prediction, operational efficiency, and treatment decision-making. [15]

2. MATERIALS AND METHOD

Alternative:

Image: An image is a visual representation of an object, idea, or scene, such as a photograph, illustration, or painting. In computer science, it usually refers to a two-dimensional grid of pixels that represents a visual scene.

Spectroscopy: Spectroscopy is the scientific study of how matter absorbs and emits light or other electromagnetic radiation. It involves separating this radiation into its component wavelengths, similar to how a prism produces a spectrum of colours from light.

Optics: Optics is the science of measuring the intensity of light perceived by the human eye. The term comes from the word "photo" meaning light and "merry" meaning the process of measuring.

Light curve: A light curve is a graph showing the variation in the brightness of an astronomical object over a period of time. It is an important tool for observing objects with fluctuating brightness, such as variable stars, novae, and supernovae.

Time Series: Time series analysis involves analyzing data points collected at regular intervals over time. This method is used to identify patterns and trends and distinguish them from random or irregular data sets.

Evolution parameters:

Classification: Classification is the process of arranging objects into categories based on shared features. It is widely used in fields ranging from biology to data science to identify patterns and bring structure to complex information.
Regression: Regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. It helps predict outcomes and analyze how variations in the predictor variables affect the target variable.
Clustering: Clustering involves grouping data points with similar characteristics into clusters. This technique helps to reveal hidden patterns and relationships by organizing data into meaningful subgroups.
Forecasting: Forecasting is the process of predicting future outcomes using historical and current data. These predictions can then be evaluated by comparing them with actual results to assess accuracy.

GRA method: Gray Relational Analysis (GRA) is a technique used to address complex relationships between various performance measures. It simplifies the optimization process by transforming multiple objectives into a single one. With GRA, a relational grade is calculated, which provides a comprehensive measure for evaluating various performance attributes. This method helps to integrate multiple, complex performance measures into a single evaluation attribute. [16] The GRA method has been extended to address cases where information regarding attribute weights is partially unknown. A new distance-based intuitionist GRA method has been introduced to assess the development potential of cultural and creative gardens. In addition, a version of the GRA method has been developed to deal with decision-making problems involving interval-valued Pythagorean fuzzy data. [17] The theory of gray systems, proposed by Deng in 1989, was developed to model uncertain systems where information is incomplete, unreliable, or ambiguous. As a key component of this theory, gray relational analysis (GRA) was introduced. GRA is a valuable tool for solving a variety of problems involving uncertainty, including discrete data, incomplete information, multi-criteria decision making, and optimization challenges. [18] The Gray Relational Analysis (GRA) method was initially developed by Deng and has since become a widely accepted and valuable tool for analyzing unique information and making decisions in various domains. The main advantages of the GRA method include the use of original data for analysis, the straightforward computational process, and its effectiveness as an optimal decision-making tool in various business settings. Kung and Went used GRA to investigate the Gray MADM problem within venture capital firms. [19] Gray correlation analysis (GRA), a major branch of gray system theory, focuses on assessing the similarity between sequences by analyzing the geometric shape of their curves. The primary method involves converting the observed values of discrete behaviours into continuous lines through linear interpolation. [20] Gray relational analysis (GRA) is a fundamental component of gray system theory, which focuses on dealing with uncertainty in information. If all information about a system is known, the system is referred to as a white system. Conversely, if no information is available, it is called a black system. If only partial information is known, the system is classified as a gray system. [21] The results of using the GRA method to analyze the impact of electrochemical discharge machine parameters showed its effectiveness. In addition, GRA was used for multi-objective optimization of thermal system designs and to evaluate response variables on the electrochemical mechanical performance of aluminium metal matrix composites. GRA was also used for geometric optimization of strain gauge force transducers. [22] In their study, a combination of Gray Relational Analysis (GRA) and Taguchi Design Experiments using vertical arrays were used to systematically optimize the process. The results revealed that rapeseed biodiesel, when combined with hexadecane, was particularly effective in generating optimal system responses. Similarly, Oslo et al. conducted similar investigations. [23] Gray relational analysis (GRA) is used to solve problems by analyzing data envelopes in various facilities. Both layout and dispatch rules are used for selection problems and the GRA process is demonstrated using the main process of GRA. First, the performance of the alternatives is compared through a series of translations, which is referred to as the relational generation. Next, the Gray correlation between all the sequences and the reference sequence is calculated by determining the correlation coefficient. Finally, Gray relational values are calculated based on these coefficients, comparing each sequence against the reference sequence to determine the relative quality of each comparison. [24] GRA is an element-based, radio-transfer imaging technique that can reveal the spatial density distribution of an element within the material being examined. The method was introduced to the US Federal Aviation Administration (FAA) by the Soar NRC (SNRC) in 1985 as a way to detect explosives in aircraft bags using nitrogen-based radiographic imaging. Since high nitrogen density is a key indicator, nitrogen GRA shows potential for use in automated explosives detection systems (EDS). [25] Carbon fibber reinforced plastic composites were used in the experiment. This approach revealed a variation when making comparisons. Adam conducted a study on the drilling process using the Taguchi method and examined the effects of cryogenic treatment on surface finish and roundness errors. The results indicated that cutting speed has the most significant impact on reducing hardness and roundness errors, as analyzed using the GRA method. [26] In this experimental study, the influence of break parameters on the surface roughness of machined composites was investigated. Taguchi's L16 vertical array was used to design the experiments and gray correlation analysis (GRA) was used to optimize the process parameters. [27] The hybrid -GRA- method combines two robust multi-criteria decision-making techniques with three distinct normalization strategies to produce results that closely mimic real-world situations. Weights are calculated using one method, while the Gray Relational Analysis (GRA) technique - used with normalization - is used to rank alternatives. Decision-making, an intrinsic human trait, is considered a cognitive process that involves selecting the most appropriate option from a set of possibilities. [28] The keywords and terms in the Medical Subject Headings (MESH) were as follows: “Toxoplasma Gondi”; “GRA antigens”; “DNA-vaccination”; “protection”; “recombination” and “immune responses”. All references from selected studies were thoroughly reviewed manually so that no relevant articles were overlooked. Abstracts of research papers presented at conference proceedings were excluded from the analysis. [29] Gray Relational Analysis (GRA) method operates on multiple variables and proves effective in dealing with problems involving complex attribute relationships. It is particularly advantageous in situations characterized by uncertainty and incomplete information. Analytical Hierarchy Process (AHP) is used to assign relative importance to various service criteria, while GRA is used to determine the most suitable access network. Multi-criteria decision-making (MCDM) techniques such as AHP and GRA are implemented by Imax Information Server (IS) to facilitate Wi-Fi acquisition. This study uses both AHP and GRA to evaluate and identify the optimal network selection algorithm. [30].

3. ANALYSIS AND DISCUSSION

Table1. Machine Learning and Artificial Intelligence

	Classification	Regression	Clustering	Forecasting
Image	22.89	78.22	23.00	40.00
Spectroscopy	46.67	46.89	29.34	35.67
Photometry	98.60	80.00	38.56	48.56
Light curve	64.89	25.56	57.78	45.89
Time Series	60.67	35.45	65.00	70.67

Table 1 illustrates the interoperability of various data types in AI and machine learning tasks evaluated using the GRA approach - classification, regression, clustering and forecasting. Photometry achieves the highest performance in classification (98.60), whereas time series data shows excellent results in forecasting (70.67) and clustering (65.00), indicating versatile applicability.

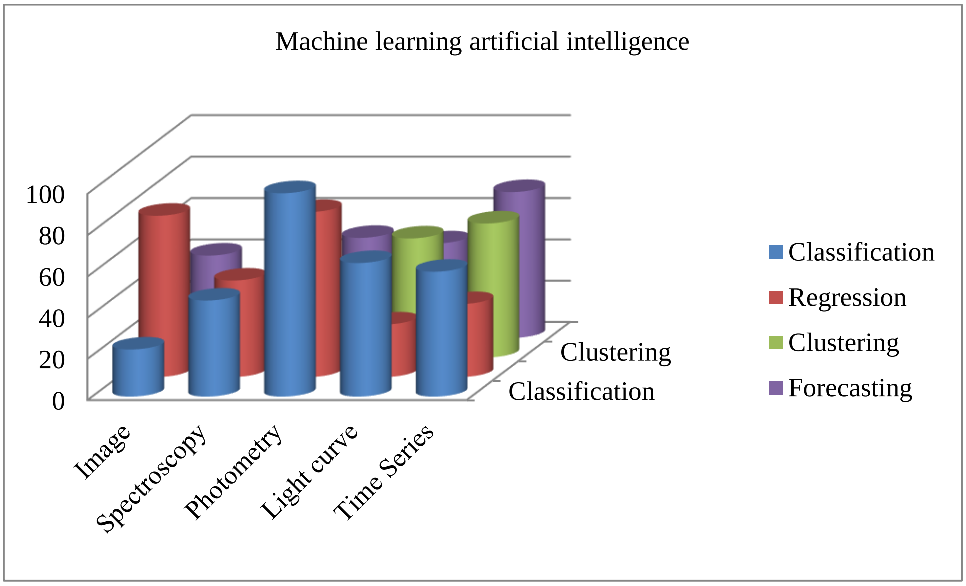

FIGURE 1. Machine Learning and Artificial Intelligence

Figure 1 compares the performance of various machine learning and artificial intelligence techniques using the GRA method in various fields: imaging, spectroscopy, photometry, light bending, and time series. The metrics for classification, regression, clustering, and prediction show varying performance, with photometry achieving the highest performance in classification and regression.

Table 2. Normalized Data

	Classification	Regression	Clustering	Forecasting
Image	0.0000	0.9673	1.0000	0.8763
Spectroscopy	0.3141	0.3918	0.8490	1.0000
Photometry	1.0000	1.0000	0.6295	0.6317
Light curve	0.5547	0.0000	0.1719	0.7080
Time Series	0.4990	0.1817	0.0000	0.0000

Table 2 Provides normalized data used in machine learning and AI tasks. based on the GRA method. Photometry ranks highest in classification and regression (1.0000), while spectroscopy excels in prediction (1.0000). Image data achieves the highest clustering value, while time series shows the weakest overall performance.

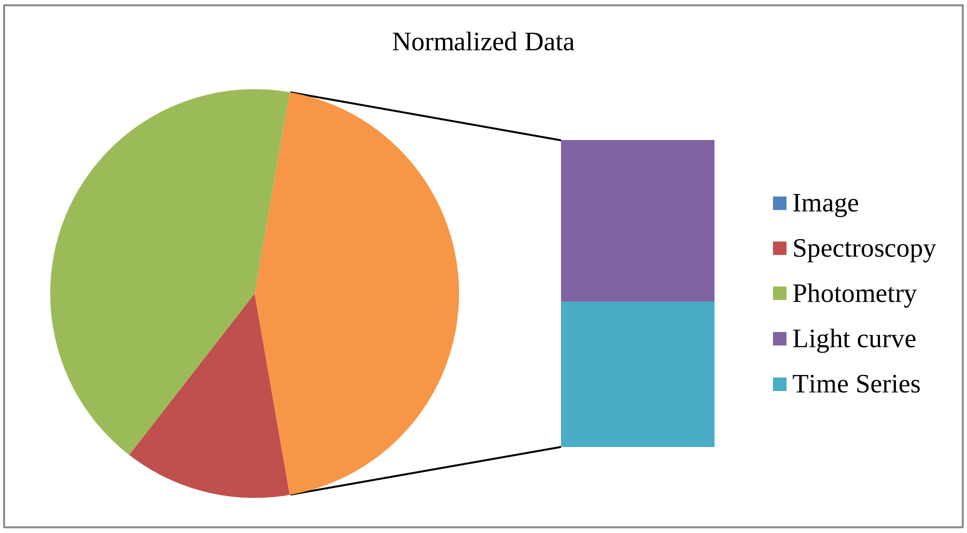

FIGURE 2 Normalized data

Figure 2 depicts the structure of the normalized data types perform against each other using the GRA method in machine learning and AI tasks. Photometry scores the highest (1.0000) in classification and regression, while image data shows peak performance in clustering (1.0000). Spectroscopy performs best in forecasting (1.0000), while time series data shows weak overall performance.

Table**3**. Deviation sequence

	Deviation sequence			
	Classification	**Regression**	**Clustering**	**Forecasting**
Image	1.0000	0.0327	0.0000	0.1237
Spectroscopy	0.6859	0.6082	0.1510	0.0000
Photometry	0.0000	0.0000	0.3705	0.3683
Light curve	0.4453	1.0000	0.8281	0.2920
Time Series	0.5010	0.8183	1.0000	1.0000

Table 3 presents the deviation rankings of various data types in machine learning and AI tasks using the GRA method. Photogrammetric shows the least deviation in classification and regression (0.0000), and image data shows zero deviation in clustering (0.0000). In contrast, time series data shows the greatest deviation in clustering and forecasting (1.0000).

TABLE 4 Grey Relation Coefficients

	Grey relation coefficient			
	Classification	**Regression**	**Clustering**	**Forecasting**
Image	0.3333	0.9386	1.0000	0.8016
Spectroscopy	0.4216	0.4512	0.7681	1.0000
Photometry	1.0000	1.0000	0.5744	0.5758
Light curve	0.5290	0.3333	0.3765	0.6313
Time Series	0.4995	0.3793	0.3333	0.3333

Table 4 presents the gray correlation coefficients for various data types in machine learning and AI tasks using the GRA method. Photogrammetric performs best in classification and regression (1.0000), while image data achieves the highest coefficient in clustering (1.0000). Time series has the lowest coefficients across all tasks.

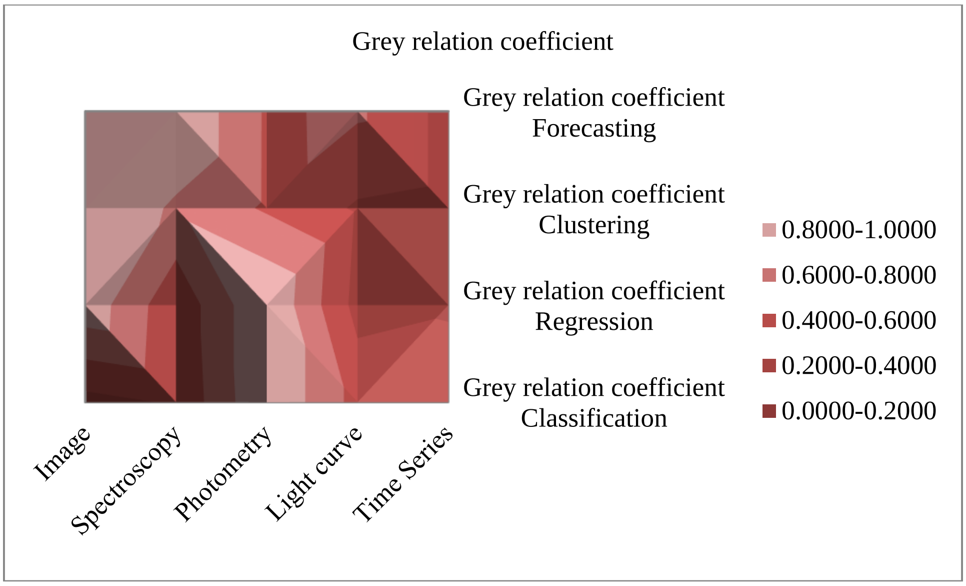

FIGURE 3. Grey relation coefficient

Figure 3 presents the gray correlation coefficients for various data types in machine learning and AI tasks using the GRA method. Photogrammetric stands out in classification and regression (1.0000), while image data leads in clustering (1.0000). Time series have the lowest coefficients, especially in forecasting.

TABLE .5 Result of final GRG Rank

	GRG	**Rank**
Image	0.7684	2
Spectroscopy	0.6602	3
Photometry	0.7876	1
Light curve	0.4675	4
Time Series	0.3864	5

Table 5 presents the final GRG (Gray Relationship Quality) rankings using the GRA method. Photometry ranks first, achieving the highest GRG (0.7876), followed by image data in second place (0.7684). Time series ranks fifth, with a GRG of 0.3864.

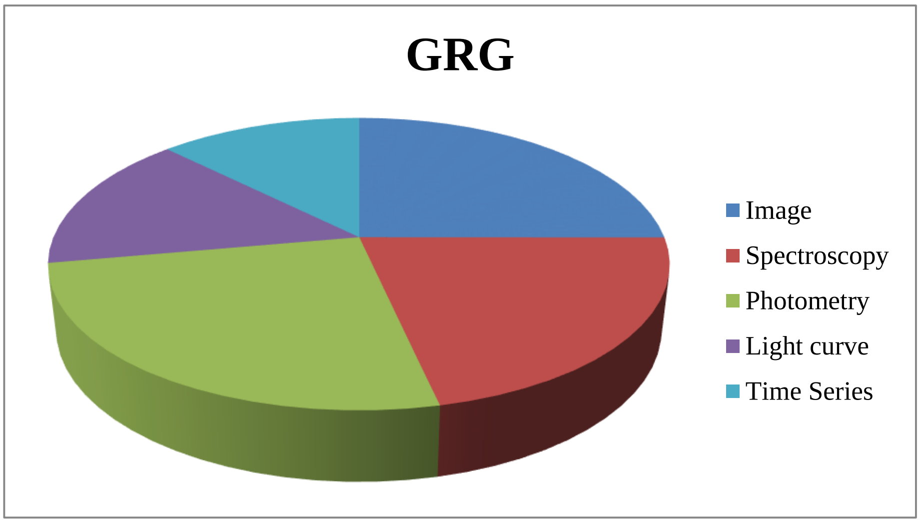

FIGURE 4 GRG

Figure 4 presents the final GRG (Gray Relationship Quality) rankings based on the GRA method. Photometry ranks first with a GRG of 0.7876, followed by image data in second place (0.7684). Time series ranks fifth with a GRG of 0.3864, reflecting its relatively low performance.

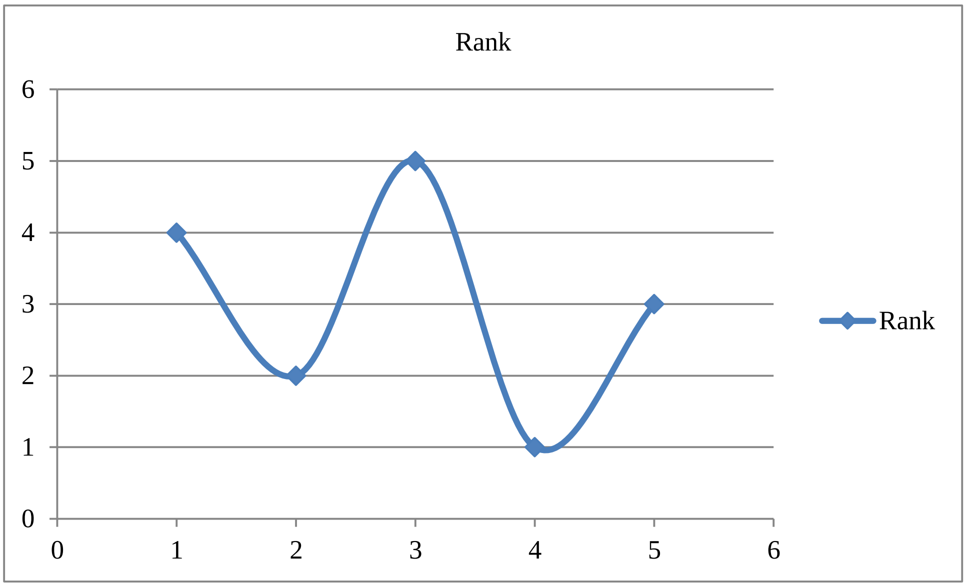

FIGURE 5. Shown the Rank

Figure 5 as presented in the rankings established using the GRA method. It compares the performance of various data types on different machine learning and AI tasks and provides an overview of their relative positions based on their Gray Relationship Grade (GRG), which indicates their performance on each evaluated task.

4. CONCLUSION

This study has comprehensively evaluated five different data types across four key machine learning tasks. The results provide meaningful insights for researchers and practitioners in selecting the most suitable data types for specific AI applications. Photometry emerged as the most versatile data type, achieving the highest Gray Relational Grade (GRG) of 0.7876. It showed excellent performance in classification (98.60) and regression (80.00) tasks, indicating that photometric data, which measures light intensity, provides rich and valuable information that is very useful for prediction and classification in various fields. Image data came in second with a GRG of 0.7684, showing particular strength in clustering applications (23.00) and consistent performance in prediction (40.00). Visual information in images has been shown to be suitable for pattern recognition, supporting its widespread use in computer vision tasks. Spectroscopy data ranked third with a GRG of 0.6602, providing well-rounded performance across all tasks, particularly in forecasting applications. This highlights the usefulness of spectral data in predictive modelling environments. Light curve data ranked fourth (GRG: 0.4675), while time series data ranked fifth (GRG: 0.3864). Despite the lower overall ranking, time series data showed significant strengths in forecasting (70.67) and clustering (65.00), emphasizing the importance of selecting data based on task-specific requirements rather than relying solely on generic performance metrics. The RA method has proven effective in transforming multi-objective optimization problems into single-objective evaluations, enabling researchers to make more informed data selection decisions. By measuring the relative performance of each data type across multiple dimensions, this study provides a framework for optimizing AI applications based on specific task requirements. The findings highlight that no single data type excels in all machine learning applications. Data selection should be driven by the specific requirements of the task, available resources, and desired outcomes. For classification and regression tasks, photometric data offers unique advantages, while time series data, despite its lower overall ranking, is more suitable for forecasting. Future research should explore the potential of combining multiple data types to leverage their complementary strengths for improved performance across a variety of machine learning tasks. Additionally, examining how these performance patterns hold across different domains and dataset sizes will further our understanding of optimal data selection in AI applications.

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