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Predicting the Mutual Impact of Indicators of Legatum Prosperity Index using Bagging and Boosting Algorithms

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ABSTRACT

Decision-making is a critical aspect of governance, and data mining and machine learning algorithms can significantly enhance this process. By leveraging predictive models generated through these algorithms, policymakers can make more informed and accurate decisions. Since such models rely on historical data, the Legatum prosperity index serves as a valuable source for this analysis. In this study, Bagging and Boosting algorithms are employed to develop predictive models and analyze various indicators across different continents. The results demonstrate the effectiveness of these algorithms in forecasting key indicators and reveal notable differences in the influential factors across regions. These findings can support policymakers in formulating targeted strategies to enhance governance and living standards, considering regional characteristics and priorities. Furthermore, providing predictive models for each indicator allows countries to forecast and assess the impact of improving a specific indicator on others.

Keywords: Data mining, Prediction models, Bagging and Boosting algorithms, Legatum prosperity index.

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1 Introduction

Today, countries are engaged in intense competition for development and progress. To effectively participate in this global race, policymakers must first understand their country's position relative to others, as well as their national strengths and weaknesses. In this regard, the Legatum Prosperity Index provides valuable insights for political leaders [1]. This index ranks countries based on 12 key indicators, offering data that can help identify areas of strength and weakness and serve as a guide for promoting national development and prosperity. However, the impact of these indicators can vary significantly across geographic regions, influenced by local and regional factors. While the Legatum prosperity index offers important information, further valuable insights can be extracted through data mining. Data mining is the process of identifying patterns and relationships that can help solve problems through data analysis. Data mining techniques and tools help enterprises to predict future trends and make more informed decisions [2]. Among the important algorithms of data mining can be mentioned BaggingRegressor and XGBoost [3] [4] [5]. These ensemble methods have demonstrated superior performance and generally offer higher accuracy compared to many traditional algorithms. BaggingRegressor is an ensemble meta-estimator that fits base regressors each on random subsets of the original dataset and then aggregates their predictions (either by voting or by averaging) to form a final prediction. Such a meta-estimator can typically be used as a way to reduce the variance of a black-box estimator (e.g., a decision tree), by introducing randomization into its construction procedure and then making an ensemble out of it. On the other hand, XGBoost, or eXtreme Gradient Boosting, is an advanced and optimized method of the Gradient Boosting algorithm. This algorithm significantly improves model accuracy by using a set of small decision trees that are trained sequentially to reduce the errors of previous models.

In this paper, BaggingRegressor and XGBoost are used to provide predictive models for indicators of the Legatum prosperity index across different continents of the world, including Europe, America, Asia-Pacific, and Africa. This study aims to identify and determine the indicators that have the greatest impact on others in each continent. This information can help countries to purposefully strive to improve key indicators based on their geographical location. The results obtained can serve as a decision-making tool for policymakers and planners in countries, enabling them to take effective steps toward improving governance and the living conditions of the people by utilizing these analyses.

The remaining part of this paper is organized as follows. Section 2 presents background information on the Legatum prosperity index, and Bagging and Boosting algorithms. Section 3 introduces the related works in the field of using machine learning algorithms in topics such as politics, economy, and people. In Section 4, statistical data analysis of the data of the Legatum prosperity index is presented and then prediction models using machine learning algorithms are presented. Finally, Section 5 concludes the paper.

2 Background Information

2.1 The Legatum Prosperity Index

The Legatum prosperity index is a comprehensive analytical tool designed to assess and compare the level of prosperity in different countries around the world [1] [6]. This index is prepared and published by the Legatum institute and is widely used among researchers, policymakers, and economic and social analysts. In a way that, by providing a multidimensional framework, analyzes the strengths and weaknesses of various countries in different areas and seeks to present a more comprehensive picture of well-being and quality of life on a global scale. According to Fig. 1, this index is designed based on three main areas: inclusive communities, open economies, and empowered people, each of which is divided into various cases, 12 indicators in total [1] [6]. This index calculates each country's score by averaging the values of its 12 indicators and then ranks each country by comparing it with the scores of other countries. Figure 2 shows the rank and score of the top 5 countries in terms of the Legatum prosperity index in 2023. Additionally, Figure 3 shows a heat map of countries based on their score.

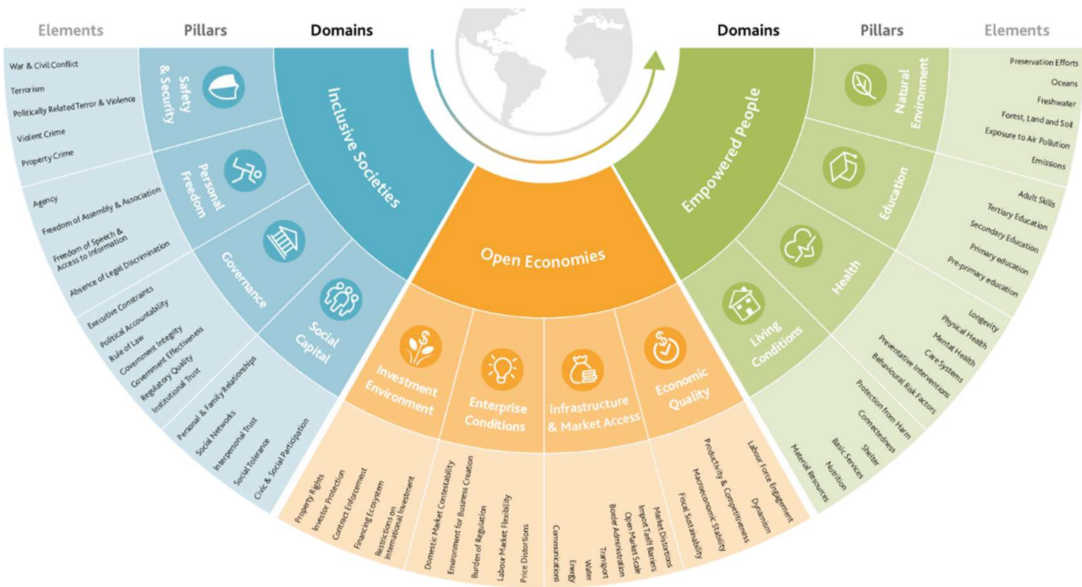


Figure 1 The domains, pillars, and elements of the Legatum prosperity index [1]

RANK	COUNTRY												
ADJUST PILLAR WEIGHTING		x1	x1	x1	x1	x1	x1	x1	x1	x1	x1	x1	x1
1	Denmark	6	2	3	1	8	8	9	7	2	16	5	5
2	Sweden	10	4	7	4	6	15	7	8	3	9	8	1
3	Norway	3	1	2	3	9	14	20	5	4	7	10	9
4	Finland	15	3	1	7	2	12	10	20	7	15	2	2
5	Switzerland	2	12	4	12	12	1	11	2	5	10	4	6

SCORE	COUNTRY												
ADJUST PILLAR WEIGHTING		x1	x1	x1	x1	x1	x1	x1	x1	x1	x1	x1	x1
84.55	Denmark	92.59	94.09	89.45	82.56	82.42	79.64	78.79	76.81	95.77	81.07	87.48	73.94
83.67	Sweden	90.97	91.90	86.41	78.29	82.81	75.54	79.67	76.18	95.33	82.28	85.92	78.74
83.59	Norway	93.30	94.10	89.66	79.03	82.24	75.95	75.87	77.25	94.70	82.98	85.68	72.37
83.47	Finland	89.56	91.96	90.41	77.27	84.12	77.25	78.77	70.28	94.46	81.19	88.38	77.99
83.42	Switzerland	95.66	87.50	87.67	69.14	80.81	83.84	78.65	79.71	94.66	82.11	87.72	73.60

Figure 2 The rank and score of top 5 countries in terms of the Legatum index in 2023 [1]

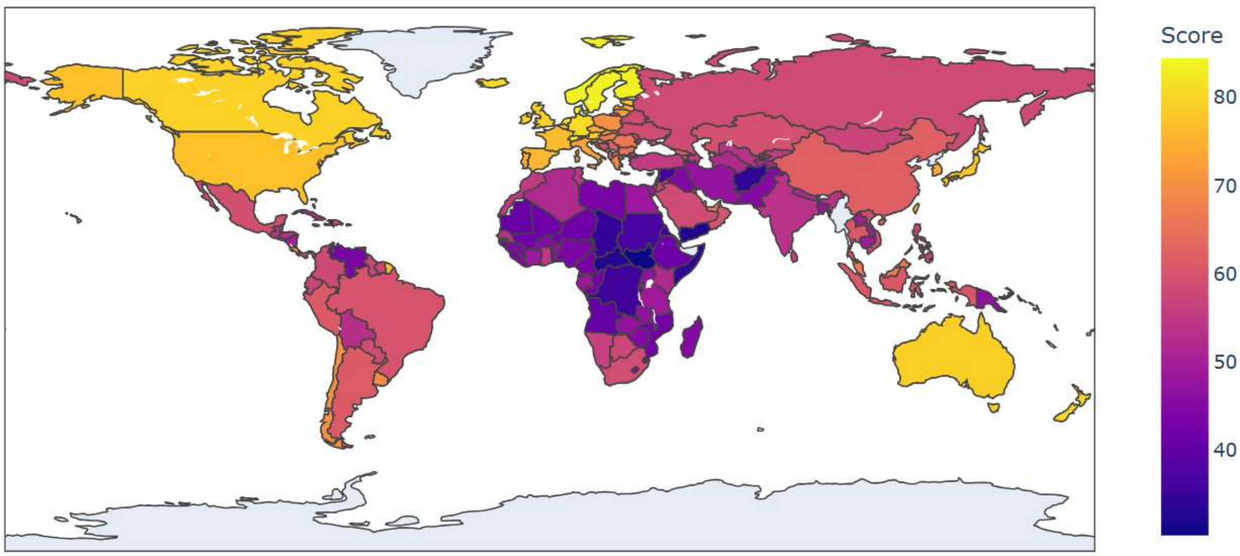


Figure 1 Heat map of countries based on their score

2.2 Bagging and Boosting

There are various algorithms for analyzing and extracting information from data, which can be broadly categorized into predictive and descriptive types [7] [8]. In predictive data mining algorithms, the main goal is to forecast future outcomes or events by utilizing past data and examining existing patterns and trends. Among the important algorithms of this type, BaggingRegressor and XGBoost can be mentioned [3] [4] [9]. According to Fig. 4, in these algorithms, a combination of decisions is used to create a new structure of prediction results. BaggingRegressor is an ensemble meta-estimator that fits base regressors each on random subsets of the original dataset and then aggregates their individual predictions (either by voting or by averaging) to form a final prediction. Such a meta-estimator can typically be used as a way to reduce the variance of a black-box estimator (e.g., a decision tree), by introducing randomization into its construction procedure and then making an ensemble out of it. On the other hand, XGBoost, eXtreme Gradient Boosting, is an advanced and optimized method of the Gradient Boosting algorithm. This method significantly improves model accuracy by using a set of small decision trees that are trained sequentially to reduce the errors of previous models.

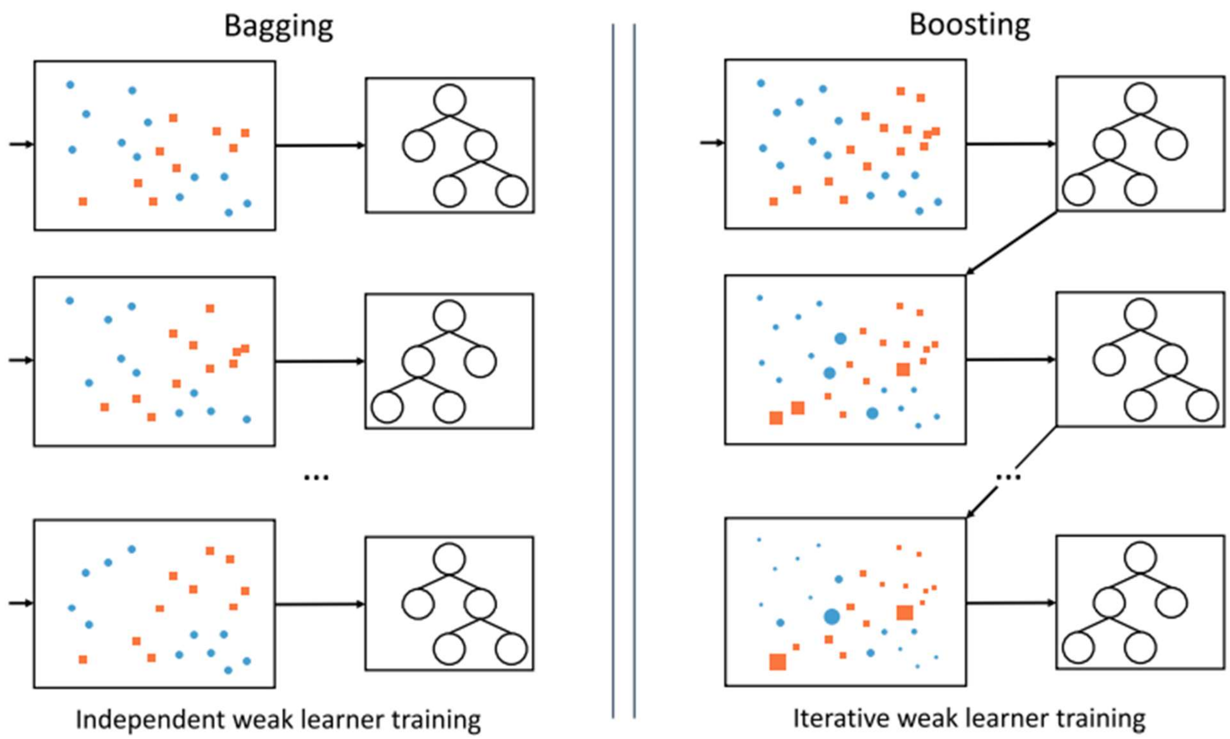


Figure 4 Bagging vs Boosting [9]

2.3 Evaluation measures

There are various measures for evaluating the predictive models obtained from the data mining process. In this paper, the correlation coefficient (CC) using Eq. (1), the mean absolute error (MAE) using Eq. (2), the root mean square error (RMSE) using Eq. (3), the absolute relative error (RAE) using Eq. (4), and the relative root mean square error (RRSE) using Eq. (5) are used to compare the predicted values obtained from the model (y_i) and the actual values (x_i) [10] [11]. If the CC measure is close to one or the MAE, RMSE, RAE, and RRSE measures are close to zero, it means that the actual and predicted results are slightly different.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (2)$$

$$CC = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (1)$$

$$RAE = \frac{\sum_{i=1}^{N}|y_i - \hat{y}_i|}{\sum_{i=1}^{N}|y_i - \bar{y}_i|} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \quad (3)$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}} \quad (5)$$

3 Related Work

Machine learning algorithms have been used in various research and topics. In some of these researches, these algorithms have been used to provide predictive models in topics such as politics, economy, and people. However, in many of them, either the Legatum prosperity index has not been investigated or ensemble learning algorithms have not been used. Table 1 compares the differences between our paper and other related works. For example, machine learning algorithms have been used in [12] to analyze time series data, use various models and methods of intelligent data analysis to mine data laws from huge data, statistical data reports, and find problems in economic development. In [13], the data mining method has been used to measure China's digital economy development index. The influence of AI on enterprise investment efficiency (EIE) has been explored in [14] with a focus on the role of accounting information transparency. Its findings demonstrated that AI development significantly enhances EIE. In [15], a multi-objective fuzzy robust possibilistic model has been proposed to solve a multi-objective portfolio optimization problem in a multi-period setting with the aim of maximizing the created jobs – as a key factor in social welfare – as well as intended profit while minimizing the risk of inappropriate portfolio selection. In [16], the thirteen sub-goals of the Health and Wellbeing Sustainable Development Goals (SDG) have been investigated, along with six additional related SDGs, to assess the impact of digital technologies and AI on their attainment. A four-stage methodology such as cluster analysis, data mining, partial least square path modeling, and importance-performance analysis has been applied in [17] to the Legatum prosperity index to identify the critical paths to the multi-dimensional prosperity of nations. In [18], the differences in the Legatum prosperity index between 15 non-cooperative tax jurisdictions and the rest of the countries in their geographic regions have been specified. In [19], countries have been divided into groups with Ward's algorithm and the similarities between the countries have been determined with the K-Means. Its results show that countries are divided into three clusters according to their prosperity levels. Furthermore, the most effective indicators in dividing them into clusters are "market access and infrastructure, education, investment environment", and the least effective indicators are "social capital, natural environment, safety and security". Panel quantile regression on the Legatum welfare index has been used in [20] to investigate the impact of the dependence on natural resources and Institutional quality index on social welfare in fuel exporting developing countries during the period 2007–2020.

Table 1: Comparing our paper with the state-of-the-arts

Ref.	Factors Investigated	Algorithms Used
[12]	China's time series data	machine learning algorithms such as mother wavelet
[13]	China's digital economy development index	data mining method
[14]	Enterprise investment efficiency	Enhancing enterprise investment efficiency through artificial intelligence
[15]	Social and economic impact on job creation	A multi-objective fuzzy robust possibilistic model
[16]	Global health and Sustainable Development Goals	Using artificial intelligence to achieve sustainable development goals
[17]	Legatum Prosperity Index	A four-stage methodology such as cluster analysis, data mining, partial least square path modeling, and importance-performance analysis
[18]	differences in the Legatum Prosperity Index between 15 non-cooperative tax jurisdictions and the rest of the countries	Friedman test to verify the significance of the differences
[19]	Legatum Prosperity Index	Ward's algorithm and K-Means algorithm
[20]	Legatum Prosperity Index	Panel quantile regression

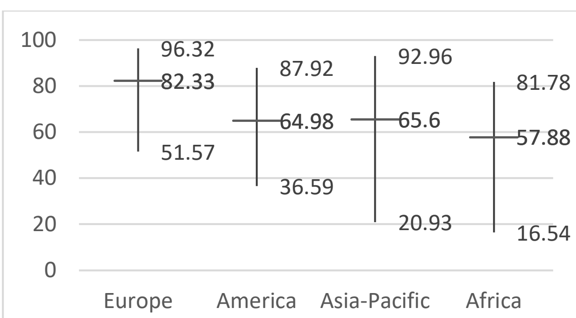
Ours	Legatum Prosperity Index	Bagging and Boosting Algorithms

4 Data analysis and prediction models

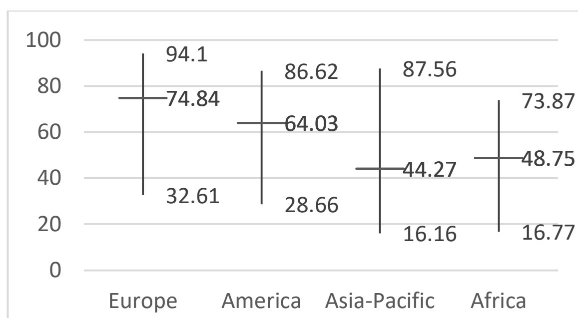
In this section, we first provide statistical data analysis of the data of the Legatum prosperity index and then, we predict the most influential indicator for each indicator on each continent using BaggingRegressor and XGBoost algorithms. Identifying the most influential indicator in each continent will help policymakers understand which indicator is more important than others and how many other indicators are likely to improve as it improves. For this purpose, the Python programming language and NumPy, pandas, and sklearn libraries have been used in the colab environment.

4.1 Statistical data analysis

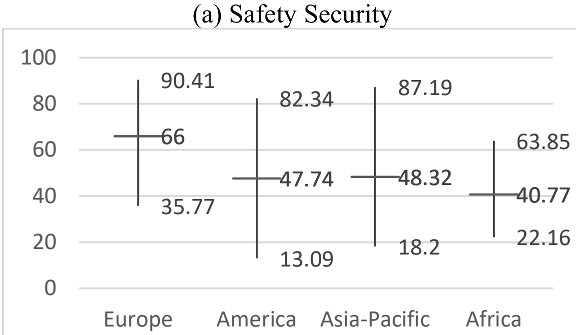
As mentioned in Section 2.1, the Legatum prosperity index ranks and scores countries based on 12 key indicators. To analyze each continent, we first organized the data provided by the index according to the world's continents. Figure 5 presents the minimum, maximum, and mean values for each indicator across the continents, allowing us to assess the degree of disparity among countries within each region. A larger gap between the minimum and maximum values for a given indicator suggests a greater disparity, or class difference, among the countries on that continent. Additionally, if a continent's mean value for an indicator is closer to the minimum (or maximum), it implies that most countries in that region are in a relatively unfavorable (or favorable) position for that indicator. As shown in Figure 5, European countries exhibit low disparity in indicators such as Safety Security, Market Access Infrastructure, Living Conditions, Health, and Education. In contrast, African countries show low disparity in Personal Freedom, Governance, Social Capital, Investment Environment, Enterprise Conditions, Economic Quality, and Natural Environment.

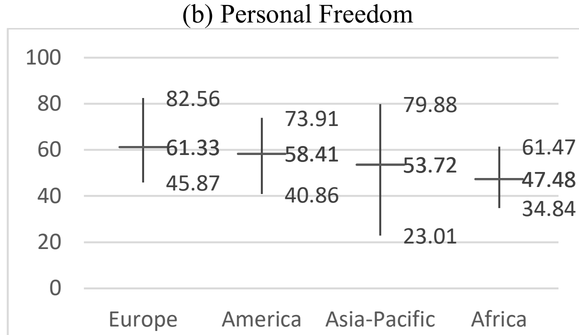


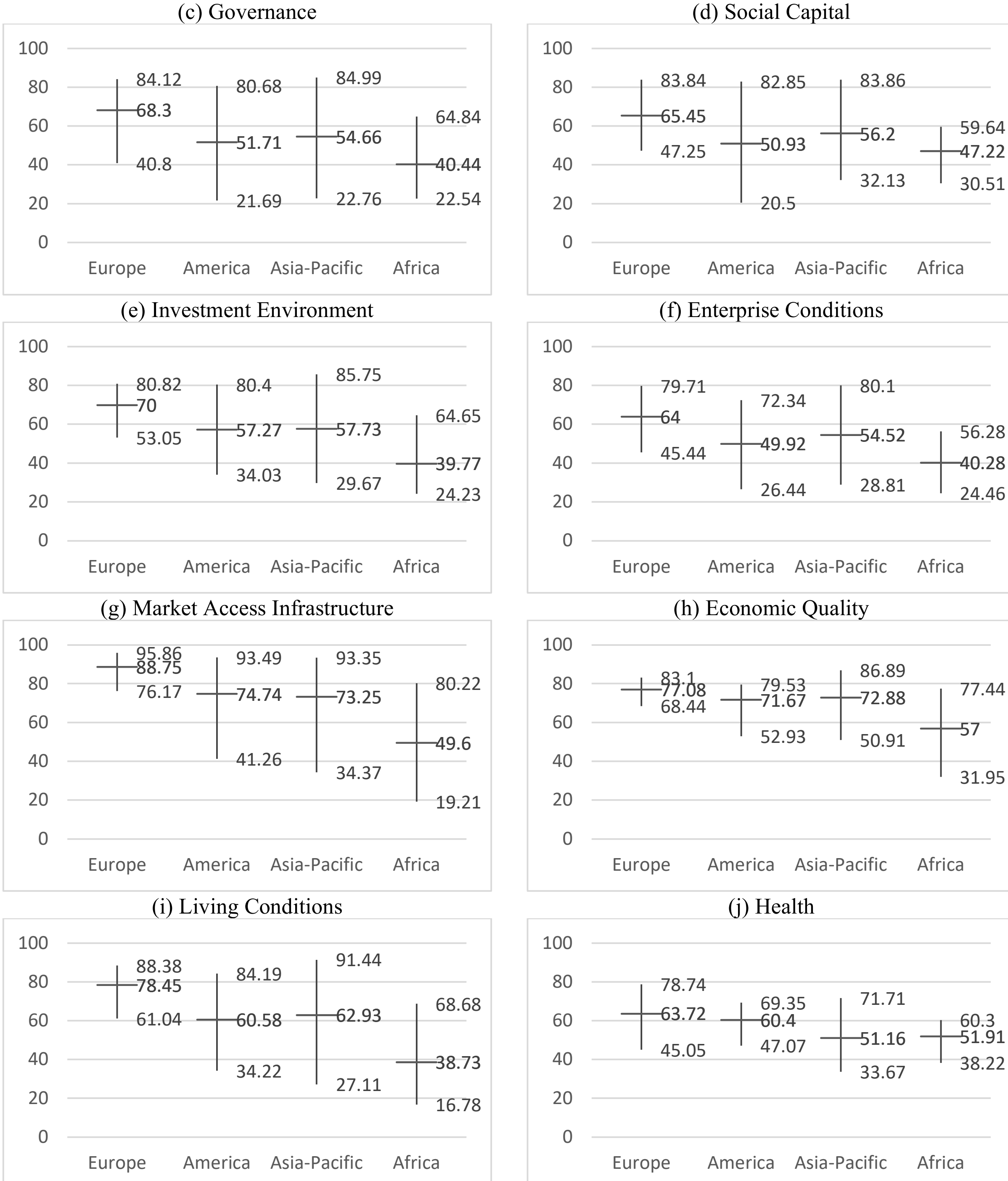
(a) Safety Security



(b) Personal Freedom







(c) Governance (d) Social Capital

(e) Investment Environment (f) Enterprise Conditions

(g) Market Access Infrastructure (h) Economic Quality

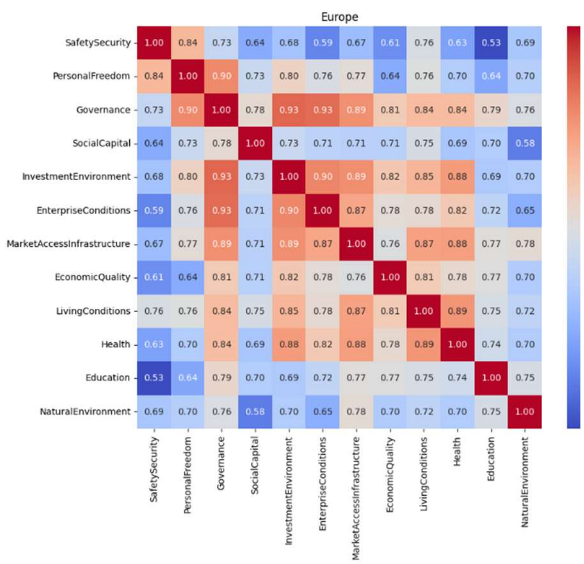
(i) Living Conditions (j) Health

(k) Education (l) Natural Environment

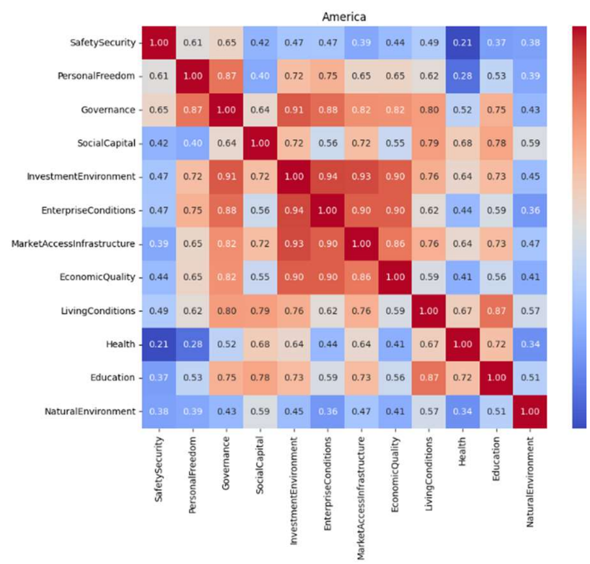
Figure 5 Minimum, maximum, and mean value of each indicator of the Legatum prosperity index by continents

4.2 Prediction models

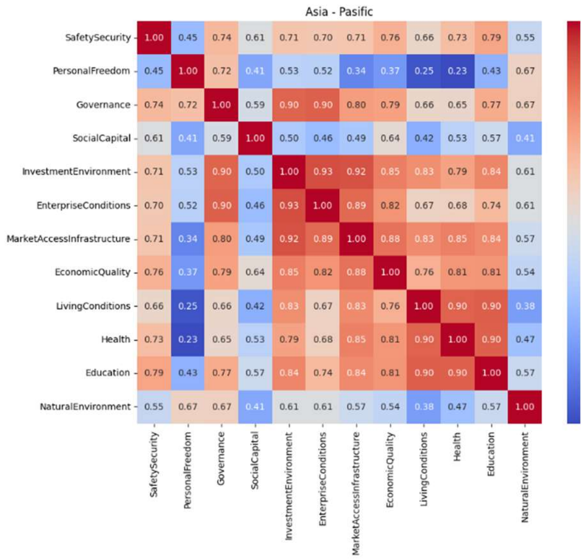
The first step in identifying key variables is to use a heat map. The heat map is a data visualization plot that represents the magnitude of the mutual impact of the value of variables within a dataset as a color [21]. In this study, we employ heat maps to illustrate how each indicator influences others within each continent. Figure 6 presents the mutual relationships among 12 indicators of the Legatum Prosperity Index across different continents, based on the Pearson correlation coefficient matrix. This statistical tool measures and analyzes the strength and direction of linear relationships between pairs of variables, yielding a coefficient ranging from -1 to 1. These values are visualized in the form of a heat map. According to Table 2, in Europe, the most influential indicator is governance, which significantly impacts six other indicators. In the Americas, the most influential indicator is the investment environment, affecting four other indicators. In the Asia-Pacific region, investment environment and education are the most influential, each impacting three other indicators. In Africa, investment environment also stands out as the most influential, affecting three other indicators. Table 2 further reveals that, regardless of geographical location, governance has the greatest influence on both safety security and personal freedom. Similarly, enterprise conditions most strongly influence governance and investment environment, while investment environment plays a key role in shaping enterprise conditions, market access & infrastructure, and economic quality. Health and education are the primary drivers of living conditions, with education also being the most influential factor for health. Conversely, living conditions most strongly influence education, and social capital has the greatest impact on the natural environment.



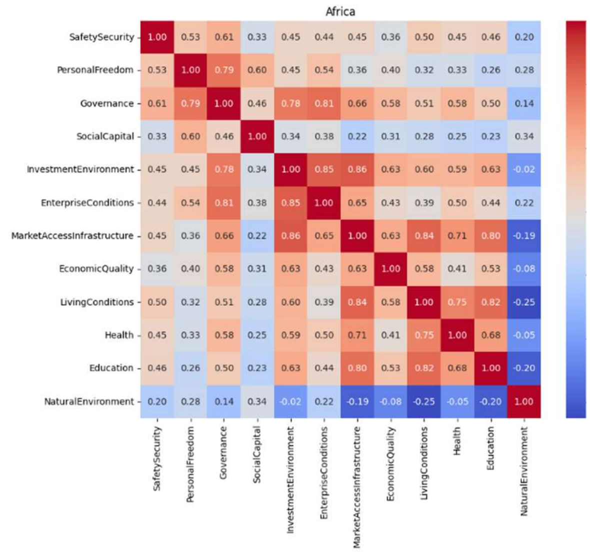
(a) Europe



(b) America



(c) Asia-Pacific



(d) Africa

Figure 6 Heat map of 12 indicators of the Legatum prosperity index by continents

Table 2: The most influential indicator for each indicator on each continent using heat map

Indicators	Europe	America	Asia-Pacific	Africa
Safety Security	Personal Freedom	Governance	Education	Governance
Personal Freedom	Governance	Governance	Governance	Governance
Governance	Investment Environment/ Enterprise Conditions	Investment Environment	Investment Environment/ Enterprise Conditions	Enterprise Conditions
Social Capital	Governance	Living Conditions	Economic Quality	Personal Freedom
Investment Environment	Governance	Enterprise Conditions	Enterprise Conditions	Market Access Infrastructure
Enterprise Conditions	Governance	Investment Environment	Investment Environment	Investment Environment
Market Access Infrastructure	Governance/ Investment Environment	Investment Environment	Investment Environment	Investment Environment
Economic Quality	Investment Environment	Investment Environment/ Enterprise Conditions	Market Access Infrastructure	Investment Environment/ Market Access Infrastructure
Living Conditions	Health	Education	Health/ Education	Market Access Infrastructure
Health	Living Conditions	Education	Living Conditions/ Education	Living Conditions
Education	Governance	Living Conditions	Living Conditions/ Health	Living Conditions
Natural Environment	Market Access Infrastructure	Social Capital	Personal Freedom/ Governance	Social Capital

As discussed in Section 2.2, various algorithms can be used to analyze and extract insights from data. In this study, we employ the BaggingRegressor and XGBoost algorithms due to their superior performance in this context. Specifically, for each indicator in each continent, two predictive models are developed using these algorithms. To train the models, 90% of the data is used, while the remaining 10% is reserved for testing. To ensure optimal model performance, the random state parameter was configured. This parameter controls the randomness involved in processes such as data splitting and model initialization. By setting this value, the results remain consistent across multiple runs, enhancing reproducibility and making model comparisons more reliable.

Table 3 presents the most influential indicator for each target indicator in each continent, as identified by both algorithms. Indicators highlighted in the table denote alignment between the most influential predictor identified by the model and the one indicated in the heat map. Underlined indicators represent the algorithm (either BaggingRegressor or XGBoost) that performed better based on evaluation metrics. In other words, for certain indicators in some regions, BaggingRegressor yielded better results, while in others, XGBoost outperformed. Table 4 provides a more detailed breakdown of Table 3, showing the evaluation metrics for each algorithm beneath the corresponding most influential indicator. Highlighted values indicate cases where one algorithm outperformed the other. Despite minor differences, both algorithms demonstrate high accuracy based on evaluation metrics, confirming their overall effectiveness. According to the best-performing models (as shown in Table 3):

- In Europe, the most influential indicators are governance and health, each significantly impacting three other indicators.
- In America, governance is the most influential, affecting four other indicators.
- In the Asia-Pacific region, investment environment and education are the most impactful, each influencing three other indicators.
- In Africa, market access infrastructure is the most influential, affecting five other indicators.

Additionally, the results in Table 3 indicate consistent patterns across continents:

- Governance is the most influential indicator for personal freedom and social capital, regardless of geographic location.
- The most influential indicators for governance are personal freedom and enterprise conditions.
- Market access infrastructure most strongly influences investment environment and economic quality.
- Enterprise conditions are primarily influenced by governance and investment environment, while education is most influenced by health.
- Finally, safety security is the most influential indicator for the natural environment.

Table 3: The most influential indicator for each indicator on each continent using prediction models

Num	Indicators	Algorithms	Europe	America	Asia-Pacific	Africa
(1)	**Safety Security**	Bagging	(2)	(2)	(11)	(3)
		Boosting	(12)	(12)	(11)	(9)
(2)	**Personal Freedom**	Bagging	(3)	(3)	(12)	(3)
		Boosting	(3)	(3)	(12)	(3)
(3)	**Governance**	Bagging	(2)	(2)	(6)	(6)
		Boosting	(5)	(2)	(6)	(6)
(4)	**Social Capital**	Bagging	(1)	(3)	(3)	(2)
		Boosting	(1)	(11)	(8)	(2)

(5)	**Investment Environment**	Bagging	(3)	(7)	(7)	(7)
		Boosting	(3)	(9)	(6)	(7)
(6)	**Enterprise Conditions**	Bagging	(3)	(8)	(3)	(5)
		Boosting	(3)	(3)	(5)	(5)
(7)	**Market Access Infrastructure**	Bagging	(10)	(8)	(8)	(5)
		Boosting	(9)	(8)	(5)	(5)
(8)	**Economic Quality**	Bagging	(5)	(7)	(10)	(7)
		Boosting	(5)	(7)	(10)	(7)
(9)	**Living Conditions**	Bagging	(10)	(3)	(10)	(7)
		Boosting	(7)	(11)	(11)	(7)
(10)	**Health**	Bagging	(9)	(11)	(11)	(7)
		Boosting	(9)	(11)	(11)	(7)
(11)	**Education**	Bagging	(9)	(9)	(10)	(7)
		Boosting	(10)	(10)	(10)	(7)
(12)	**Natural Environment**	Bagging	(1)	(1)	(2)	(4)
		Boosting	(1)	(11)	(5)	(4)

5 Conclusion and future works

We utilized the Legatum prosperity index to analyze statistical data and develop predictive models using Bagging and Boosting algorithms. Our primary objective was to identify the most influential indicators on each continent. By applying these machine learning techniques, we were able to determine which indicators had the greatest impact on others within each region. In summary, our findings revealed that the governance indicator had the most significant influence on other indicators in Europe and America. Therefore, countries in these continents may enhance their rankings in the Legatum Prosperity Index by focusing on improving governance. In the Asia-Pacific region, investment environment and education emerged as the most influential indicators. In Africa, market access infrastructure had the strongest impact on the other indicators.

It is important to note that our analysis was based solely on 2023 data from the Legatum Prosperity Index. For future work, it would be beneficial to collect and analyze data from multiple years to develop more robust and time-aware predictive models. Additionally, rather than analyzing entire continents, future studies could focus on individual countries to create customized prediction models tailored to their specific conditions using machine learning algorithms.

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