The Determinants of Indonesia Export Performance: Gravity Model and Random Forest Model

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***Abstract*—In the last six decades, economists have used the gravity model to predict one country's exports and their determinants. However, this method is sensitive to a large dataset, a heavy missing value dataset, and an unbalanced dataset. This method needs to normalise the data heavily and cherry-picked a subset of data to make the model work. Recently, a new method from the computer science field called machine learning was implemented by applied economists in their respective problems. One machine learning method to predict a dependent variable from its independent variable is a random forest. This method does not need to normalise, can process raw data, and handles large and sparse datasets. We are experimenting with this new method to handle the large dataset we collect from various sources. Some variables in our dataset have been proven to affect exports, but another researcher has not yet explored others. This paper uses a random forest to predict exports and their determinants. We achieve the result of a 92.5% R^2 after some experiments. This is higher than the result from the gravity model that has 63.8% R^2 with Fixed Effect and 85.2% R^2 with Pooled Least Square. With random forest, we can also list the variables that determine Indonesia's export to the target country, with the degree of importance of each variable.**

Keywords—Random forest, export performance, variable importance, decision tree, Indonesia export

I. INTRODUCTION

Prediction is an integral part of the economic study. One thing that is often predicted in the economy is a country's exports. The export of a country plays a vital role in predicting that country's wealth, GDP, wealth of its citizens, and modernity. One method to make an export prediction is called the gravity model.

However, the gravity model cannot keep up with the modern economic problem. Now, economists can gather abundant data from the macroeconomy sector to better predict exports. A simple gravity model cannot process all this data and produce a better prediction. We need a modern approach that can process all this data. After an extensive literature review, we found no proof that some researchers approached this problem for Indonesian export data.

The objective of this study is to analyse the determinants of Indonesian exports using the gravity model and compare it with random forest to see which approach could produce a better prediction of Indonesia's exports. We also analyse whether this approach could point out what variables determine how big exports to one country are. With the result of this study, the Indonesian government could make a policy focusing on these variables to make a more significant export value.

II. RELATED WORK

The gravity model was invented by Tinbergen [24]. The gravity law from Newton inspired this model, hence the name gravity model. Gravity law states that attraction between a planet or planet and a star is influenced by its mass and distance; the bigger mass will have more attraction. Nearer distances will have more attractions, and farther away will have less attraction.

Tinbergen adopts this law empirically in the field of economics. He shows that trade flow between countries could be approximated using each country's "mass", usually represented by their GDP (Gross Domestic Product). The distance could be the actual distance between the country or another kind of "distance" that separates the country, like the similarity of its culture, language, or religion. The gravity model started as an empirical study, now becoming the workhorse model of economists, backed by a theoretical approach from some writers in the following decades.

In Indonesia, economic researchers explore the gravity model to forecast Indonesia's trade flow, mainly exports from Indonesia to other countries. Since economists believe that the one that brings benefits is the export side, Bary [2], the prospect of Indonesian trade with China and India uses a gravity model. He just analysed two countries with five variables: the GDP of Indonesia, the GDP of China, the GDP of India, the export of Indonesia to China and Indonesia to India. The data frame is quarterly, from 1999Q1 until 2008Q4, in a 40-row dataset.

A different approach from fellow Indonesian researchers is using only a few variables, like an author's [7] approach uses the exchange rate value to determine the quarterly performance of Indonesia's exports from 2005Q1 until 2012Q4. So, in total, he has a 32-row dataset in his study.

Rindayati's [21] research only focuses on Indonesia's tuna export commodity with data from 2009–2013. They use the gravity model method, and the results show that the GDP per capita of the importing country, the population of the importing country, and economic distance are the factors affecting Indonesian tuna exports. However, the real exchange rate has no significant effects.

Siti and Trias's research [25] focus on estimating the effect of the GDP of export destination countries, inflation of export destination countries, economic openness of export countries and the Indonesian exchange rate against the US dollar to Indonesia's non-oil exports to non-traditional trading partner countries.

While Deni and Randy's study [26] looks only at determinants of coal exports to six Asian countries, the variables that they're testing are exchange rate, foreign exchange reserves, population, and coal production.

After six decades, the gravity model faces a challenge. The challenge comes from the amount of data that economists can access. From the country list, economists could look at hundreds of other countries instead of cherry-picking some countries with excellent trade flow relationships with Indonesia. So, we could find a better model to predict Indonesia's exports accurately to all countries in the world. We could also expand the number of variables, not just a few that another researcher has already explored, but more variables that have never been studied. So, we can see which variable is essential to determine Indonesia's exports to other countries.

One field that could successfully tackle this challenge is computer science, with its machine learning method. This method works well empirically despite the general belief that machine learning is a kind of "black box" that is not interpretable and lacks a theoretical foundation. Machine learning can handle many, unbalanced, and rich variable datasets. We also do not necessarily normalise the dataset because it could work end-to-end as it is with minor adjustments from its default setting. It just runs well for so many problems in the computer science field, including forecasts. That is what some economists do, in our case, forecast exports from Indonesia to another country and analyse which variable determines how much Indonesia exports to another country.

Machine learning has already been adopted in some areas like biology, medicine, physics, etc. For the economy itself, the adoption of machine learning is still at an early age. As Mullainathan [14] and Athey [1] suggest, machine learning could benefit the applied econometric field since econometrics already dealt with the empirical dataset for a long time. We can use machine learning to predict function y that fits into some number of x variables. This prediction could fit correctly both in the training and outside training sets. Some researchers are naming outside training sets as validation sets.

When the model can make a reasonable prediction for the validation set, the prediction model is not overfit. We could use the model for the dataset, which has never been seen before. This process is called regression, and machine learning, based on some research work, has proved to be an excellent tool for regression.

Machine learning models are also used in forecasting, such as forecasting the rising demand for electric vehicles applicable to Indian Road Conditions [19], and a team of authors implemented machine learning in the finance field to predict the inflation rate in Indonesia [15].

One machine learning algorithm that is well suited for regression problems is a random forest. This algorithm was first publicised by Breiman [3], who proposed an algorithm of decision-tree combined into bagging or the ensemble of decision-tree; hence comes the name forest because it contains many trees. He also introduces randomness inside the tree's construction to remove the collinearity of the variable and each tree itself. So, in the end, the random forest could produce an accurate prediction that does not overfit in the training set and could generalise well in the validation set.

After Breiman invention in a random forest, some author started to use this algorithm in their set of problems. Oliveria [18] used the random forest to predict fire occurrence in Mediterranean Europe; this prediction was made with rich variables, a total of 37 variables included in this work. That comes from topography, land cover, climate, infrastructure, demographics, and socio-economics. With this rich dataset, they reached 94% R^2 results.

There is one crucial feature from a random forest called feature importance. With this feature, the researcher could see which variable is essential to determine the dependent variable. Feature importance makes results from random forests more interpretable and easy to understand. Some authors explored this feature deeply to justify its general property [6,8,10].

After an extensive literature review, we found no evidence that another author had already explored Indonesian export determinants using a random forest method. Hence, this paper contributes to giving a new approach for economic policymakers in Indonesia to analyse what factors determine Indonesia's exports. How important each factor is also could be determined. So, the Indonesian government could focus its resources on exploiting potential export countries that show important characteristics of the factor.

Moreover, this paper is organised as follows: Section 2, Related Work from another researcher. Section 3, Research Method, explains how the dataset was collected and how the model was employed as a regressor. Section 4, Result and Analysis of our experiment. Section 5, Conclusion drawn from our study.

III. RESEARCH METHOD

A. Dependent Variable

The dependent variable of this paper is exports from Indonesia to another country. Data was obtained from the International Trade Center, and we used a dataset from 2001 until 2022, corresponding to the most recent data available for all countries. This study covers almost all countries: 185 countries, 51 African countries, 47 Asia countries, 40 European countries, 20 North American countries, 14 Oceania countries, and 13 South American countries.

The study of exports is interesting to examine because exports are one factor driving Indonesia's economic growth. Most of Indonesia's exports are still natural products, like rubber, palm oil, forest products, shrimp, cocoa, and coffee. Besides natural products, Indonesia also exports electronics, automotive, footwear, textiles, and product textiles. The primary target market for Indonesian exports is the United States, Japan, China, India, the European Union, and ASEAN. Therefore, this paper further magnifies data on

African countries, the Middle East, South Asia, Euro Asia, South America, and Oceania as a new target market.

B. Independent Variable

A total of 24 independent variables were extracted from several databases covering the economic size of Indonesia, the economic and market size of the target country, infrastructure & demographics, distance and culture. The last one is a political-economic relationship. These variables were selected based on potential relevance for export, literature review, and expert knowledge.

1. Economic and Market Size

The GDP of Indonesia and its partner countries is used as the measurement of economic size. The population is used to estimate the market size of each country. A study of economics shows that the bigger the market, the more it trades, so the market size is expected to have a positive influence. GDP and population figures were obtained from the World Bank's annual statistics.

An author [13] used multi-regression analysis and found that GDP per capita and real exchange rate influenced Indonesia's export performance to the target country. Based on this finding, we include the exchange rate in the consideration variable. Inflation is included in the variable list as well as a general macro economic variable.

We also add the country's debt percentage to GDP, data from the International Monetary Fund. Human Development Index (HDI) is also included in our variable list; HDI is a composite statistic of life expectancy, education, and per capita income from the United Nations Development Program. We also add life expectancy into our variable list; this data is taken from the World Health Organization. Debt percentage to GDP, HDI and life expectancy is the list of variables that the economic community has not yet researched, so we put it into our model to test our hypothesis.

2. Infrastructure and Demographic

The infrastructure aspect refers to a number of international seaports & airports, while demographics use total area and continent classification variables. The different aspects of demography hypothetically will have an impact on exports. For example, if the number of international seaports and airports is adequate, it could affect the ease of trade of products and lower transportation fees. The total area could indicate the ownership of resources in that country. The continent category is also put into the model as an independent variable because, hypothetically, transporting goods via land is cheaper and faster than by sea.

3. Distance and Culture

Distance represents the transportation cost, a burden when making international trade. It is calculated kilometres from Jakarta, Indonesia's capital city, to another country's capital city. The distance data is from The Centre d'Études Prospectives et d'Informations Internationales (CEPII) database on the World Economy, which measures the minimum geographical distance at the Earth's surface. This variable is expected to hurt Indonesia's export flows as transportation costs will be proportional to the distance between countries.

Religion and language are the variables that reflect the individual characteristics of the country. The religion variable is a categorical variable that shows the majority religion of each country. The language variable is a dummy variable set to 1 if the country's language is similar to the Indonesian language and set to 0 if otherwise.

4. Political-Economic Relationship

Political-economic is a variable representing political and economic relationships with partners. Free Trade Agreement is set at 1 for countries with a strategic partnership agreement with Indonesia and 0 for the rest. We get a variable of total Indonesian in a target country from General Election Committee data of the total Indonesian diaspora eligible to vote in the general election 2019.

Another variable in this category is the import variable, an essential variable in this study. We believe that when we import from one country, that country is more willing to accept exports from Indonesia.

C. Models

The model used in this work is a random forest; a random forest is a combination of tree predictors such that a tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest [3]. In our experiment, we use a random forest regressor to map a tree function from variable export as a dependent variable to its independent variable and try to predict accurately Indonesian export based on the independent variable listed on that particular country in a particular year.

We divide the dataset into two parts; the first part is the training set, where the data is used to create a random forest model. The second part is the validation set, where we measure how well the model predicts the dependent variable for data it has never seen before in the training process. We evaluate the correctness of the model to predict the dependent variable using R^2 measurement. R^2 is used in the economic field as the term for how good an independent variable is in explaining the dependent variable. R^2 with value 1 means the dependent variable 100% could be explained and predicted by the model only using the list of an independent variable in the dataset. Meanwhile, R^2 with value 0 means the model cannot predict anything based on the dataset provided.

However, one study shows that the random forest model behaves as a "black box" because the individual trees cannot be examined separately to understand how the model decides [20]. This characteristic is not good for economics because we need to influence people to change the policy based on our findings. We need to understand how our model behaves and produce the prediction to influence people. Because of that, we deploy some methods to interpret results from the random forest model, such as drawing a single tree sample using our dataset and creating variable importance to analyse which variable is the most important and how important each variable is. For each variable, what is the value of the contribution to the final prediction? Is that positive or negative, and by how many points do they contribute?

D. Equipment

A single laptop was used for this experiment, and machine learning training using a Central Processing Unit (CPU) for the random forest model takes approximately 3 seconds for 2,919 rows of dataset and 25 column variables on the machine specified in Table 1.

TABLE 1. MACHINE SPECIFICATION

Hardware / Software	***Specification***
Memory	16 Gb
Processor	I7 Intel CPU
Operating System	Linux Ubuntu
Machine Learning Program	Python library

IV. RESULT AND ANALYSIS

We perform regression on a dataset consisting of the dependent variable (export) and 24 independent variables gathered from the various databases on the internet. These 24 independent variables were chosen because they have been mentioned in the literature review before by some economists and others. After all, we want to test our hypothesis beyond determinant variables already explored by the economist.

A. Parameter Tuning

We apply a random forest regressor to the independent variables and map the model to predict the dependent variable. To create a good model, we need to tune the hyperparameter we use in random forest model creation, such as the number of trees and percentage of dataset division for the training and validation sets. To measure the effectivity for each parameter, we use the R2 metric to measure how useful each parameter is, and finally, we decide which setting produces the best R^2. R^2 in statistics and economy means how well our model uses the independent variable to predict the dependent variable. The range starts from 0, which means our model entirely does not predict anything until 1, which means our model correctly predicts every single dataset. We also use the out-of-bag method, in addition to the training set and validation set, to measure the model performance outside the sample set.

In Table 2, we experiment with the number of trees because the random forest consists of an arbitrarily chosen number of trees. A general rule of thumb is that more trees are better, but this only applies to a certain number of trees; when the tree grows too much, the model starts to overfit and make R^2 worse. Overfit is when the model does not generalise well and only fits the sample dataset it has seen.
It makes it useless to predict data it has never seen, like in a validation set. The model that overfit is not good.

TABLE 2. PARAMETER TREE TUNING

Number of Tree	***Training Set R^2***	***Validation Set R^2***	***Out-of-bag R^2***
10	0.987	0.852	0.910
80	0.993	0.879	0.954
640	0.994	0.862	0.956
1280	0.993	0.862	0.956

Based on Table 2, the best number of the tree to choose is 80 tree in our random forest model, so we keep using 80 trees for our next experiment. After that, we need to decide how to divide our dataset into a training and validation set and how much percentage of the dataset must go to training and validation. We show this experiment results in Table 3.

TABLE 3. DATASET TUNING

Training : Validation	***Training Set R^2***	***Validation Set R^2***	***Out-of-bag R^2***
80:20	0.995	0.925	0.969
70:30	0.993	0.924	0.952
60:40	0.995	0.906	0.966
50:50	0.992	0.873	0.955

Based on Table 3, the best division between the training set and validation set is 80:20, which means 2319 rows from the dataset used to train the random forest model and a 600-row dataset will be used for validation. For all of our experiments, we are using 80:20.

B. Model Interpretation

A decision tree in the Random Forest model decides the x variable that divides the data based on how important the variable is. With this property in the random forest model, we could analyse the determinant of Indonesia's exports to other countries. Table 4 shows ten variables important to prediction, ranked from the highest.

TABLE 4. VARIABLE IMPORTANCE

Variable	***Degree of importance***
Import	0.488
GDP PPP	0.203
Indonesia inside	0.068
Population	0.039
Life expectancy	0.033
Debt percentage	0.028
Seaport	0.026
Religion	0.024
Distance	0.012
Airport	0.011

Every country does international trade for the benefit of both sides. When one country exports goods in large quantities, there is pressure from a target country to raise their import, too. This theory comes from J.S. Mill's reciprocal demand theory [17]. One country produces and exports goods with the most comparative advantages and imports goods with a comparative disadvantage, which are cheaper when importing compared to making them. Every country specialises in producing a list of limited products where they have a competitive advantage. This theory verifies why imports come in the first place as the most crucial factor affecting Indonesia's exports.

Bilateral trade flow between countries is proportional to their respective GDP because it seems that when a country has a high GDP, the people in that country have better income and, thus, have a higher disposable income to increase their life quality [9]. This disposable income is spent on their domestic product and also spent on import products as well. A country with a high GDP has a bigger market for Indonesian products. This is why a country with a higher GDP has proven to be a good target market for Indonesia's exports.

Indonesia is the fourth rank for the population size in the world; there is more chance that Indonesian citizens spread around the world, like what happens to China and India [22]. Indonesian people inside a foreign country could help bilateral trade because they already understand the language and culture of the target country, so they could help the product from Indonesia enter the market. That could explain why the variable Indonesian inside ranks high in Table 5. This is a new finding for an economist to quantify how important the Indonesian diaspora is to Indonesian exports.

A country with a more significant population has more demand simply because its population consumes more. Some of this consumption could be fulfilled by domestic production. However, some products that don't have the comparative advantage need to be imported from another country, like Indonesia. So, it is reasonable to see that the variable population gets the fourth position in the rank of variable importance. The study that uses the gravity model to approximate bilateral trade also shows that the population determines exports. In the Gravity model, the population is seen as a mass, like the planet's mass; the bigger the planet's mass is, the more gravity it has, pulling another object to it.

Krugram [12] said that in traditional international trade theory, distance is not a determinant in bilateral trade. Still, in the new international trade theory, distance in physical geography is one of the determinants of bilateral trade. The gravity model confirms that distance is essential in approximating exports. So distance is expected to be one of the significant factors. However, the exciting finding is that, in our study, distance is less important than the previous research shows. It is just below the religion variable. The impact of distance is relatively low; perhaps it is because the world is getting more connected now in the modern world. Transportation is getting more efficient so that we can purchase products more cheaply and faster. As explained by Thomas Friedman's book The World is Flat, he explains how globalisation changed the world economy in the 21st century [5].

Seaports and airports are included in the transportation infrastructure category, with roads, bridges, and some others. Transportation infrastructure helps economic activity by supporting the distribution flow of goods and services, making it efficient [4]. An increase in transportation infrastructure, such as developing a new international seaport, creates more capacity for that country to make global trade. In Table 4, the seaport is more important than the airport in our study, two times more important. Perhaps because Indonesia is an island country, the best mode for international trade is via sea.

The neoclassic economist believes foreign debt is a positive sign. Debt increases foreign exchange reserves and fills the capital needed to develop the country, and later on, this development supports export growth [23]. The example is like building a road to support distribution channels in the country; this accelerates international trade flow, both for export and import. This positive impact is there as long as the country manages foreign debt well.

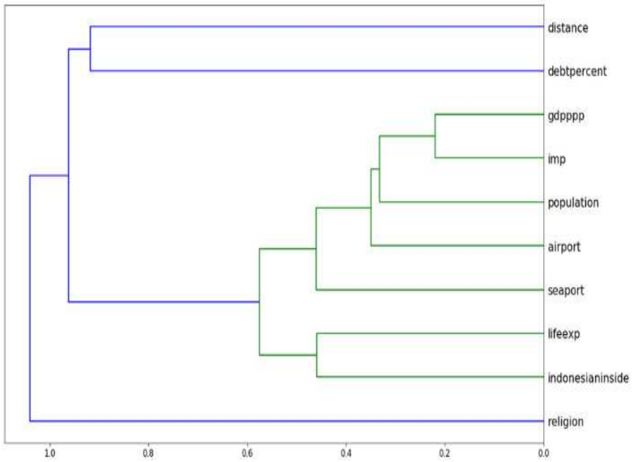

Fig. 1. Relationship between variable

Figure. 1 shows the closeness or relationship between variables, and it is great to see how random forests put each variable close to each other, and we could see the logical relationship in it. Such as gdpppp and imp are measuring economic background, while airports close to seaport represent infrastructure in that country.

C. *Performance Comparison with Gravity Model*

The equation gravity model used to determine the export of Indonesia refers to research conducted by Tinbergen [24] as the basis of the gravity model. In this study, it has been modified by adding several new variables. The gravity model equation has the following form:

$\log \mathrm{ex}ijt = \alpha 0 + \alpha 1 \log \mathrm{imp}ijt + \alpha 2 \log \mathrm{gdp}jt + \alpha 3 \log \mathrm{pop}jt + \alpha 4 \log \mathrm{gdp}it + \alpha 5 \log \mathrm{pop}it + \alpha 6 \log \mathrm{excrt}ijt + \alpha 7 \log \mathrm{inf}jt + \alpha 8 \log \mathrm{area}j + \alpha 9 \log \mathrm{dist}ij + \alpha 10\ \mathrm{ap}j + \alpha 11\ \mathrm{sp}j + \alpha 12\ \mathrm{cont}ij + \alpha 13\ \mathrm{FTA}ij + \alpha 14\ \mathrm{rlg}j + \alpha 15\ \mathrm{lang}j + eijt$ (7)

Where:

i = 1 (Indonesia)

j = 2, 3, 4,….(partner country)

t = 2001, 2002, 2003,….(year)

exijt: value export from Indonesia to country j in year t

gdpjt: GDP PPP country j in year t

gdpi$t$: GDP PPP country i in year t

impijt: value Import from country j to Indonesia in year t

popjt: population country j in year t

popit: population country i in year t

excrtijt: exchange rate between Indonesia to country j in year t

infjt: inflation in country j in year t

distij: distance from Indonesia to country j (capital)

$areaj$: area country j

apj: total airport in country j

spj: total seaport in country j

$contij$: dummy variable on the same continent

$rlgj$: religion as a culture dummy variable for the cultural gap between Indonesia and country j

$langj$: language as a culture dummy variable for the cultural gap between Indonesia and country j

$FTAij$: Strategic partner dummy variable Free Trade Arrangement between Indonesia and country j

TABLE 3. GRAVITY MODEL RESULT

	Pooled Least Square	*Fixed Effect (robust)*	*Random Effect*
R^2	0.852	0.638	
Rho		0.94	0.77

R^2 in the FE estimator shows a decrease compared to PLS, from 85% to 63%. This indicates that the PLS has an overestimation in the variable that causes R^2 to overestimate. This explains the results of the 63% R^2 square explanations are derived from existing variables estimated, namely Import, GDPj, Popj, and inflation. While the rest are variables that do not exist in estimates, including dummy variables and invariant time variables, this might be the reason R2 is relatively lower compared to other methods. R^2 in fixed effects is very reasonable; the value is small because the Fixed effect is a model that does not include variables that do not take time. So that the remaining variables allow for variables that are not included in the variable fixed effect. The rho value is also known as the interclass correlation and tells how strongly the observations within each unit resemble each other. The rho value (0.94) tells us that 94% of the variance is due to differences across time (within units).

CONCLUSION

Random forest investigation for determinants of Indonesian export is an essential problem in empiric macroeconomics. A random forest performed well in our experiment, achieving 92.5% R^2 in the validation set. Much higher compared to the gravity model result. Considering the amount of data it digests and a variety of data. To our knowledge, it is the most complex study of Indonesia's export determinant. Random forest applied to analyse Indonesia export is a novel approach to this problem; it still shows relevance and confirms the earlier study that uses a well-known method, such as the gravity model.

However, the use of machine learning techniques in the economy is generally still at an early age. A highly empirical Computer science approach seems to be a hard partner with highly theoretical economics. Further study is necessary for the theoretical validation of this work.

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