Prediction model of Illegal Wildlife Trade using genetic algorithm and Bayesian optimization

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Abstract. In this paper, genetic algorithm and Long Short Term memory network (GA-LSTM) are used to predict the amount of global illegal wildlife trade, and differential method and Bayesian optimization support vector machine (SVM) are used to predict the future trade volume of high-risk countries. GA-LSTM model combines the memory retention ability of LSTM and the optimization ability of genetic algorithm, and performs well on time series data. The differential approach identifies strict international wildlife trade restrictions that significantly reduce the volume of trade, while large-scale infrastructure investments have a positive impact on raising local incomes. Bayesian optimization support vector machine (SVM) finds the global optimal parameters of the model through the probabilistic proxy model and the return function. The results of this paper provide data support for the government to strengthen governance.

Keywords: Genetic algorithm; Long short-term memory network; Difference in Differences method; Bayesian optimization; Support vector machine.

1. Introduction

The spread of the Illegal Wildlife Trade (IWT) has become a global problem that not only poses a long-term threat to ecosystems and iconic species, but also poses a serious challenge to governments' governance capacity and enforcement [1, 2]. As the fourth largest illegal trade globally, IWT is closely linked to other forms of organised crime, including money laundering, fraud and corruption, with profits reaching as high as around £15 billion per year. Indeed, wildlife products are often more lucrative than drugs and other illegal commodities, while offenders face relatively low penalties and risks. The impact of this trade on wildlife is devastating and becoming increasingly apparent [3]. In March 2019, Vietnamese customs officials arrested the largest ever ivory smuggling case while inspecting a container of timber being transported from the Republic of Congo to Da Nang. Inside, they found nine tonnes of ivory, the equivalent of tusks from 1,000 dead elephants.

In the face of such a serious IWT problem, should we ban wildlife trade altogether? If the answer is no, what measures should be taken by governments to combat IWT? Is there any way to predict the effects of the combating beforehand? As a socio-economic problem, what are the dilemmas faced by the source countries of IWT?

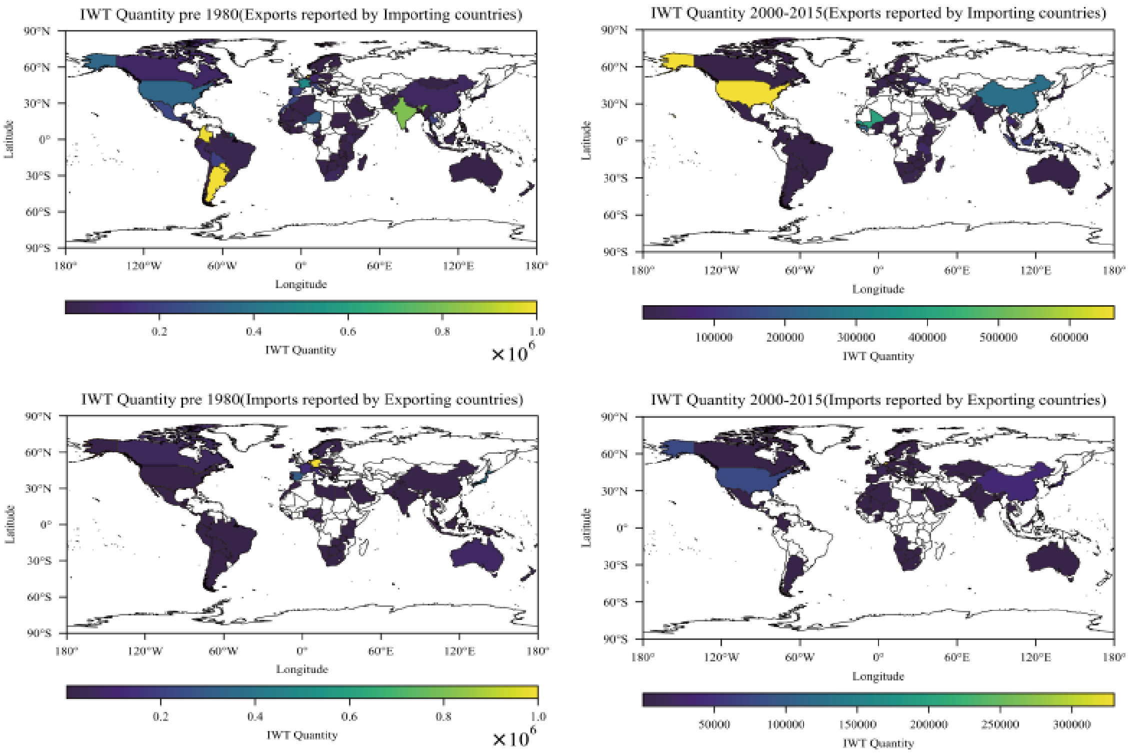

Figure 1. IWT Temporal-Spatial Distribution Map

This paper aims to solve the following problems: Given a data-driven model, provide our client with a scientifically sound solution and analyse the reasons why our solution was accepted by the client, i.e., the project's own strengths and its unparalleled feasibility.

2. DID, GA-LSTM and Bayesian optimization SVM

2.1. Data and Metrics

In order to accurately measure the amount of illegal wildlife trade, we reviewed a large amount of information to determine our metrics, and ultimately, we manually collected data from selected Unreported items based on the CITES data on the origin and purpose of wildlife trade (both legal and illegal). Unfortunately, although CITES has a large amount of WT (wildlife trade) data, it does not have a standard naming method for countries, and based on the list of countries given by the World Bank, Python was used to match the characters and unify the country codes. Then, by matching the IWT data in CITES with the World Bank's country statistics using year identifiers and unified country codes, we obtained the country-level panel data from 1975 to 2021, which contains 1447 variables, and the data volume reaches about 200MB. Obviously, there are a large number of irrelevant variables, which are then manually screened according to theoretical expectations.

Figure 1 shows the number of IWTs based on exports reported by importing countries and imports reported by exporting countries' caliber for the years before 1980 and 2000-2015. This also validates our approach of selecting clients based on TRAFFIC's classification of IWT high-risk countries. Unless otherwise specified, all governments mentioned in this paper belong to IWT high-risk countries.

2.2. GA-LSTM model prediction

GA-LSTM (Genetic Algorithm-based Long Short-Term Memory) is a method that combines Genetic Algorithm and Long Short-Term Memory Network (LSTM), which can be used for the prediction of time series data. In this paper, we use GA-LSTM to predict the number of IWTs globally, which provides data support for the government to strengthen governance [4, 5].

2.2.1 Reasons for Model Selection

LSTM is a variant of recurrent neural network (RNN) suitable for dealing with long-term dependencies [6]. In time series forecasting, especially for problems like illegal wildlife trade, where past events may have long-term effects on the future, LSTM is able to capture and exploit these long-term dependencies. And GA-LSTM is suitable for processing time series data with non-regular time intervals [7]. For global illegal wildlife trade data, there exist inconsistent or missing reporting frequencies from different countries and regions, and LSTM can better process the data in this case. In addition, GA-LSTM is adaptive and can be adjusted according to the characteristics of the data. By using genetic algorithms for parameter optimisation, the model can be better adapted to different data patterns and trends.

2.2.2 Analysis of Results

the GA-LSTM architecture showcases a remarkable fusion of LSTM's memory retention capabilities with the evolutionary optimization prowess of genetic algorithms, resulting in a high-performing model that excels in capturing intricate patterns within sequential data [4, 8]. This makes it a promising choice for a wide array of applications demanding sophisticated sequence modeling and prediction.

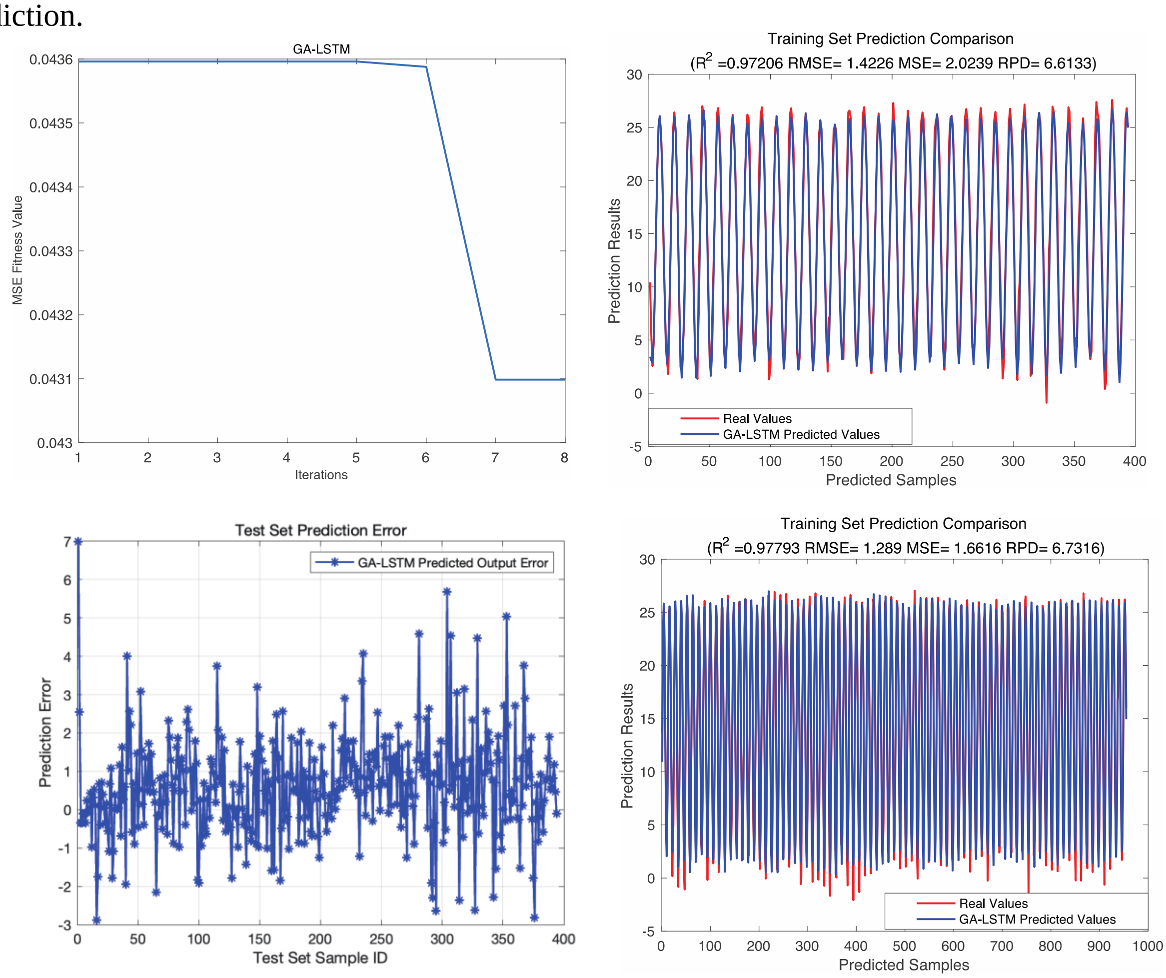

Figure 2. The results of GA-LSTM

2.3. DID and Bayesian Optimisation SVMs

In order to predict the future number of IWTs in countries with high risk of IWT exposure in advance, we use the SVM algorithm to do so. This is because even for countries with high IWT exposure, they play different roles in the IWT chain [9]. As mentioned in the previous section, the future policy implementation will also be different. Therefore, in order to better predict the number of IWTs and to scientifically filter the key parameters of SVM, namely the penalty factor C and the

RBF kernel function parameter γ, a Bayesian optimisation method is used for the iterative process. In addition, predicting future quantities alone is only a way to understand the world, and our goal is to change the current situation of IWT, which is difficult to be accepted by human beings. Therefore, we use the DID method to identify a set of economic consequences of existing IWT regulatory policies that have already occurred as a prior distribution for a second Bayesian approach to predicting the effects of the project's implementation options. Specifically, we develop a technology roadmap for this innovative approach.

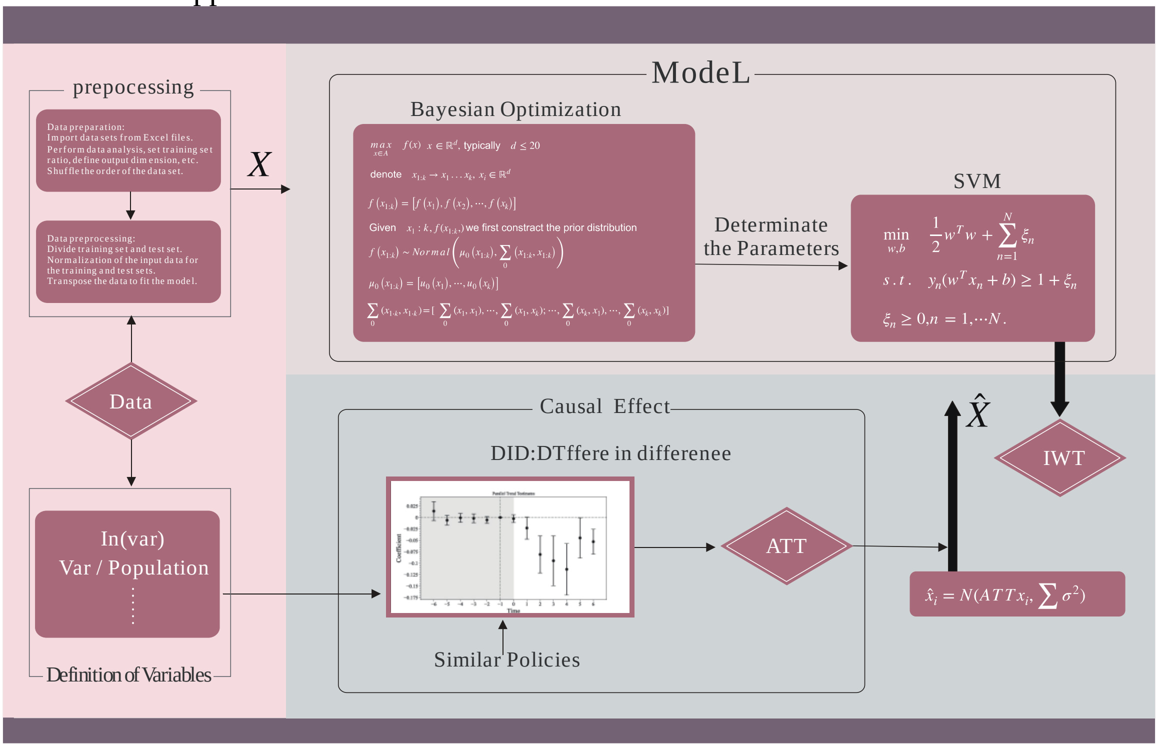

Figure 3. DID and Bayesian Optimisation SVMs

2.3.1 Variable Selection

The IWT problem is a natural ecological problem, but it is also a complex network problem rooted in human society, and there are many factors affecting it. However, the most closely related factors are the level of law enforcement, environmental protection, socio-economic development, privatisation of natural resources, and the level of international assistance. From these aspects, we have selected the following variables based on the description of the relevant variables in the statistical data provided by the World Bank.

2.3.2 Identification of ATE: Based on Double Differencing

This section is dedicated to analysing the additional resources that our clients will need once they have purchased the full framework provided by the project. The first is an increase in international IWT governance, and the second is an improvement in the well-being of the population in the IWT resource country. Such exogenously given additional resources can disproportionately assist in the implementation of the project.

First, in September 2015, the world's two largest ivory markets, the United States and China, announced that they would end the international and domestic trade in ivory. China and the United States committed to enacting bans in their respective countries to almost completely halt ivory imports and exports, including clear and timely restrictions on the import of ivory hunting souvenirs and clear and timely steps to halt their respective domestic commercial trade in ivory. We treat this event as a quasi-natural experiment, assessing the causal effects of imposing the most stringent IWT restrictions on trade volumes. Specifically, we assign a value of $Treat$ of 0 to China and the US before 2015, and a value of 1 to years after 2015. China and the US are the two largest economies in the world, which creates a serious sample self-selection problem, and for this reason we use the PSM-

DID method, which employs caliper nearest-neighbour matching, to address the problem of non-random sample selection [10].

Secondly, improved livelihoods are the basis for conservation, and once legal trade is prohibited, communities living in close proximity to wildlife may lose incentives to conserve and instead turn forests and habitats into agricultural land for crops in order to generate livelihoods and incomes. China's aid to railway construction in Africa is seen as a quasi-natural experiment, assessing the job growth and increased incomes in the countries along the railways as a result of the investment in infrastructure, which alleviates poaching at source in the countries supplying the IWT. This section will be rigorously theorised at the end of the paper. Specifically, we check the official Chinese documents on China-Africa reconstruction assistance, and if a railway starts construction in an African country in the same year, we use the year before that year as the pilot for the policy to take place, with the value of 0 assigned before the policy, and the value of 1 assigned after the policy. The reason why we use the year before the policy as the time of the policy is that, in the real world, the construction of large-scale infrastructures needs to be laid out in advance, and it is very convenient for the local people to be informed of this news, in order to satisfy the DID policy. In order to satisfy the no-policy-expectation assumption of the DID method, we set one year before the policy time.

In order to satisfy the no-policy-expectation assumption of the DID method, we set up the following econometric model for causal identification, and we use the event study method to test for parallel trends using the year before the policy's onset as the baseline.

$$\begin{aligned} Y_{it} &= \alpha + \beta Treat_{it} + \gamma Control_{it} + Perfucture_i + \varepsilon_{it}\lambda_t \\ Y_{it} &= \alpha + \sum_{\substack{k\geq 6,\\ k\neq -1}}^{6} \xi_k Treat_{it}^k + gammaControl_{it} + Perfucture_i + \varepsilon_{it}\lambda_t \end{aligned} \tag{1}$$

Table 1 DID results

	(1) Elephant	**(2)** Elephant	**(3)** Railway	**(4)** Railway
Treat	-0.012***	-0.006***	-0.027***	-0.016***
	(-9.07)	(-5.72)	(-9.41)	(-6.28)
Control	No	Yes	No	Yes
Country FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	3128	4726	3128	4726
R2	0.848	0.926	0.66	0.759

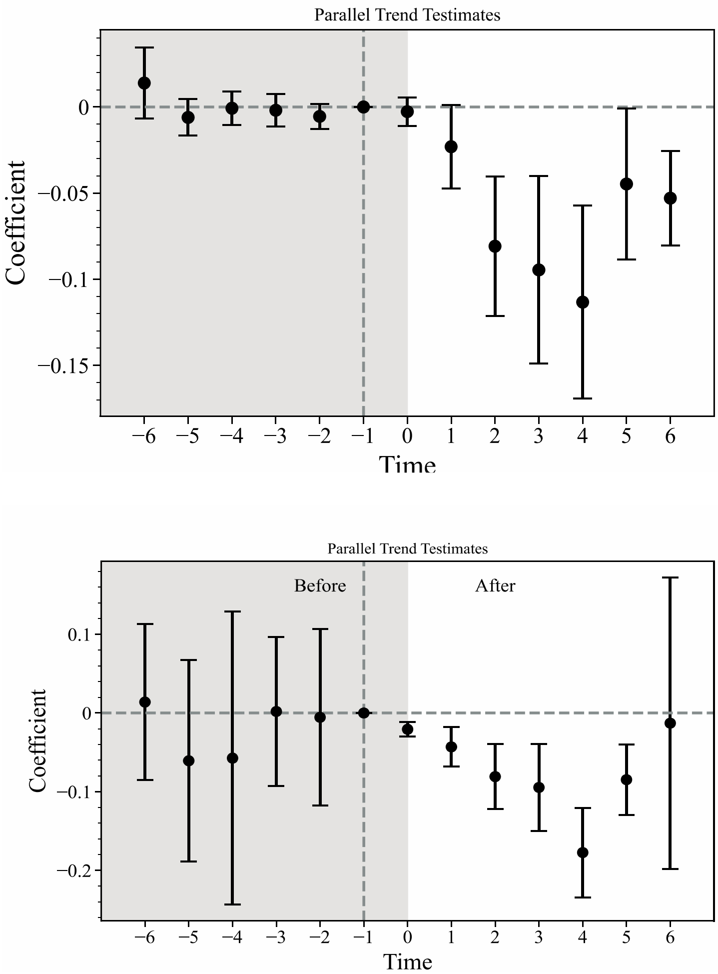

Figure 4. Parallel Trends Test

The left graph depicts the quantity of IWTs for elephant species as the dependent variable, while the right graph represents income levels, CI95

The results show that strict IWT restriction policies at the international level significantly reduce the volume of trade. In addition, large-scale infrastructure investment has a significant positive effect on the improvement of local income. The specific mechanism of this effect will be explained in the last model.

2.3.3 Analysis of results of SVM algorithm for Bayesian optimisation

The ratio of the training set to the dataset is 0.7. The following table reports the enriched model evaluation metrics, and it can be found that the model performs well. Bayesian optimisation achieves the goal of finding the global optimal parameters of the model by means of a probabilistic proxy model and a payoff function [11]. It makes full use of complete historical information, avoids unnecessary parameter evaluation, and achieves efficient parameter optimisation, thus improving the performance of SVM models. The performance of the SVM model based on Bayesian optimisation reaches the optimal level. Since Bayesian optimisation is suitable for model parameter optimisation for low-dimensional data, and SVM is suitable for classification and regression with small samples, data dimensionality reduction can significantly improve the performance of SVM models. In addition, a small number of samples in a particular category will affect the classification effect of the SVM model, leading to a weakening of the model generalisation performance.

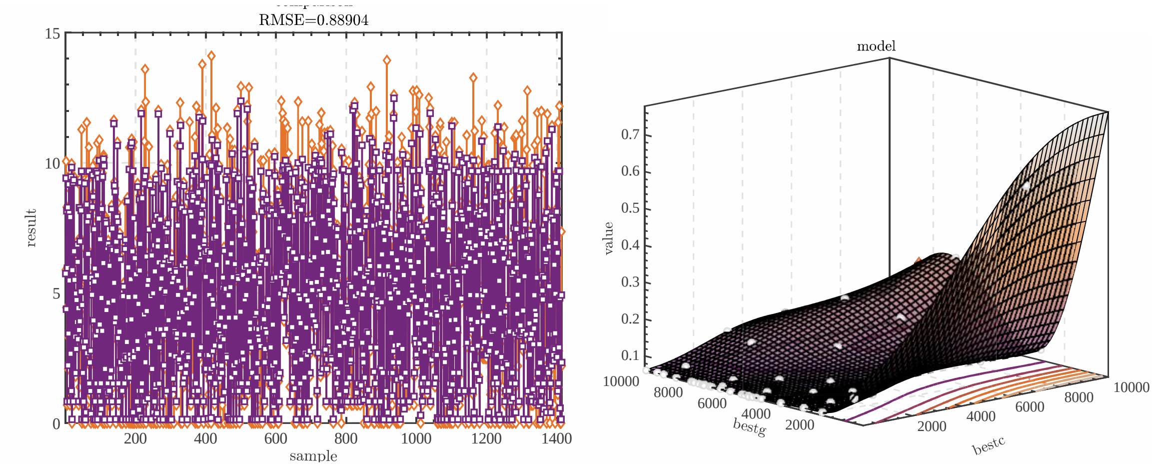

Figure 5. The results of Bayesian Optimization for Support Vector Machines (SVMs)

The specific operation of the combined application of DID and Bayesian optimised SVM is considered as a sensitivity test of this model.

3. Conclusions

In this paper, the GA-LSTM model is used to predict the amount of global illegal wildlife trade, and the difference method and Bayesian optimization SVM are used to predict the future trade volume of high-risk countries. GA-LSTM model performs well, and Bayesian optimization SVM finds the global optimal parameters. The results of the differential method show that strict international trade restriction policies and infrastructure investment can reduce the volume of illegal trade. The research of this paper provides a scientific basis for the government to formulate policies, and is of great significance for the fight against illegal wildlife trade.

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