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# Predicting The Import And Export Of Commodities Using Support Vector Regression And Long Short-Term Prediction Models

**Razia Sulthana A[1] and Pranav Ramesh[2]**

[1]*Department Of Computer Science And Engineering, BITS Pilani, Dubai, United Arab Emirates*
[2]*Department Of Computer Science And Engineering, BITS Pilani, Dubai, United Arab Emirates*

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**Abstract:** The prediction of import and export of commodities has occurred between countries to buy or sell goods essential for humans. Governments need to keep track of the number of imports or exports to ensure the increase of their country's Gross Domestic Product (GDP). Support Vector Machine (SVM) is a robust classification algorithm to classify data efficiently. Support Vector Regression (SVR) is a modification of SVM that predicts absolute values. Fine-tuning the parameters of SVR is not easy, and it is hard to visualize their impact on the dataset. SVR uses the support vectors obtained during the running of the algorithm to predict the dataset's outcome. The new version of the SVR algorithm is proposed, assisted with modified RBF Kernel to improve the model's efficiency. The paper's main contribution is towards the field of economic data analysis, as in, to predict the commodities of goods imported and exported for each country. The purpose of this paper is to use SVR in a commodity dataset to predict each commodity's price being imported and exported for limited countries and encourage the use of machine learning in economics. Further, LSTM is applied for prediction in layers to predict the weight of some incoming commodities to countries. We then obtain the expected results and find the model's accuracy using this result over a real dataset. The problems faced during the research were that data were not available for some countries and information for commodities and countries was not uniform throughout the years. Due to this, the model did not fit the data accurately for those countries. The interpretation of the model shows that the overall error for the proposed model is very trivial and hence produces higher accuracy. To conclude, the predictions were accurate using SVR.

**Keywords:** Support Vector Machine, Regression model, Commodity Prediction, Kernels, LSTM

## 1. Introduction

Analyzing the import and export of a country is crucial for the Gross Domestic Product (GDP) of the country [1]. A country's GDP decides the economic stability and values the country amidst others. Excessive import to a country harms the GDP for the importing country. On the contrary, excessive export from a country has a positive impact on the exporting country's GDP. It is important to keep track of commodities entering and exiting to ensure the merchandise received or given is safe and to ensure the product received can be taken by all goods transporters available on that day [2].

By predicting the amount of import and export, it helps identify how many carriages should be there at each port and uses methods to reduce the amount of time for planning, the cost for traveling, carriage etc. The study of influential factors to GDP and the patterns in then would help in keeping up a country stable, which however requires intelligent prediction algorithms.

Machine Learning operates on artificial learning techniques that trains a machine to learn on its own from the previously acquired knowledge [3]. Artificial Intelligence (AI) is used in solving complex tasks to ease labor. Machine Learning has many algorithms for forecasting, image processing, facial and sound recognition, natural language processing (NLP), etc. This paper will focus on applying on a supervised learning algorithm, Support Vector Machine (SVM) (Figure 1).

SVM, a powerful classification algorithm developed from statistical learning. It was proposed by Vapnik in 1963 and has attracted many researchers to apply this model to various datasets ever since. This algorithm is subjected to fluctuation in performance based on how the cost parameter and the programmers set the kernel parameters [4]. Hence, in this paper an extensive cross-validation is performed to

*E-mail address: razia@dubai,bits-pilani.ac.in, f20180089@dubai.bits-pilani.ac.in*

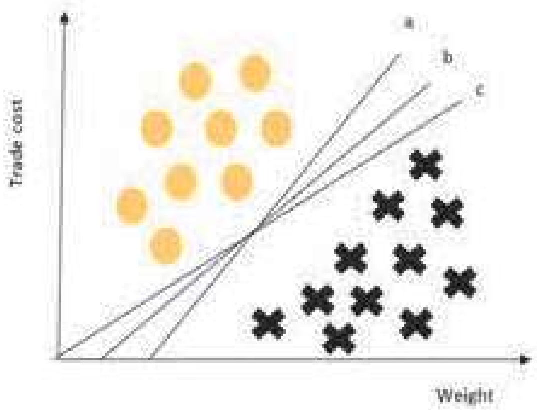


Figure 1. Hyperplanes generated by SVM for classifying data points

find an optimal parameter setting.

Vapnik built another form of the supervised algorithm called Support Vector Regression (SVR) [5]. This algorithm proves to be a very efficient algorithm compared to other regression algorithms due to a kernel that instructs the algorithm to predict the data in any fashion. The high volume of trade along with its multidimensional features can be supervised by SVR. In general, Import means to shop for goods and services from a distinct country to the house country. Therefore, these goods and services are produced in an exceedingly foreign land and bought by the actual domestic country. Export means transporting goods or services to a different country. As a result, it brings within the foreign income to the domestic country. The sale of goods adds to the nation's gross output. On applying SVR the future import and export values of certain commodities can be appropriately predicted.

Long Short-Term Memory (LSTM) is another deep learning neural network. It can process multiple unstructured data from the input gate. It is used to infer information based on data that has a time series. This was initially developed to remove the problems that occurred due to gradient descent. Over time this is used for image, speech, and handwriting recognition and is very powerful when analyzing stock market data. This proves to be a powerful recurrent neural network (RNN) compared to other RNN present in the outside world, such as Gated Recurrent Unit, and Echo state network. It is well known to make accurate predictions on time-series datasets such as stock market, temperature predictions, etc.

The section split of the paper is given here. Section 2 discuss in detail the literature review related to the proposed work. Section 3 describes the methodology involved throughout the paper. Section 4 gives the results obtained on applying the algorithm to the dataset. Section 5 concludes the findings of the paper. Finally, references are provided to support the claim of the paper.

## 2. Literature Review

In this section, we will see some major augmentations towards SVM, SVR, and LSTM. Yingjie et al.,[6] in their paper has shown that SVM can be used not only in solving simple optimization problems, for example, Linear Programming, Quadratic Programming, etc., but rather can solve more general optimization problems, for example, integer programming, semi-infinite programming, etc. They have also proposed a real-time application of these general optimization problems in the field of economics.

The author in [7] have shown that the RBF the kernel has shown maximum accuracy Linear, Polynomial, and Sigmoidal on various datasets collected by them, for example, MIT, Yale, etc. Another article [8] have shown SVM's application in Data Mining and how essential it is to this field by providing various literature reviews. Also, they have provided an application for various SVM models.

Various known kernel methods have been compared in [9] and have shown how each kernel could be used in termite detection. They found that the polynomial kernel had better accuracy than the other kernel methods for termite detection.

Vikas et al.,[10] have compared various kernel on remotely sensed satellite data gathered from QuickBird and Landsat Enhanced Thematic Mapper Plus (ETM+) and have shown that for QuickBird polynomial kernel performed the best and for the ETM+ sigmoid kernel gave the best accuracy. However, they also proposed larger data. It depends on how well we optimize the parameters for the kernel functions to get the best accuracy.

In [11] kernel performance on a multi-class vowel data is compared and has shown that the RBF with 36-dimensional MFCC data performs better than the remaining kernels. Laura and Rouslan [12] have used SVM in Solvency Analysis and compared this to traditional approaches, such as logistic regression and discriminant analysis. They have shown that SVM can be an alternative to measure the company rating.

A new and better kernel function is proposed in [13] called Radial Basis Polynomial Kernel (RBPK). This kernel combines the characteristics of both the Polynomial and Radial Basis Function. They have proved the new kernel to be a valid kernel and a more accurate kernel than Linear, Polynomial, and Radial Based Function Kernels individually.

In a similar way, support vector regression along with RBF kernel and multiple linear regression predicts the absorption rate of lead (II) ions. They show that Support

Vector Regression provides a near perfect result compared to multiple linear regression [14]. SVR is also applied in [15] and have given an overview of SVR and different areas from where this concept is derived from. They also give new ideas which have emerged from this Support Vector Regression which is still in research in current times.

Support Vector Regression is used for Newspaper and Magazine Sales and compares this model using linear and RBF kernel [16]. Both showed equally good results and are dominant when predicting the sales of newspaper and magazine. An enhanced support vector regression is developed in [17] with more un-interpretable kernel and has used this model for weather forecasting.

Several research works is done in stock prediction using SVM and SVR. The method in [18] predicts the stock prices for IBM INC. from historical data using an old machine algorithm known as Support Vector Machine. The model is aided with the kernel, radial basis function, to gain more data accuracy. A systematic study of various journal papers is done in [19] to comprehend the machine learning algorithm that will be most effective for stock market predictions.

In [20], the authors provide a deep learning model to predict Chinese stock market data's stock prices. The authors developed a new algorithm known as feature extension. Finally, they compared their deep learning model to traditional machine learning models. The results clearly showed that the deep learning model was advantageous as compared to conventional ML models, and it is a topic for further study.

A Random Forest technique to predict stock prices with actual data and sentiment data is proposed in [21] which proves the effectiveness of random forest on various volatile data. Hence its erratic to say that a specific ML and DL algorithms will not suit for all problems.

In [22] the authors use and compare the prediction made by Linear Regression, Exponential Smoothing, and Time Series Forecasting on Amazon, AAPL, and Google stocks obtained from Yahoo Finance. The results show that the exponential smoothing provides lesser error and higher accuracy compared to the others. The authors in [23] compare the performance of Linear Regression, Polynomial Regression, and Support Vector Regression on stock prices of the S&P 500. The results showed that Support Vector Regression outperformed as compared to Linear and Polynomial regression.

LSTM is applied in [24] to foresee the future pattern that might take place on stock prices based upon a dataset. The results obtained had 55.9% accuracy when checked where the stock will go in the future, up or down. Also, a model that predicts how long stock will last and how essential it will be for traders is given in [25]. The accuracy of the random forest shows higher value than that of the Support Vector Classifier. Artificial neural networks and support vector machines (SVM) and applied together to predict future stock market prices [26]. A comparative work over the best ML algorithm to predict the stock market data is shown in [27]. Once again, random forest produced the highest accuracy and recall rate as compared to KNN.

The motivation behind this paper is to encourage other enlightened researchers to use machine learning algorithms in economics and logistics.

The paper's significance is to effectively use a known Machine Learning algorithm to predict the import and export of goods.

The paper's objectives are to predict the commodity price from the weight of the commodity being imported and exported using SVR and to predict the commodity price for each year using LSTM. In the proposed research we divide the data and focus on the import and export of specific commodities of each country. Hence, the scenario does not end in under-fitting as the model sufficiently learns from the dataset.

## 3. Methodology

The implementation model is done by analyzing the import and export data separately. As a first step of implementation, the dataset is split into import and export data by splitting the training and test data. This is to ensure to avoid overfitting.

Step 1: Search for data records that has flow which is 'import' and flow that is 'export' and assign it to separate variables as shown below.

Step 2: The dataset is split using a function named train_test_split() present in python module named sklearn.model_selection. This function is a black box that is applied to implicitly split the data randomly into train and test data.

The step-by-step analysis of the algorithm shows the way how the decision boundary of the SVR is derived. The concepts rests on the principles of linear algebra.

### A. *SVM and SVR architecture diagram*

The dataset contains 8225871 rows × 10 columns taken from Kaggle and have received the data from the United Nations Statistics Division website. The link to the dataset is given in [28]. The entire dataset is given in (Figure 2).

The dataset is about the import and export of each country for different commodities and the trade price of each commodity (Figure 2).

The information given in (Figure 3) are all the attributes present in the dataset. The "country_or_area" attribute indicates the country or area where the data is from, for example India, United Arab Emirates, etc. The "year" column signifies the year of when the commodity was

Figure 2. The dataset

```
[ ]  data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8225871 entries, 0 to 8225870
Data columns (total 10 columns):
 #   Column           Dtype
---  ------           -----
 0   country_or_area  object
 1   year             int64
 2   comm_code        object
 3   commodity        object
 4   flow             object
 5   trade_usd        int64
 6   weight_kg        float64
 7   quantity_name    object
 8   quantity         float64
 9   category         object
dtypes: float64(2), int64(2), object(6)
memory usage: 627.6+ MB
```

Figure 3. Attribute information of the table

imported or exported. The "comm_code" attribute uniquely differentiate various commodities. The "commodity" field specifies the commodities available in the dataset. The "flow" attribute distinguishes whether a commodity is exported or imported. The" trade_usd" is the value of the commodity in US Dollars. The "weight_kg" is the weight of the commodity in kilograms being imported or exported. The "quantity_name" is the quantity measurement type given the type of the commodity. The "quantity" field gives the count of commodities based on the "quantity_name" field.

The size of the training and test data varies per commodity for individual countries. Hence, the specific size for each commodity cannot be mentioned. On an average, the import and export tuples of each commodity will vary from 9000 to 11000 over which the train-test split ratio is applied and processed.

Support Vector Machines is used to classify the data into two or more classes based on their similarities to that class, with known class labels. This algorithm classifies the data by drawing a hyperplane that splits the datasets and ensure each class is as far as possible from the decision boundary. Given below is the architecture diagram shown in the (Figure 4).

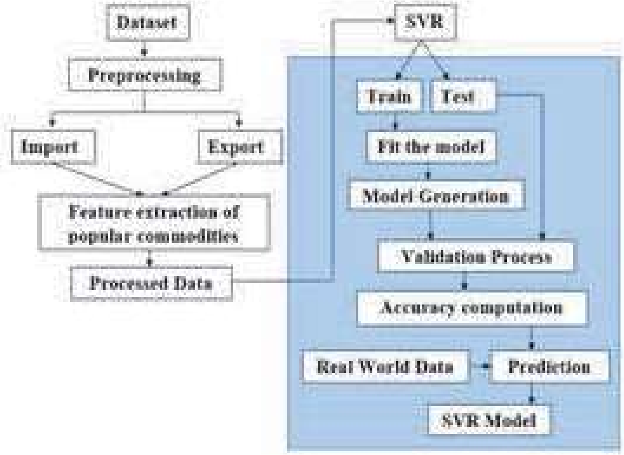


Figure 4. Architecture diagram of SVR Model

## *B. The Algorithm*

The step-by-step analysis of the algorithm is derived and narrowed down to end in the decision boundary. For this we choose a $\vec{w}$ which results in a decision boundary with higher width from the data set to reduce the error of misclassification.

Step 1: Project $\vec{x}$ onto $\vec{w}$ and set it greater than or equal to a constant c.

$$\vec{x}.\vec{w} \geq c \tag{1}$$

Step 2: Without losing generality (WOLOG)

$$\vec{x}.\vec{w} - c \geq 0 \tag{2}$$

$$\vec{x}.\vec{w} + w_0 \geq 0, where w_0 = -c \tag{3}$$

Step 3: The above equations are for a discriminant function, now for SVM.

$$\vec{x_+}.\vec{w} + w_0 \geq 1, if y_i = 1 \tag{4}$$

$$\vec{x_-}.\vec{w} + w_0 \leq -1, if y_i = -1 \tag{5}$$

Step 4: Now we have two equations, because there are two classes present in different areas of the data, but it is better to have one equation that can work for both cases.

Multiply (4) with $y_i$ in the LHS side

$$y_i(\vec{x_+}.\vec{w} + w_0) \geq 1 \tag{6}$$

Multiply (5) with -$y_i$ in the LHS side

$$-y_i(\overrightarrow{x_-}.\overrightarrow{w} + w_0) \leq -1 \quad (7)$$

Rearranging we get,

$$y_i(\overrightarrow{x_-}.\overrightarrow{w} + w_0) \geq 1 \quad (8)$$

Now we see that (6) and (8) are the same only difference is the point which can be generalized.

$$y_i(\overrightarrow{x}.\overrightarrow{w} + w_0) \geq 1, where i = 1, 2, ..., N \quad (9)$$

$$y_i(w^T x + w_0) \geq 1, where i = 1, 2, ..., N \quad (10)$$

This is due to the fact in Machine learning the algorithm performs the above step more frequently on the data. Now, x can be processed to something more useful, and we call that $\phi$(x)

Where, $\phi : R^n -> R^n$ is a mapping from features to high dimensional feature space, where these points can become linearly separable.

The distance of the point $x_i$ from the hyperplane is given by:

$$d(x_i) = \frac{y_i(x)}{\| w \|^2} \quad (11)$$

$$d(x_i) = \frac{| w^T \phi(x_i) + w_0 |}{\| w \|^2} \quad (12)$$

To find the optimal hyperplane that separates the data is by solving the following optimization problem:

$$min\, \varphi(w) = \frac{1}{2} \| w \|^2 \quad (13)$$

The solution to the above problem is given by the saddle point of the Lagrange formula

$$L_{p1} = \frac{1}{2} \| w \|^2 - \sum_{i=1}^{n} \alpha_i [y_i(w^T \phi(x) + w_0) - 1],\ \alpha_i \geq 0 \quad (14)$$

So far, we have based on the assumption that the data is separable. Now, to apply this to a general case we introduce a slack variable $\xi_i$ such that:

$$y_i(w^T \phi(x_i) + w_0) \geq 1 - \xi_i,\ where\, \xi_i \geq 0\, and\, i = 1, 2, ..., N \quad (15)$$

We add an additional cost to the objective function as there is an upper bound to the slack variable.

$$min\, \varphi(w, \xi) = \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi_i \quad (16)$$

$$L_{p2} = \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi_i - \sum_{i=1}^{n} \alpha_i [y_i(w^T \phi(x) + w_0) - 1 + \xi_i] - \sum_{i=1}^{n} \beta_i \xi_i, \alpha_i,\ \beta_i \geq 0 \quad (17)$$

Applying the Karush–Kuhn–Tucker (KKT) conditions we get

$$\frac{\partial L_{p2}}{\partial w} = w - \sum_{i=1}^{N} \alpha_i y_i \phi(x_i) = 0 \quad (18)$$

$$\frac{\partial L_{p2}}{\partial w_0} = - \sum_{i=1}^{N} \alpha_i y_i = 0 \quad (19)$$

$$\frac{\partial L_{p2}}{\partial \xi_i} = C - \alpha_i - \beta_i = 0 \quad (20)$$

$$y_i(w^T \phi(x_i) + w_0) \geq 1 - \xi_i,\ \xi_i, \alpha_i, \beta_i \geq 0 \quad (21)$$

$$\alpha_i [y_i(w^T \phi(x) + w_0) - 1 + \xi_i] = 0,\ \xi_i, \beta_i = 0 \quad (22)$$

Hence, we get

$$w = \sum_{i=1}^{N} \alpha_i y_i \phi(x_i) \quad (23)$$

We get an interesting observation that $\xi_i = 0$ to calculate $w_0$

$$w_0 = y_j - w^T \phi(x_j) \quad (24)$$

For numerical reasons we use mean and get

$$w_0 = \frac{1}{N_s} \sum_{0<\alpha_i<C} y_j - w^T \phi(x_j),\ N_s\, is\, no\, of\ support\, vectors \quad (25)$$

For a new data we use the following function

$$f(x) = Sign(w^T \phi(x) + w_0) \quad (26)$$

$$f(x) = Sign(w^T \phi(x) + \frac{1}{N_s} \sum_{0<\alpha_i<C} y_j - w^T \phi(x_j)) \quad (27)$$

$$f(x) = Sign(w^T \phi(x) + \frac{1}{N_s} \sum_{0<\alpha_i<C} y_j - \alpha_i y_i \phi(x_i)^T \phi(x_j)) \quad (28)$$

And if we use a kernel then

$$k(x_i, x) = \phi(x_i)^T \phi(x) \quad (29)$$

$$k(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (30)$$

Kernels in SVM helps to convert the data to a high dimensional space and thereby ensures classifying the data using linear or non-linear boundaries.

**Kernels:** A few of the regular used kernel types and equations are listed here.

1. Polynomial $k(x_i, x_i) = (x_j^T x_i + t)^d$
2. Gaussian Radial Basis Kernel $k(x_i, x_i) = e^{\frac{-\|x_i - x_j\|^2}{\sigma^2}}$
3. Sigmoid Kernel $k(x_i, x_i) = \tanh(x_j^T x_i + t)$

*C. Long Short-Term Memory*

The input passes to the input gate of the LSTM model (Figure 5). It passes through various layers in the model and passing through layers comes with a model with a reasonable prediction rate. This model is used to predict the test data set, and we get the model's accuracy with the help of the $R^2$ score.

The equations at the gate are

Input Gate: $i_g = sigmoid(w_i.input + b_i)$

Output Gate: $o_g = sigmoid(w_0.input_0 + b_0)$

Final Gate: $h_t = o_g * \tanh(c^t), c^t$ represents cell state at time t.

*D. Feature Extraction*

In the feature extraction step, the countries which has uniform distribution of data for every commodity is picked and analyzed further. Hence every iteration works with the data of a specific country. This avoids the Curse of Dimensionality problem and hence majority of the contribution is done in the prediction phase.

*E. Performance Measure*

1) $R^2$ score: Here, we will use square of Pearson product-moment correlation coefficient ($R^2$) score as the measure of performance of the model. This is an important measure of degree for regression problems. Many researchers refer this as correlation coefficient. $R^2$ is defined as

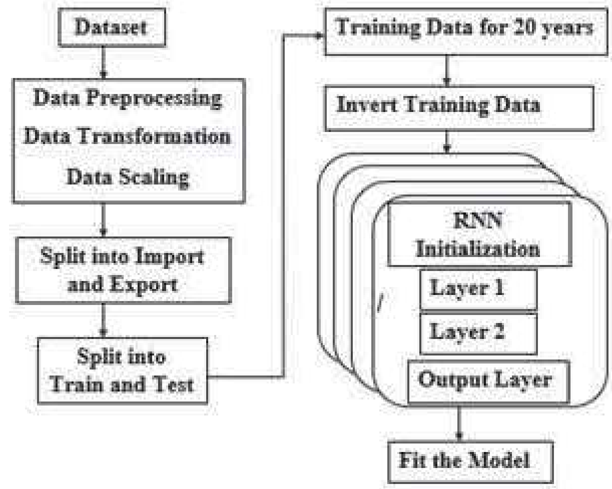


Figure 5. LSTM architecture

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (31)$$

Where, SSR is sum of squared regression

SST is sum of squared total

SSE is sum of squared error

It measures the amount of variance in dependent variable compared from the independent variable. Python provides a beautiful function present in sklearn.metrics module called r2_score which implicitly does this calculation, also the score() function of the model by default uses $R^2$ score.

$R^2$ score is generally in the range between 0 and 1, where values near 0 indicates the model does not fit the data and values near 1 indicates the prediction of the regression model is perfect. However, if it is out of this range, then the model is worse than a horizontal hyperplane. $R^2$ score for training dataset and test dataset also matters. If the $R^2$ score of the training set is greater than the $R^2$ score of the test set then it is underfitting, if $R^2$ score for test is greater than the $R^2$ score, and if they are close then the model is perfect.

The C and gamma values are randomly chosen to best fit, so the model had to be iterated for different commodities and countries. Since the $R^2$ score captures the variance in the data proportionally, it provides enough information to measure the accuracy of the developed model. Hence, the model is evaluated sufficiently using the $R^2$ score.

2) Root Mean Square Error (RMSE):RMSE is a metric used to measure the performance of various models. It is derived by taking the square root of the mean squared error. Mean squared error is obtained by squaring the difference between the predicted value from the target value and dividing the result by the total number of training dataset. This is a distinctive measure that tells the machine algorithm to reduce the difference between predicted and target values for the values to come closer to each other. It is given by the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)}{N}} \tag{32}$$

N – No. of training examples

$y_i$ – Target Value

$\hat{y}_i$– Predicted Value

## 4. Results

The models are analyzed with different countries for various commodities. As a first step export data is analyzed and following which import data is analyzed.

### A. *Export - Aircraft parts necessary*

This commodity represents the amount of aircraft parts required by the country to make airplanes. Here is the table for Aircraft parts commodities only. Now we are going to analyze for the following countries (Table I):

1. United Arab Emirates
2. Australia
3. Japan
4. India

The analysis is between weight of the commodity vs trade cost of the commodity using SVR and RBF Kernel. The following Table I shows the parameters for each country taken by the model to try and perfectly fit the model along with the $R^2$ score for each of them.

1. For the country UAE the data nearly fits the model perfectly with $R^2$ score of 0.82032062 for the train and 0.871285262 for the test, with parameters C = $10^{10}$ and gamma = $10^{-11}$. This shows that our model is perfect for the case of UAE (Figure 6).
2. For the country Japan it gets a near perfect fit model with $R^2$ score of 0.983540155 for the train and 0.972947001 for the test, with parameters C = 9.1029x$10^{11}$ and gamma = 4.0949x $10^{-15}$ . This shows that the model is perfect for Japan the only issue that can arise is overfitting (Figure 7).
3. When it comes to the case of Switzerland the model over fits the data with $R^2$ score 0.583154081 for test and 0.925789726 for train (Figure 8).
4. When we see India, the prediction is perfect with R2 score 0.868845563 for test data and 0.985850276 for

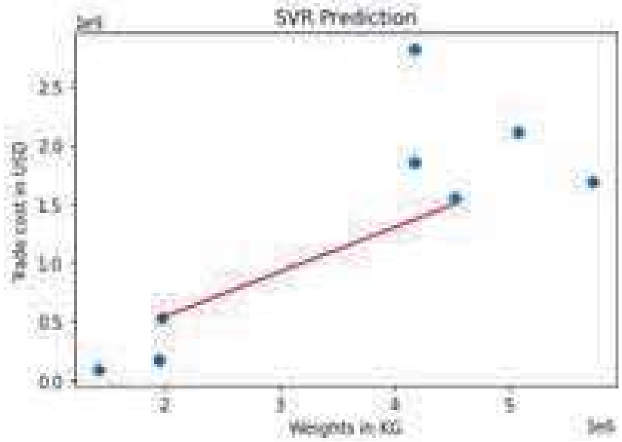


Figure 6. UAE export Aircraft parts necessary
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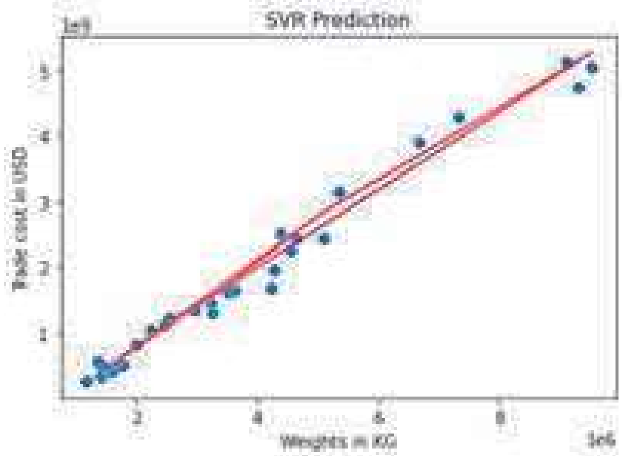


Figure 7. Japan export Aircraft parts necessary

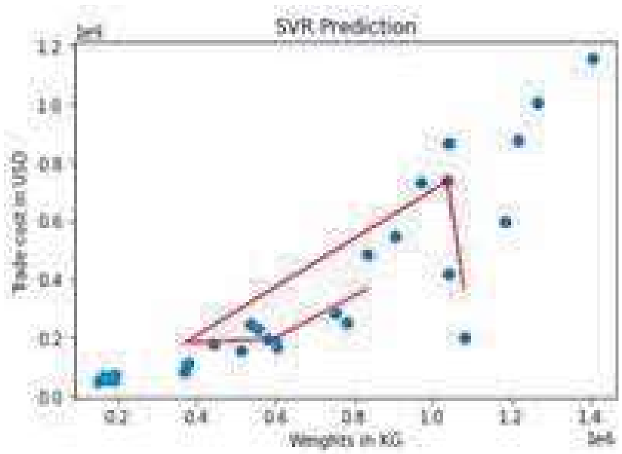


Figure 8. Switzerland export Aircraft parts necessary

TABLE I. $R^2$ value of export values of different countries Aircraft Parts

| Country | c | Gamma | Epsilon | $R^2$ Score (For Test) | $R^2$ Score (For Train) |
|---|---|---|---|---|---|
| UAE | 10E10 | 1.00E-10 | 0.1 | 0.871285262 | 0.82032062 |
| Switzerland | 4.1979*10E8 | 10E-8 | 0.1 | 0.583154081 | 0.925789726 |
| Japan | 9.1029*10E11 | 4.0949*10E-15 | 0.1 | 0.972947001 | 0.983540155 |
| India | 3.089*10E9 | 5.6898*10E-13 | 0.1 | 0.868845563 | 0.985850276 |

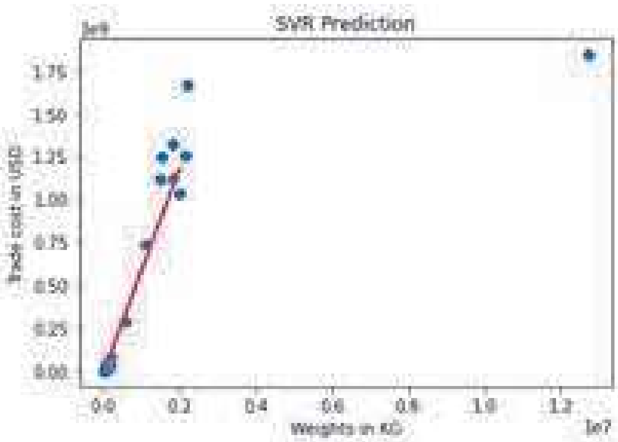


Figure 9. India export Aircraft parts necessary

train. With parameters C = $3.089 * 10^9$ and gamma = $5.6898 * 10^{-13}$ (Figure 9).

*B. Export - Food preparations necessary*

The data over necessary food enquired for export is analyzed and $R^2$ values are obtained for countries (Table II).

1. India
2. Republic of Korea
3. Japan
4. Portugal

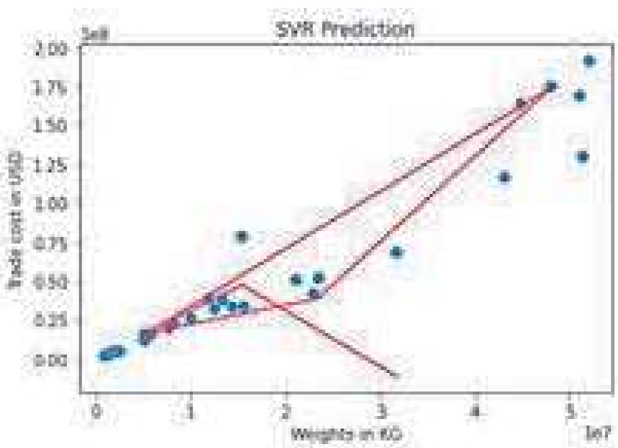


Figure 10. India export food preparations necessary

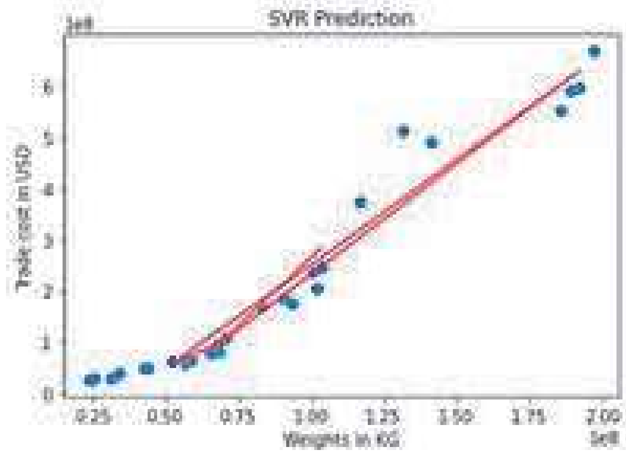


Figure 11. Republic of Korea export food preparations necessary

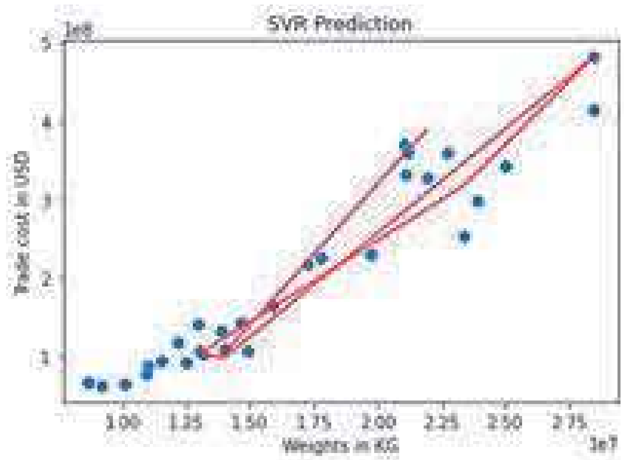


Figure 12. Japan export food preparations necessary

1. For India, the prediction is perfect with $R^2$ score 0.967032865 for test and 0.941698703 for train (Figure 10).
2. For Republic of Korea, it is a perfect fit model with $R^2$ score 0.992613125 for test and 0.999309569 for train (Figure 11).
3. For Japan, $R^2$ score 0.836825022 for test and 0.987301212 for train (Figure 12).
4. For Portugal, a fine fit with $R^2$ score 0.830464177 for test and 0.882549269 for train (Figure 13).

TABLE II. $R^2$ value of export values of different countries food preparation

| Country | c | Gamma | Epsilon | $R^2$ Score (For Test) | $R^2$ Score (For Train) |
|---|---|---|---|---|---|
| India | 1.0985*10E9 | 1.00E-14 | 0.1 | 0.967032865 | 0.941698703 |
| Rep. of Korea | 6.2505*10E9 | 1.00E-14 | 0.1 | 0.992613125 | 0.999309569 |
| Japan | 4.9417*10E9 | 9.5409*10E-14 | 0.1 | 0.836825022 | 0.987301212 |
| Portugal | 1.04811*10E9 | 9.54095*10E-15 | 0.1 | 0.830464177 | 0.882549269 |

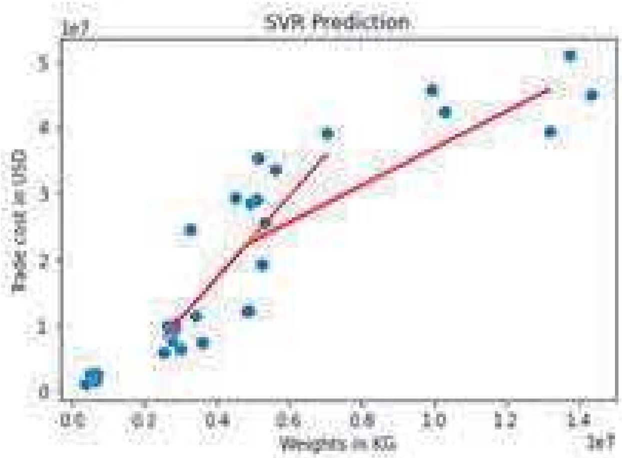


Figure 13. Portugal export food preparations necessary

### C. Import - Aircraft Parts Necessary

The import details of the aircraft parts required by the country to make airplanes is analyzed for

1. United Arab Emirates
2. Japan
3. Finland (Table III)

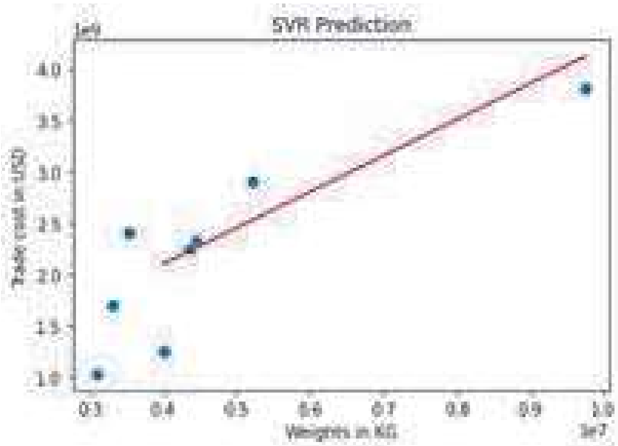


Figure 14. United Arab Emirates import airport preparations necessary

1. For UAE $R^2$ score for test is 0.749316537 and train is 0.649830112 and Switzerland R2 score for test is 0.678877689 and train is 0.897543098 (Figure 14).

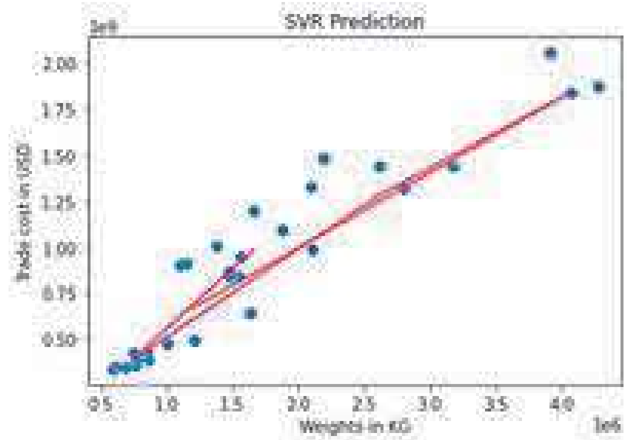


Figure 15. Japan import airport preparations necessary

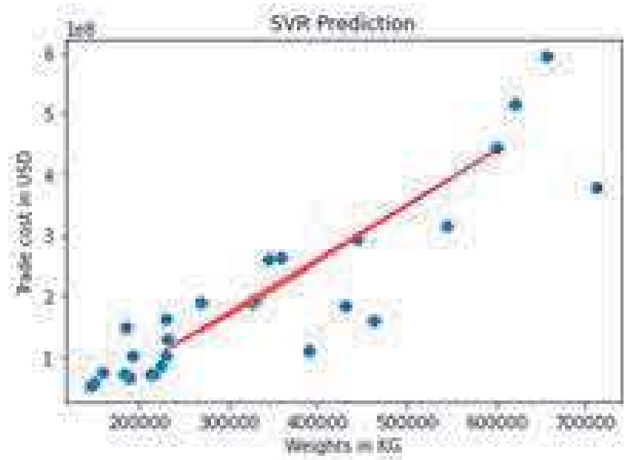


Figure 16. Finland import airport preparations necessary

2. For Japan $R^2$ score for test is 0.937966151 and train is 0.901391771 (Figure 15)
3. For Finland the $R^2$ score for test is 0.692244907 and train is 0.812882187 (Figure 16).

### D. Import - Food preparations necessary

The data over necessary food enquired for import is analyzed and $R^2$ values are obtained for countries (Table IV).

1. India
2. Republic of Korea
3. Japan

TABLE III. $R^2$ value of import values of different countries Aircraft Parts

| Country | c | Gamma | Epsilon | $R^2$ Score (For Test) | $R^2$ Score (For Train) |
|---|---|---|---|---|---|
| UAE | 10E10 | 1.00E-14 | 0.1 | 0.48259007 | 0.649830112 |
| Japan | 7.906*10E11 | 1.00E-13 | 0.1 | 0.937966151 | 0.901391771 |
| Finland | 1.00E10 | 1.00E-11 | 0.1 | 0.692244907 | 0.812882187 |

4. Portugal

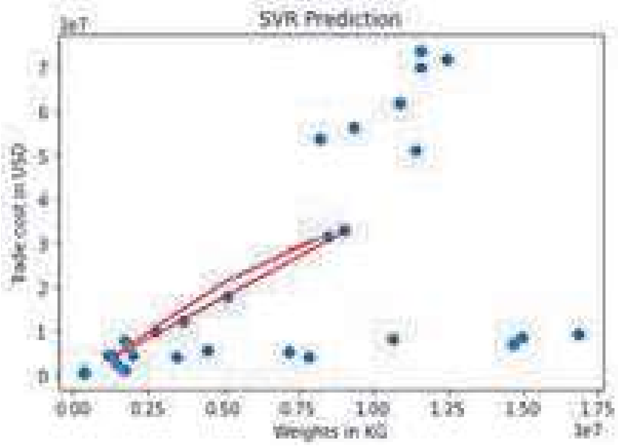


Figure 17. Indian import food preparations necessary

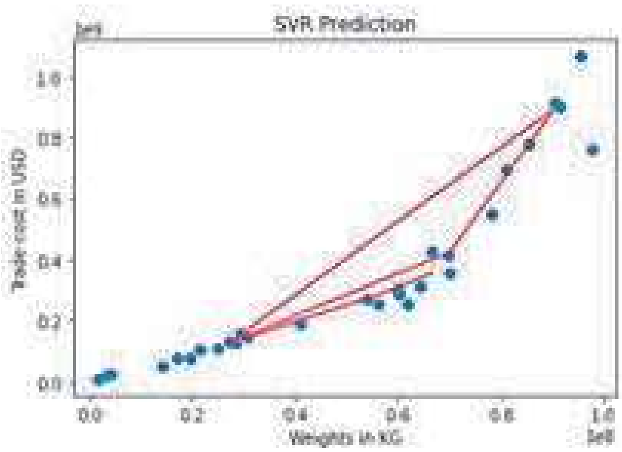


Figure 18. Republic of Korea import food preparations necessary

1. For India $R^2$ score for test is 0.418481896 and train is 0.456681645 (Figure [17]).
2. For Republic of Korea $R^2$ score for test is 0.971703336 and train is 0.973352841 (Figure [18]).
3. For Japan $R^2$'score for test is 0.714932007 and train is 0.990669898 (Figure [19]).
4. For Portugal $R^2$ score for test is 0.907346882 and train is 0.906586624 (Figure [20]).

The import and export data were insufficient for some countries, and information for specific commodities and countries was not uniform throughout the year. For such

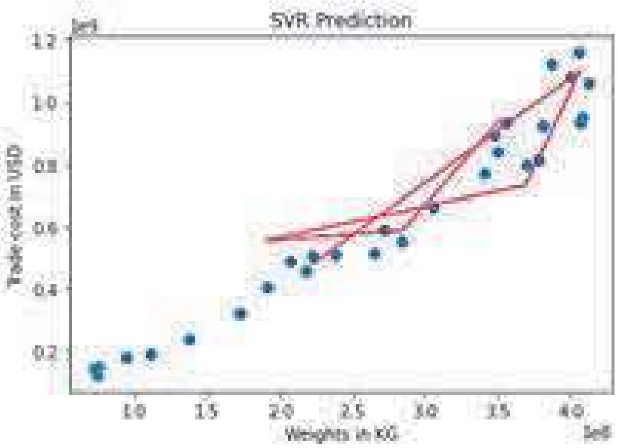


Figure 19. Japan import food preparations necessary

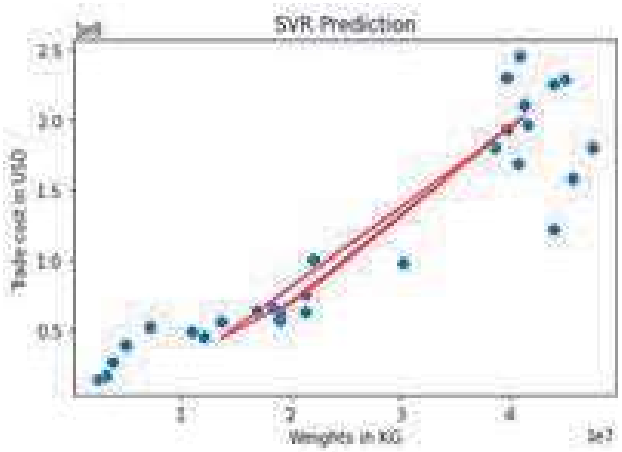


Figure 20. Portugal import food preparations necessary

countries, the model did not fit the data accurately. The addition of import and export data to these countries and a uniform dataset might improve the results further. In addition, the model can be evaluated using other performance measures to identify a clear idea of the commodity import and export.

As seen in (Table V), the model presented in this paper does better compared to paper [10], [11] and [14]. Each of the model applies SVM and SVR to classify the datasets on applying different combination of C and Gamma Values. In the same way the proposed method applies SVR to predict the import and export of commodities.

TABLE IV. $R^2$ value of import values of different countries food preparation

| Country | c | Gamma | Epsilon | $R^2$ Score (For Test) | $R^2$ Score (For Train) |
|---|---|---|---|---|---|
| India | 1.0985*10E9 | 1.00E-14 | 0.1 | 0.967032865 | 0.941698703 |
| Rep. of Korea | 6.2505*10E9 | 1.00E-14 | 0.1 | 0.992613125 | 0.999309569 |
| Japan | 4.9417*10E9 | 9.5409x10E-14 | 0.1 | 0.836825022 | 0.987301212 |
| Portugal | 1.04811*10E9 | 9.54095x10E-15 | 0.1 | 0.830464177 | 0.882549269 |

TABLE V. Comparative Analysis

<table>
<tr><th>Ref No</th><th>Objective</th><th>Evaluation Metrics</th></tr>
<tr><td>10</td><td>The four different kernels of SVM is applied to predict the accuracy (OA), Kappa Index Analysis (KIA), Receiver Operating Characteristic (ROC) and Precision (P). Its applied over Landset and quickbird dataset for classification.</td><td><table>
<tr><td>SVM</td><td colspan="2">ROC</td></tr>
<tr><td></td><td>Landsat Dataset</td><td>Quickbird Dataset</td></tr>
<tr><td>Linear</td><td>0.93</td><td>0.95</td></tr>
<tr><td>Polynomial</td><td>0.94</td><td>0.96</td></tr>
<tr><td>RBF</td><td>0.92</td><td>0.95</td></tr>
<tr><td>Sigmoid</td><td>0.94</td><td>0.94</td></tr>
</table></td></tr>
<tr><td>11</td><td>SVM with different kernels for vowel recognition with the TIMIT speech recognition corpus.</td><td><table>
<tr><td>SVM</td><td colspan="4">Accuracy</td></tr>
<tr><td>C Value</td><td>10000</td><td>1000</td><td>100</td><td>10</td></tr>
<tr><td>Polynomial</td><td>40.10</td><td>40.10</td><td>40.10</td><td>40.35</td></tr>
<tr><td>RBF</td><td>44.44</td><td>44.44</td><td>44.29</td><td>46.00</td></tr>
<tr><td>Sigmoid</td><td>15.86</td><td>15.86</td><td>15.86</td><td>15.86</td></tr>
</table></td></tr>
<tr><td>14</td><td>SVR is applied to predict the lead ion concentration</td><td><table>
<tr><td>SVR, C =32768, Gamma=0.058</td><td>SVR Model</td></tr>
<tr><td>Average absolute relative error</td><td>3.38</td></tr>
<tr><td>Correlation coefficient</td><td>0.9915</td></tr>
<tr><td>Root mean square error</td><td>0.0025</td></tr>
</table></td></tr>
</table>

As the import export dataset of the countries are partially available, majority of the time was spent in collecting the dataset and evaluating them. Otherwise the implementation is done in an extensive way.

For some countries, the import and export data were limited and information for specific commodities and countries were not uniform throughout the year. For such countries the model did not fit the data accurately. Addition of import and export data to these countries and a uniform dataset might improve the results further. The model can be evaluated using other performance measures so that a clear idea over the commodity import and export would be identified.

## 5. Conclusion

In this paper, the import and export values are analyzed using a joint approach using SVR and LSTM. The purpose of this paper is to use SVR in a commodity dataset to predict each commodity's price being imported and exported. SVR uses the support vectors obtained during the running of the algorithm to predict the dataset's outcome. The SVR algorithm is assisted with RBF kernel to improve the model's efficiency. The predicted results and the accuracy of the model obtained shows that the model produces better results with minimal error as compared to other models. The $R^2$ values tabulated signifies the model is good. This can be extended for predicting other logistics demand. The recommendations to the paper are to use sentimental analysis to the data for more accurate predictions, compare the results obtained in SVR with other machine learning algorithms, and use SVR and LSTM algorithms for other economics-related topics.

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**Razia Sulthana A** completed her Bachelor of Technology (B.Tech) in Information Technology under Anna University India and Master of Engineering in Computer Science from Anna University. She holds MBA from University of Madras. She then completed her Doctor in philosophy in Computer Science from SRM Institute of Science and Technology. She is currently working with BITS Pilani, Dubai Campus in the department of Computer Science. She has published a number of research articles in reputed journals and in conferences. Her area of interest includes, Machine Learning, Recommendation System. A number of certifications is made by her with Microsoft and Cambridge. She is the reviewer of a number of Elsevier and Springer journals.

**Pranav Ramesh** is final year Computer Science Engineering student at Birla Institute of Technology & Science Pilani, Dubai. He is a lover of mathematics and well versed in Python programming. He always strives to find the bridge between Mathematics and Computer Science. He is currently pursuing a minor in Data Science and is working forward to publish papers