Risk Management in customs using Deep Neural Network

Ram Hari Regmi
Ministry of Finance
(Department of Customs)
Kathmandu, Nepal
mail@ramhariregmi.com.np

Dr. Arun K. Timalsina
Institute of Engineering
(Tribhuwan University)
Central Campus
Lalitpur, Nepal
t.arun@ioe.edu.np

***Abstract*— Increasing trade volume adds up various challenges and risks for customs to maintain balance between trade facilitation and strong border control. With limited resources and manpower, it's quite difficult to have exhaustive physical examination of all import and export consignments. To balance control and facilitation Revised Kyoto Convention (RKC) and World Trade Organization (WTO) Trade Facilitation Agreement (TFA) have clearly stated about implementation of effective risk management system. In this paper, deep learning model was trained and tested to segregate high risk and low risk consignment on randomly selected 200,000 data from Nepal Customs of the year 2017. Model was tested using supervised learning utilizing inspection result provided by Nepal Customs. Deep learning has improved accuracy and seizure rate than that of decision Tree (DT) and Support Vector Machine (SVM). All three methods have achieved a better result than current rule based risk management system. ANN had achieved better result than DT and SVM, by achieving 81% of seizure rate under 9% inspection.**

Keywords—Risk Management, Customs risk, artificial neural network, risk based on compliance, fraud detection, data mining, Machine learning

I. INTRODUCTION

Every customs needs to tackle huge volume of international trade under limited resources on daily basis. Volume of the trade is increasing day by day as growing population and advancement in living standards. Increasing number of customs officials as increasing trade volume is not possible for any country. Inspecting all trade is also not viable in the customs yard considering time, space and other resources. Effective control of declared consignment in customs needs considering time and compliance traders. Introduction of technology for effective risk management is standing as pillar to clear all consignment efficetively. Customs administrator are introducing automation system to facilitate trade and speed the customs clearance process.

Nepal Customs have introduced the risk management to reduce the trade time and properly inspect consignments with potential risk. Time release study done by DoC have showed that the average, minimum and maximum time taken between Phase 1 assessment till the completion of Customs clearance process for consignment being imported are 3 hours 58 minutes; 36 minutes; and 1 day 2 hours and 58 minutes respectively [1]. Currently total number of declarations that have been penalized for non-compliance is only 3.3% of total declaration that is selected red. This shows that 96.7% of resources is being wasted and same number of declaration is bearing cost of delay. To save trade and resource cost, implementation of better risk management engine, that enhanced customs clearance process by speeding up time is required. Nepal customs is utilizing random based targeting based on some sequence rule, which is one solution but proper managed and adding intelligence in the current system which will reduced the volume of consignment that need to be examined. This will ultimately reduced the trade cost for the compliance traders.

This research paper have analyzed Decision Tree, Support Vector machine and Deep Neural Network to implement compliance based risk approach in the Customs perspective to facilitate legitimate and complaint trade while maintaining a strong control function on non-compliant trade. Among different types of security risks in customs, this research focused only on revenue risk.

II. RELATED WORKS

Nepal has approved a proposal to be the internationalized nation of Revised Kyoto Convention (RKC) on customs and harmonization of the customs process on 3rd February 2017. Under the RKC, on chapter 6 Customs control, it is mentioned in 6.3 that "In the application of customs control, the customs shall use risk management" [2]. Similarly, under 6.5 of same document, there is a clear mentioning of "The Customs shall adopt a compliance measurement strategy to support risk management" [2]. Risk management has also been discussed in the context of WTO trade facilitation negotiations under Article 7: Release and clearance of goods. WTO have also focused that assessment of risk should be done on the basis of compliance record of traders [6].

Nepal has defined Selectivity system as "means a system so determined by the Department in guidelines for the purpose of making clearance of goods by taking into account the risks determined on the basis of goodwill of supplier, importer or customs agent"[3]. Department has also accepted the different selectivity lanes (Red, Yellow, Blue and Green) to be applied in major Customs offices for the purpose of goods clearance [3]. Department has also set the goal of eighty percent of import cargo to be cleared through Yellow and Green channel [4].

To ensure that better informed and smarter decisions are taken, some Customs administrations have embarked on big data initiatives, leveraging the power of analytics, ensuring the quality of data and widening the scope of data they could use for analytical purposes. Y. Okazaki have collected priority secotor of different customs offices. Storage of data is a priority for Hong Kong customs, consolidation of data is considered as a priority by Canada Customs, quality of the

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data is considered as a priority by UK customs and analytics on data is considered as a priority by New Zealand customs[5].

SVM based supervised learning on China customs data achieved the 78% accuracy in fraud detection[6]. The study also explored different flexibilities and appropriate measures in evaluating the performance of models [6]. Among the various machine learning techniques applied in detecting credit card fraud detection, RNN with LSTM turned out to be superior to SVM and RNN without LSTM methods through analyzing the behavioral patterns, suspicious web accesses and logs [7].

Using automated risk management incorporated system, 96 % of Ukrainian customs declarations and good clearance are done through Green and Yellow lanes only. In addition, manual intervention is required only for the alert cases either through any complaint received from other legal agencies regarding the suspect of the goods that is still in the customs yard or already being cleared by customs. The whole process is primarily utilizing risk profiling based on the compliance level, which is a typical one among other various researches [8].

Loukakos [9] showed that the unsupervised method was able to accurately identify frauds, as more than 73% percent of high-risk goods has been detected successfully using that the proposed unsupervised learning method. Unsupervised method is faster and more rapid than other methods. This method requires less processing than supervised method and more than 30 percent CPU usage has been improved using unsupervised learning. The approach is independent of distribution and scattering of data samples. It also has the ability to work with samples by different clusters, densities, and no limitation on dimension of data [9].

III. SYSTEM OVERVIEW

Quantitative analysis of customs data was done focusing on data pre-processing and data analytics. Primary source of data was collected from Nepal Customs. Data collection was done from different customs offices to cover all varities of goods declarations. Data collected was analyzed and mathematical learning algorithms for risk management was tested and formulated using sensitive attributes of single administrative document (SAD). Risk management system was developed using the systematic step by step procedure as shown in figure 1.

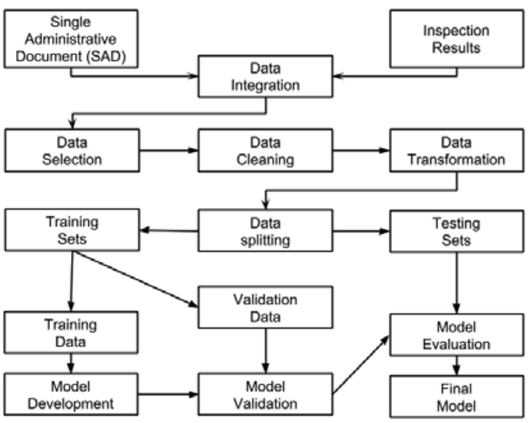

Fig. 1. Research Methodology Flow Diagram

Result of physical verification from customs office were considered for model training and testing. Inspection result of customs was considered and developed model was trained and tested using supervised learning methodology. Data were divided into Training sets and test sets in the ratio of 70-30 percentage. Initially data received from SAD and Inspection results were combined and data preprocessing was applied.

A. Data Preprocessing

During data preprocessing less frequently imported, commodities, fully compliance importers such as government agencies, Diplomatic agencies have been removed and focus on compliance level of commercial importation of the goods. Among 55 fields of SAD analysis was done using sensitive features and removing redundent fields. Fourteen attributes that was selected for analysis are importer, declarant, country of origin, trading country, commodities, item price, mode of transport, number of items, gross mass, net mass, tax Amount, invoice amount, quantity and statistical value.

Data was categorized into two different sections as categorical data and statistical data for the purpose of data transformation. First type of data is categorized as category data which includes the features commodities, Country of Origin, Trading Country, Mode of Transport, Importer Code and Declarant Code. Categorical data was converted using one hot encoding so that only one value of that category is active in tuple of data. These attributes were first encoded into numerical values by assigning 0 to n-1 number of labels where n is the total number of different values in each attribute. Then these data are converted into a vector such that all elements of vector are zero except one, which has 1 as it's value.

Second type of data is categorized as statistical data in which features includes Tax Amount, Gross Weight, Net Mass, Statistical Value, Invoice Amount, Package Number and Quantity. To avoid attributes in greater numeric ranges dominating those in smaller numeric ranges, it was considered features scaling for the different attributes using mathematical transformation. These features were converted into the range of [-1, 1] using the normalization technique (1).

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

where μ is mean and σ is standard deviation.

Preprocessed data were combined and passed through the Artificial Neural Network model, which assigns weight of 80 for non-compliance declarations and 20 for compliance declaration. This weight different minimize misclassification of noncompliance declarations. Model developed have input layer neuron with same number of features and 4 hidden layers with 500 neurons on each hidden layers.

B. Artificial Neural Network

Combining multiple neuron in different level of network and training the network using supervised network based on the principle of feed forward and feed backward network. A neural network is directed graph whose nodes correspond to neurons and edges correspond to links between them. The idea behind neural networks is that many neurons can be joined together by communication links to carry out complex computations.

C. Activation function

This model have utilized sigmoid as activation function on output layer and tanh as activation function in input and hidden layers.

D. Model Evaluation

This model deals for maximizing detecting negative examples so sensitivity and specificity are two major factors that have been considered for evaluation of model.

E. Training Environment

Developed model was trained and tested on MacBook Pro with Intel core i7 processor having 2.5 GHz speed under 1 processor with 4 cores. Memory used was 16 GB with 6 MB L3 cache and 256 KB L2 cache. All the programming was done on the python 2 using Keras and Tensorflow library for machine learning. Scikit Learn and Pandas library of python were used for data preprocessing and visualization.

IV. Experiment And Results

Three different classification methods Decision Tree (DT), Support Vector Machine (SVM) and Artificial Neural Network (ANN) were tested using three different number of features. Testing was done on 14 features, attributes identified by Nepal Customs Act/Regulations and attributes available in Automated System for Customs Data (ASYCUDA). All the models were compared on the basis of these three different number of attributes.

A. Experiment 1: Maximize sensitivity

Table 1 describes the experimental results using DT based classification method using the different standard features that is currently being used. Comparing Accuracy and Sensitivity result shows that 14 features have best result to balance on these measures achieving 82% accuracy with 98% of sensitivity.

TABLE 1: COMPARISON OF DT MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	AW Features	14 Features
Accuracy	32.43%	93.59%	82.02%
Precision	99.56%	96.66%	98.52%
Recall	26.27%	96.32%	81.58%
F1 Score	41.57%	96.49%	89.25%
Sensitivity	99.56%	96.66%	98.52%
Specificity	11.07%	61.99%	30.42%

Table 2 describes the experimental results using SVM based classification using the different standard features that is currently being used. Comparing Accuracy, Sensitivity result shows that ASYCUDA World (AW) features have best result to balance on these measures achieving 93.8% and 96.52% respectively.

TABLE 2: COMPARISON OF SVM MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	AW Features	14 Features
Accuracy	39.75%	93.80%	49.09%
Precision	99.77%	96.52%	99.75%
Recall	34.23%	96.70%	44.42%
F1 Score	50.97%	96.61%	61.47%
Sensitivity	99.77%	96.52%	99.75%
Specificity	12.28%	63.94%	14.31%

Table 3 describes the experimental results using ANN based classification using the different standard features that is currently being used. Comparing Accuracy and Sensitivity result shows that ASYCUDA World (AW) features have best result to balance on these measures achieving 92.65% and 97.88% respectively.

TABLE 3: COMPARISON OF ANN MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	AW Features	14 Features
Accuracy	82.55%	92.65%	63.86%
Precision	99.00%	97.88%	99.69%
Recall	81.75%	94.00%	60.66%
F1 Score	89.55%	95.90%	75.42%
Sensitivity	99.00%	97.88%	99.69%
Specificity	31.69%	54.87%	18.95%

B. Experiment 2: Maximize specificity

Table 4 describes the experimental results using DT based classification method using the different standard features that is currently being used. Comparing Accuracy and Specificity result shows that 14 features have best result to balance on these measures achieving 95.21% and 96.98% respectively.

TABLE 4: COMPARISON OF DT MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	AW Features	14 Features
Accuracy	92.93%	50.61%	95.21%
Precision	96.40%	99.33%	96.98%
Recall	95.86%	46.31%	97.80%
F1 Score	96.13%	63.17%	97.39%
Sensitivity	96.40%	99.33%	96.98%
Specificity	57.46%	14.38%	73.94%

Table 5 describes the experimental results using Support Vector Machine based classification method using the different standard features that is currently being used. Comparing Accuracy, Sensitivity and Specificity result shows that 14 features, have best result to balance on these measures.

TABLE 5: COMPARISON OF SVM MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	AW Features	14 Features
Accuracy	92.75%	46.10%	94.02%
Precision	97.06%	99.68%	96.78%
Recall	94.96%	41.21%	96.68%
F1 Score	96.00%	58.31%	96.73%
Sensitivity	97.06%	99.68%	96.78%
Specificity	55.50%	13.53%	64.61%

Table 6 describes the experimental results using Artificial Neural Network based classification method using the different standard features that is currently being used. Comparing Accuracy, Sensitivity and Specificity result shows that 14 features have best result to balance on these measures.

TABLE 6: COMPARISON OF ANN MATRICES WITH DIFFERENT NUMBER OF FEATURES

	Nepal Customs	**AW Features**	**14 Features**
Accuracy	92.10%	81.62%	96.68%
Precision	97.98%	99.17%	98.22%
Recall	93.30%	80.58%	98.13%
F1 Score	95.58%	88.92%	98.18%
Sensitivity	97.98%	99.17%	98.22%
Specificity	51.93%	30.83%	81.05%

C. Experiment 3: Comparison between different models

Table 7 describes the comparison of different models and using the 14 features as the input of the model. Comparing result from three different model ANN have higher accuracy, sensitivity and specificity which makes the model superior that other two models that have been compared.

TABLE 7: COMPARISON BETWEEN DT, SVM AND ANN

	DT	SVM	ANN
Accuracy	95.21%	94.02%	96.68%
Precision	96.98%	96.78%	98.22%
Recall	97.80%	96.68%	98.13%
F1 Score	97.39%	96.73%	98.18%
Sensitivity	96.98%	96.78%	98.22%
Specificity	73.94%	64.61%	81.05%

Figure 2 shows the graph of loss vs epoch under the training and validation dataset. It shows that loss is decreasing as epoch increases whereas the loss under the validation set goose on increasing as the number of epoch increases.

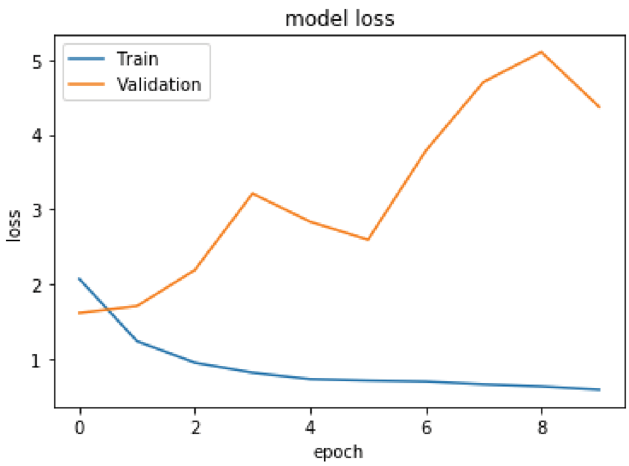

Fig. 2. Loss vs Epoch graph

Figure 3 shows the graph of accuracy vs epoch under the training and validation dataset. It shows that accuracy of both training and validation set is increasing as number of epochs increases.

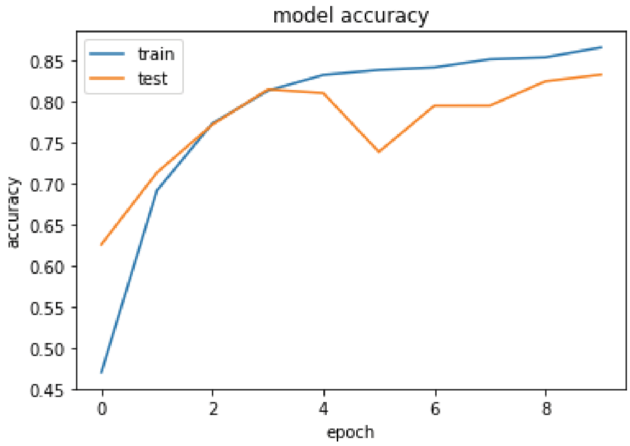

Fig. 3. Accuracy vs Epoch Graph

V. CONCLUSION

In conclusion, customs administrator should consider using the power of Artificial Intelligence (AI) for the trade facilitation by reducing clearance time in customs yard for fair and compliant consignment. In the meantime, customs should also maintain strong control over non-compliant consignment by paying strong attention on them for social security and reducing revenue risk. These have been supported by experiment on the two hundred thousand data provided by Nepal Customs by achieving 81% of seizure rate under only 9% inspection. This shows current inspection rate of 60% can be reduced to 9% which reduces 51% of inspection rate in customs. Seizure rate have been improved from 3.3% to 81% which have increased the 77.7% success rate for identification of non-compliance declarations. Comparing the result of different models developed it is seen than decision tree can classify data with accuracy of 95.21%, SVM with an accuracy of 94.02% and highest accuracy is obtained using ANN with an accuracy of 96.68%.

VI. FINDINGS

For the identification of fraud detection the major comparison will was be done on the part how accurately developed model can predict fraud declaration. Figure 20 shows that ANN method is comparatively better in different major but in the Specificity ANN is the far best than Decision tree and Support vector machine.

Comparing the result obtained from ANN and current statistics published by Department of Customs it is seen that Inspection rate have been reduced from 54.5% to 9% which have successfully reduced the inspection rate. On the other hand, same model with respect to the current statistics the ratio of seizure has been drastically improved to 81% from the 3.3%.

VII. FUTURE WORKS

For the limitations of variety of data collected in this paper, some future researches could be done by collecting data from different agencies concern with trade for the analysis of non-compliance declarations along with data from customs. Researcher could also consider analyzing based on images obtained from x-ray scanner, which will provide additional detail about the declaration. Among the different risk in customs, classification risk could be examined using text mining by considering the HSCode, HS Description and Local name declared by the agent or importer. Customs authorities may consider revisiting current risk management parameters and consider developing sub-modules that will assist customs personnel for taking decision on updating risk parameter on customs clearance system. Customs authorities should also consider developing an advance methodology using Artificial Intelligence for assessing risk.

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