A NEURAL NETWORK ANALYSIS OF THE ECONOMIC CONDITION OF THE CHINA – CENTRAL ASIA ECONOMIC CORRIDOR

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PURPOSE

THE present study is an attempt to examine the economic conditions of Central Asia in its interest in becoming a strategic economic partner to China on the economic corridor of China's Belt and Road Initiatives.

Design/Methodology/Approach: *Using neural network as a tool for pattern recognition, the Central Asia's national accounts were assessed to ascertain its fitness in becoming a worthy partner to China on the Belt and Road Initiatives. The 18-year economic period data that was used was obtained and corroborated from the Asian Development Bank, World Bank, and the respective National Statistical Bureaus.*

Findings: *The results of the assessment showed that these five countries of Central Asia are economically not sound and venturing further into this partnership would and could push an adverse outcome. Albeit with the fundamentals being restored and, in some ways, improved (drastically slow), China has shown interest in the region for the longest time. With the region's economy not being strong and solely based on commodities coupled with a floating rate, the shift in global uncertainness will run the course for Central Asia.*

Research Limitations: *The main limitation for this study was on the data and its representation of the countries. Some components of the data were consolidated and represented as a single indicator. This misled the data interpretation and required corroboration from multiple sources to verify the data.*

Managerial Implications: *The national accounts of each of these countries were assessed with inflation omitted displayed a downward trend in its overall 18-year economy period. For a developing region, the national economy cannot rely only on one or a few economic activities. Strong sectors can become weak should it be neglected or be impacted exogenously, especially energy and commodities, and weaker economic sectors that could potentially become main drivers of the country need due focus as well. However, there were no trace of evidence in the assessment to show a potential economic activity becoming the catalyst of growth for the region and for the respective countries.*

Originality/Value: *This study showcased the use of artificial intelligence in the area of international economics to distinctively characterize and cluster countries according to the realities of their respective economic conditions.*

Key Words: *Neural Network, Development Economics, China, Central Asia, Economic Condition*

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Introduction

A holistic view was taken to assess the state of Central Asia. From the analysis carried out and drawing from past research findings and conclusions, it was clear that progress, growth, and development were relatively significant in the region causing a convoluted result in identifying whether Central Asia could be categorized as a rich or poor region. Certain countries in the region fit the profile of a poor state where intense work for development was needed and an overhaul in the political and economic climate was desperately needed as well. In some countries, slow progress was made but advertently moving in the right direction towards becoming a stable global front for future investments and economic endeavours. The region however was bounded by an interplay of rising-and-dropping commodity prices and a stronger-weaker demand from its economic partners. A scenario of such made Central Asia vulnerable to shocks thus making recovery an uphill battle but at the same time a pleasant place to trade when its currencies were at a low caused by global shifts. A key factor towards economic stability is in the currency exchange (Frankel, Proposed Monetary Regime, 2003). Sovereigns exchange rates are "usually" fixed and are not floated to adjust according to the whims and fancies to the world's changes. Many would and will argue that a floating rate is better than a fixed one, and the contrary as well. A floating currency deems untrustworthy and unreliable to foreign and domestic direct investments. A fixed rate however informs that the government of a country is using other means of economic counter measure to sustain the country's economy yet alone keeping the confidence of investors, be it foreign or local. Countries that adopt and adapt to a fixed exchange rate system are developing and undergoing certain changes and are therefore associated with having unsophisticated and inefficient capital markets and weak institutions of authority. When a country devalues its currency (naturally or by force), economic reforms are inevitable. Of such reforms are not limited to just implementing greater transparency to strengthen financial institutions, it needs to be competitive. This was what took place in Uzbekistan to remain relevant and competitive. Rates adoption is at the discretion of the ruling government. Some governments prefer a floating rate while others prefer a fixed rate "*crawling*", this is where the ruling government will examine the exchange rate on a regular basis and then adjust its acceptable and competitive benchmark rate. Under normal circumstances this would cause devaluation but is exchange rates are controlled to avoid a panic in the market. Such a method is often used in the transition from fixed to floating exchange rates, and this would then allow the ruling government to protect its national interest and avoid a forced devaluation during crisis.

It is certainly not an easy task to impose nor forces a government to pick a currency exchange and rating method that suites the country (Frankel, Choosing an Exchange Rate Regime, 2011), especially if the country is in full frontier of development like Central Asia. But the volatility and vulnerability of Central Asia's currency rates can be seen below from 2000 to 2017, as reported by the World Bank.

Fast forward to the present, the World Exchange Rate reports the exchange rate for China – Central Asia to USD 1 for the periods of February 8^{th} – March 8^{th} 2019 as follows:

***Note**: Data for Tajikistan was not made available for the mentioned period.*

On the surface, past research has established economic sentiments that the region of Central Asia is somewhat precarious, and this has been proven from the data of the economic overview of the region, and from various studies. From this point forth, this research took a deeper look into the granules of the national accounts and the economic sectors in Central Asia to have a better pulse feel of the economic condition. The national account assessment provided a magnified comprehension of the region towards becoming a reliable Chinese partner on the Belt and Road Initiatives, BRI.

Economic Condition Assessment

Contribution from each economic sector adds to the overall value of a country's gross domestic product. This was then further assessed based on the country's performance year-on-year, either by weighted

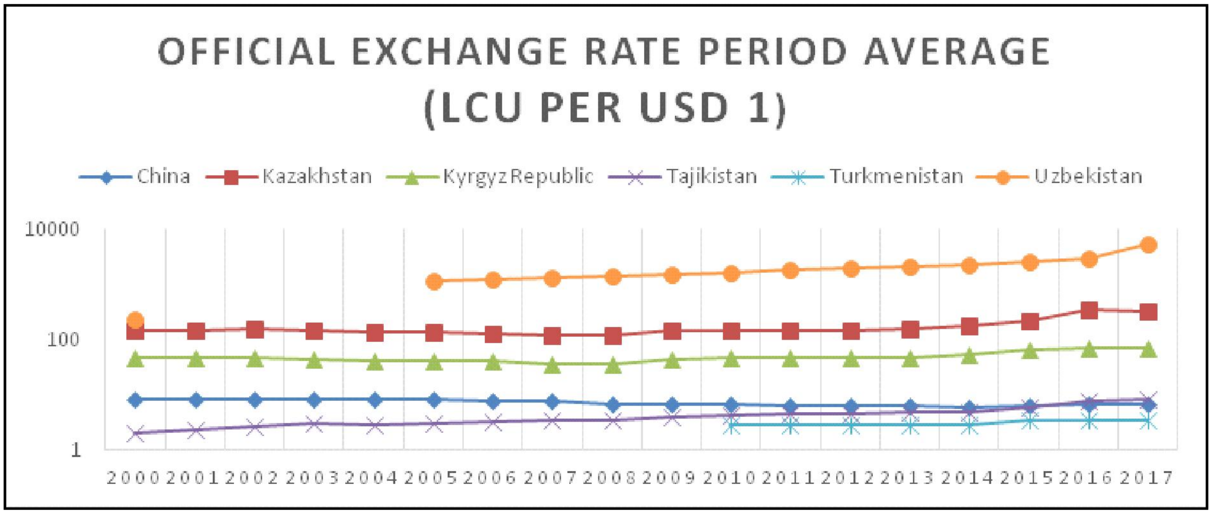

Figure No. 1: China – Central Asia Official Exchange Rate, 2000 - 2017

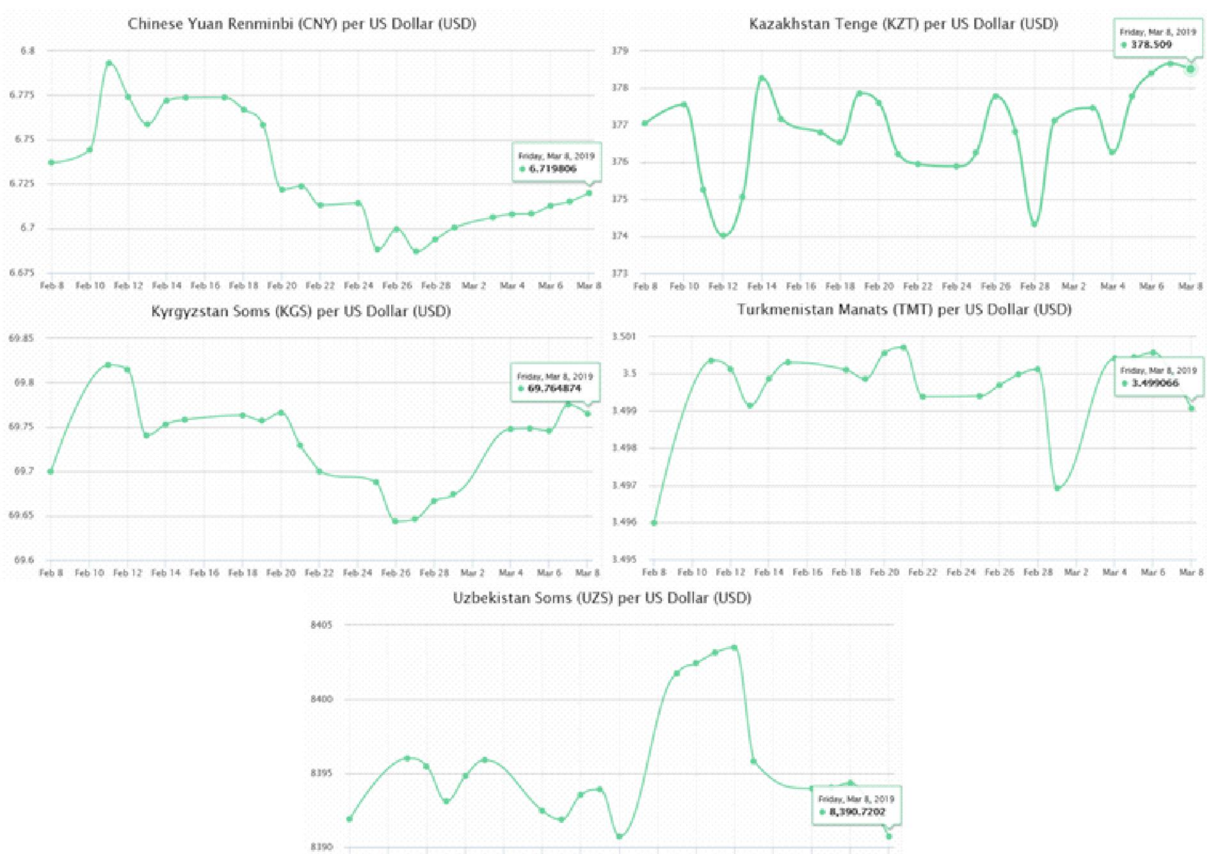

Figure No. 2: China – Central Asia Currency Exchange Rate (Feb – Mac 2019)

average or magnitude. A country's economic performance can be measured in terms of current price (nominal), constant price (real) or by annual rate of change (%). An idealistic assessment was to plot the numbers on a scaled graph and then draw inferences, conclusion, and judge the trend line. So long the trend line was progressing upwards year-on-year, it can be said that the economy was doing well. This was and is still generally acceptable (not accurate) if the economic judgement was only made towards one country. When GDP trend lines are compared with another or more countries then the same approach of assessment, inference, conclusion, and judgement cannot be used. National Account's activities, purchases, and expenditures are a better way to measure economic performance. Geographical and economic endowment unevenness would then require more sophisticated means for assessment. Central Asia's 5 nations vary in so many aspects and Central Asia itself as a whole is very different when compared to China. To carry out economic assessment for the region and for the partnership, it must be done separately while assessing the same variables. A systemic form of testing must be employed to feed the data to then generate what befits the country and then an educated and informed conclusion can be drawn for the whole. The test was to gauge the condition of the countries given the various economic sectors using Artificial Neural Network, ANN. This was a holistic assessment to then determine on the economic significance of each country. This is an important element to look at the economic health status (overall) of the region in ascertaining its fitness to be a valuable and reliable economic partner to China and to test the following hypothesis in order to establish a premise for the study's objective and to answer the study's question;

Study Objective Assess the economic health and standing of the Central Asian region.

Study Question What is the economic health status of Central Asia?

H0: The economic health condition of Central Asia is positively significant and is a good fit to be a partner to China.

H1 The economic health condition of Central Asia is adversely insignificant and is not a good fit to be a partner to China.

National Account Economic Indicators

The datasets for this phase of the assessment was obtained from the Asian Development Bank for the year 2018 outlook. The economic indicators datasets used for the assessment was from 2000 – 2017. The datasets were cross-checked with the World Bank and the International Monetary Fund for data cohesion. The updated datasets were then checked against the respective countries Bureau of Statistics for data correction. Majority of the country data matched with the data spreadsheet from the World Bank which then coincided with the data from the Asian Development Bank. The only differences found in the datasets was the rounding up of numbers and the number of decimal places. The biggest challenge from this dataset clean-up was that parts of the data in the various years were not made available. Empty economic indicators and empty data for a particular economic year had to be omitted. This has caused an uneven and asymmetry testing condition. To resolve the unevenness and the data voids, standardization was applied. The following national account economic indicators were chosen based on 2010 constant price (real).

Table No. 1: National Account Sectorial Economic Indicators

Agriculture, forestry, and fishing
Mining and quarrying
Manufacturing
Electricity, gas, steam, and air-conditioning supply
Water supply; sewerage, waste management, and remediation activities
Construction

Wholesale and retail trade; repair of motor vehicles and motorcycles
Accommodation and food service activities
Transportation and storage
Information and communication
Financial and insurance activities
Real estate activities
Professional, scientific, and technical activities
Administrative and support service activities
Public administration
Education
Human health and social work activities
Arts, entertainment, and recreation
Other services activities
Activities of households as employers
Activities of extraterritorial organizations and bodies

The naming convention for each sectorial economic indicator was adopted as per the naming convention from the Asian Development Bank. A total of 21 indicators for 6 countries were to be used, however, indicators with no data or consolidated data or incomplete data had to be removed. These 21 sets of industrial indicators make up the National Account of any country. A National Account is characterized by definition as a degree of macroeconomics measure and performance of categories of productions and purchases in a country (Blades, 2014). National Accounts are used to measure a country's economic activities based upon a framework of accounting rules. It is intended to showcase economic data to facilitate policymaking. The national accounts system measures productivity outputs, household, corporations, and government expenditures, and income within the country (Joseph E. Stiglitz, 2009). The national accounts productivity categories are defined (usually) as outputs in terms of currency units measured in the local currency or in USD. Outputs are (approximately) the same as the industry revenues. Expenditures category includes from government, investment, consumption, and exports, which values are measured in the national accounts as the aggregate measures of the GDP. National accounts provide a wide range of data and its changes over time, making it very important and very interesting to economists and policymakers as they present and represent information about a country's economy (Neva Goodwin, 2008).

Table No. 2: National Account Breakdown

National Accounts (Calendar Year LCU Billion)
GDP by industrial origin
Summation of Various economic activities
= Gross value added
Taxes less subsidies on production and imports
Net factor income from abroad
= Gross National Income

Neural Network

The progression of economic testing can be clearly described in many past literature reviews. The neoclassical economic testing approach was the foundation that built upon and evolved into more complex assessment regimes. Regional economics testing and modelling was initially strongly influenced by macro-econometrics and input-output models developed for national economies (Treyz, 1993), but it has progressed and changed into models that integrated these approaches into multi-regional settings that are highly nonlinear nature and explicitly account for various forms of spatial interaction. New theoretical developments like the new economic geography and endogenous growth theory have had an impact on recent modelling developments and it is increasing the popularity of spatial econometrics. Regional economic testing and modelling has a long tradition of integrating approaches from various disciplines (Rickman, 2010). The result for any assessment using any forms of techniques and models are to judge the efficiency and performance of a country's economy and the performance of the economic contributors. It is hard to imagine modern economics assessments that do not use mathematical and statistical tools. The quantitative transformation in economics has had far reaching impacts on the practice of economic research and has penetrated in all research domains of economics. For this study, computational neural network was employed. A neural network is a mathematical model for information processing based on how neurons and synapses work in the human brain.

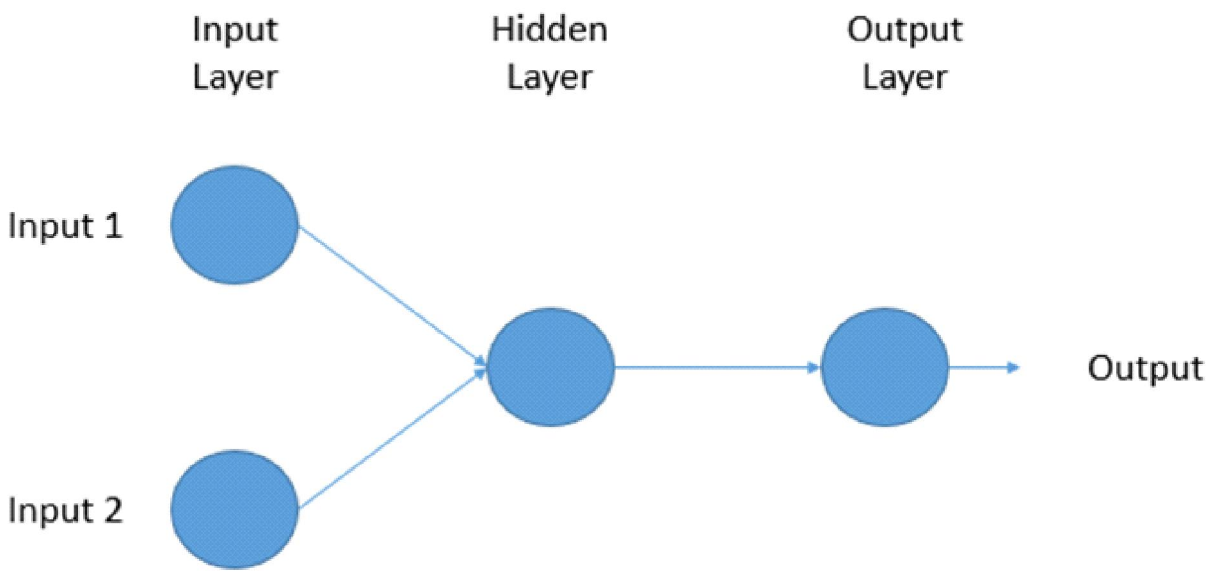

Figure No. 3: Neural Network Basic Model

Source: Own illustration.

A neural network connects simple nodes to form a network of nodes. These artificial networks may be used for predictive modeling, adaptive control and applications where they can be trained via a dataset. Self-learning resulting from experience can occur within the networks which can derive conclusions from a complex and ostensibly unrelated set of information (Kriesel, 2005). There are many types of neural network architecture and this study adopts the Artificial Neural Network, ANN.

Artificial Neural Network

Artificial Neural Network comprises of input layers, hidden layers, and output layers. Each of these layers comprises of neurons and weighting functions as shown in Figure No. 4. Artificial neurons are structured in layers with one or more hidden layers positioned in between the input layers and the output. This allows signals to be transferred and communicated forward. Each input, hidden, and output layer is associated with several neurons that are connected with other neurons in the adjoining layers. These neurons are connected via a unidirectional links (Wei Huang, 2007). The information that flows during the training process runs from the input layers to the output layers all the way through the hidden layers. The neural network structural design can consist any number of hidden layers. More layers require more learning and it produces accurate results. The hidden layers are assigned with a synaptic weighting matrix and the weights are paired with the connections made from the input layers to the output layers. ANN is able to perform a variety of tasks that are not limited to predictions, function approximations, pattern classifications, clustering, and also forecasting. The performance of the ANN is affected by neural networks structure setup, the training it will undergo, and by the data. (Eduardo Ogasawara, 2009).

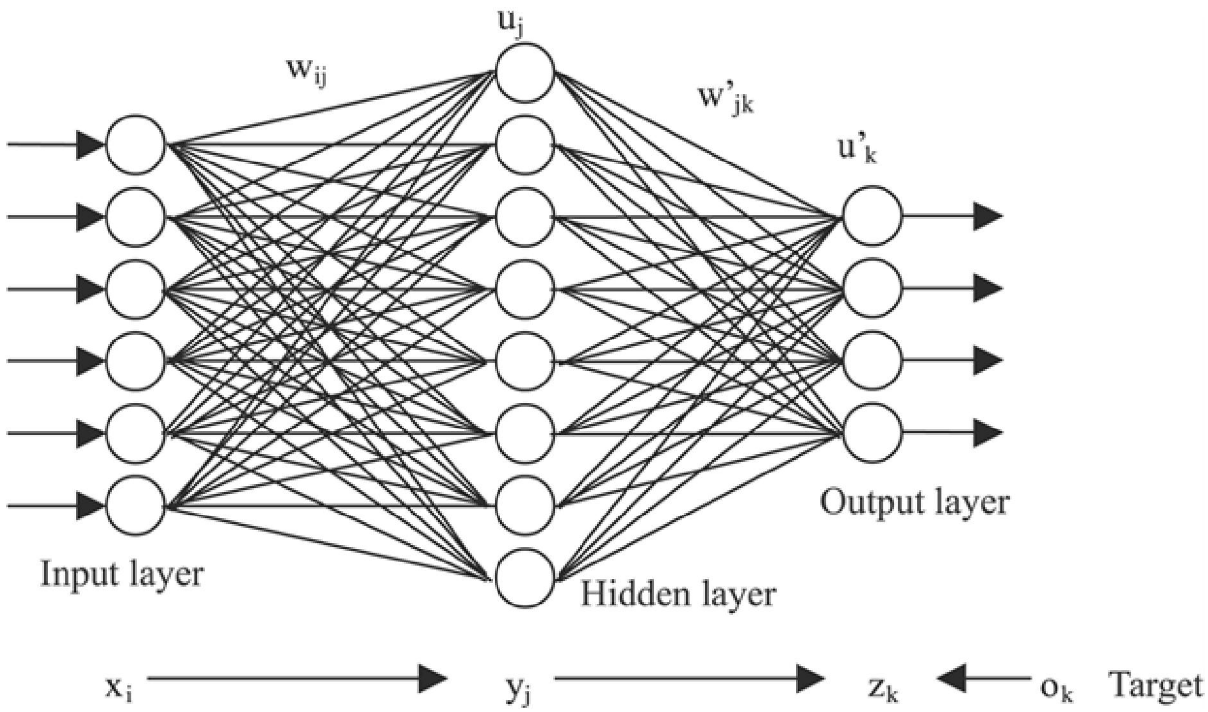

Figure No. 4: Artificial Neural Network Basic Model

Source: Extreme Tech.

A neural network can be created or setup to have dozens of artificial neurons to hundreds, thousands, or even millions in its network arrangements. Each of these neurons connects to the layers on either side. Input units are designed to receive various forms of information from the outside that the network will attempt to learn about, recognize, and process. Output units sit on the opposite side of the network and signal how it responds to the information learned. In between the input units and the output units are one or more layers of hidden units. Together it forms the majority of the artificial brain. The connections between one unit and another are represented by a number called a weight, which can be either positive or negative. Higher weights have more influence over others. There are two possible ways that the information will flow through a neural network. One, when it is learning (trained), or two, when it is operating (after training). Information patterns that flows are fed into the neural network via the input units. It will then trigger the hidden layers and the information will then reach the output layers to generate the result. This manner of information flow is a process known as feedforward. A neural network learns and optimizes its results through a feedback circuitry, and this is knowns as backpropagation (Milos Marinkovic, 2014). Backpropagation involves comparing the outputs produced to the output it was meant to produce. Using the difference between them, it modifies the weights between the layers of the network. Backpropagation causes the network to learn, and thus reduces the differences between actual and intended outputs.

National Account Assessment

Assessing the national accounts for each of the 6 countries involved the use of the published data obtained from the Asian Development Bank. The data are part of ADB's national key indicators annual statistical spreadsheet that highlights pertinent information about a country's economic outlook for the stipulated year and period. For this assessment, 18 years data from 2000 – 2017 was obtained to study the pattern of economic activities in the national account that could determine if the Central Asian countries economic health conditions are befitting in becoming ideal Chinese partners on the BRI endeavor. Country partners that are deemed to be a good fit tends to reciprocate and support one another when needed. Analyzing and recognizing the national account growth patterns over an 18-year period would suffice to show economic strengths. Within the realms and strategies of regional economic

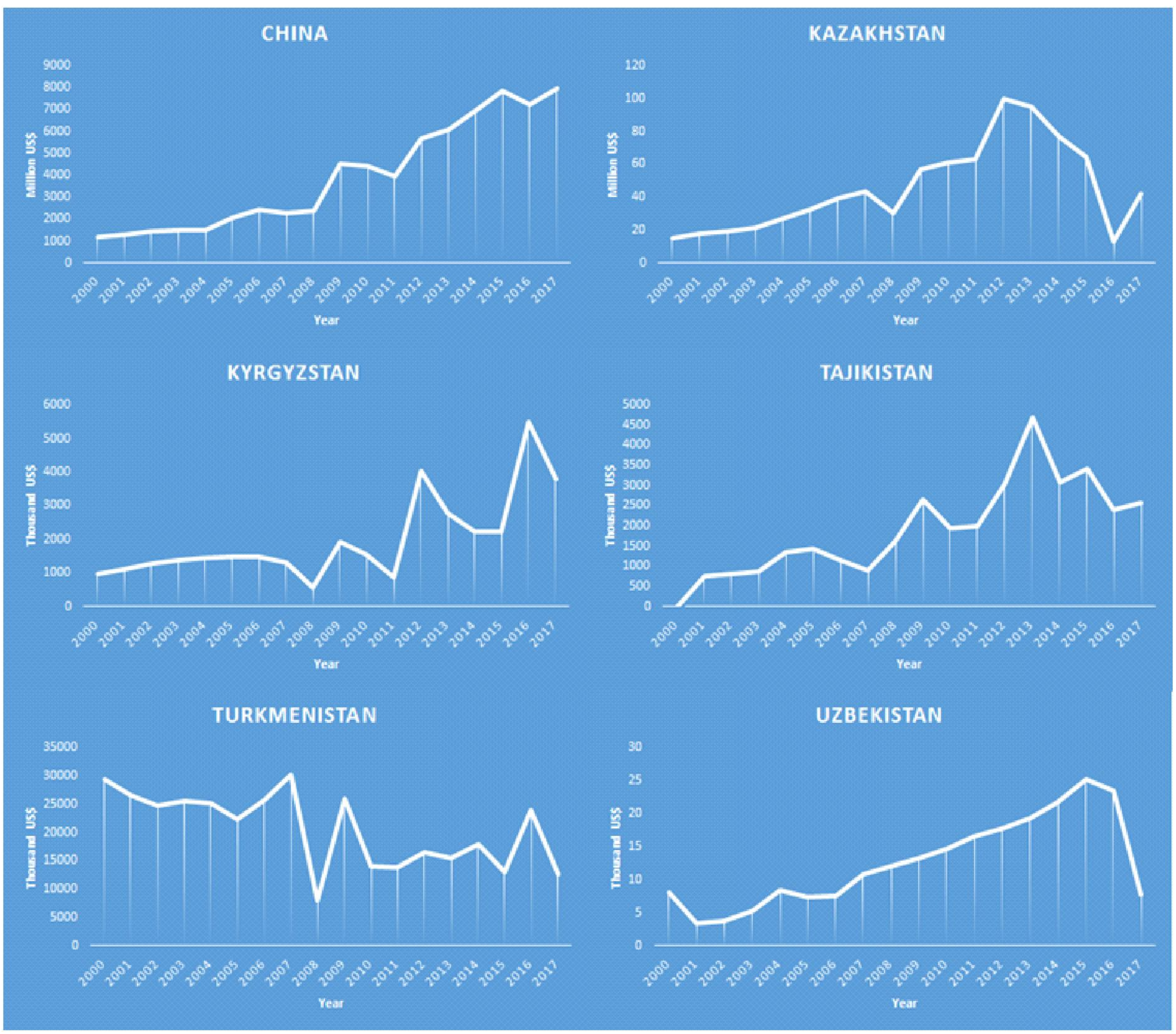

Figure No. 5: GDP (minus inflation) Growth Pattern

Source: Asian Development Bank, 2018 Economic Outlook.

integration, economic dominance is intended, and it is not welcomed. Dominance of one partner will only result in animosity between countries and the region. To appropriately analyze each national account, inflation had to be omitted from the growth equation. The real values for each country had steady growth pattern from the early periods of 2000 – 2008 but that pattern shifted downwards (except China) for the remaining period of 2009 – 2017. The figure below shows the GDP growth pattern for each country minus inflation.

As the main focus of this assessment was to assess the economic health status, the economic catalysts were also determined that could spur growth. A national economy cannot rely only on one or a few economic activities. Strong sectors can become weak should it be neglected or be impacted exogenously, especially energy and commodities, and weaker economic sectors that could potentially become main drivers of the country need due focus as well.

Assessment Findings

The methodology of performing this assessment are as follows:

Step 1 – raw data aggregation from ADB's databank, *https://data.adb.org/search/type/dataset*

Step 2 – consolidation of the raw data

Step 3 – factoring out inflations

Step 4 – establishing the median

Step 5 – classifying the data into the neural network's inputs and targets

Step 6 – program coding

Step 7 – program execution, outcome analysis and interpretation

A form of data coherence was needed to ensure an unbiased assessment. To do so, the aggregated data needed to be vetted and crossed checked against other institutions. The ADB datasets was compared with data from the World Bank and the respective national statistical bureau mainly from the central banks and also the local statistical agency. This was done to ensure that the data used for these assessments were not far off from each other. There were cases that some data points obtained were not in congruent and did not tally with the national agencies and such data were either omitted from the assessment. A clear match was obtained between the World Bank's and ADB's data and this was sufficient to rule and to deduce that the assessment was save from bias. Data consolidation was the next approach to verify. In some of the countries, parts of the list of the 21 national account items were not furnished with respective information. Some countries grouped the various sectors and published a consolidated summation of information. For example, the mining, manufacturing, and energy industries in China were combined as a unit, similar findings and data consolidation was found for the other countries as well. Kazakhstan and Kyrgyzstan had consolidated data too but only for two sectors. To conduct a proper assessment across the period, inflation had to be factored out. Real values were preferred over nominal ones that gave a better snapshot of the countries' growth pattern of the 18-year period (as seen in Figure No. 5). Also, to note that the national accounts for each country were accounted for in its local currency unit and it was then harmonized into US dollars. The exchange rates used for the harmonization exercise was based on a 12-month average annualized rate according to each country, respectively. Rates used were crossed checked against annual rates published by the various central banks. From the data *"clean up"*, a median was established. Each country's dataset on its national accounts has 21 items across 18 years that totals to 378 data points. With 6 countries, the datasets generate 2268 data points, however, not all items were represented with data. Establishing an average would skew the results on either of the far extremes causing the assessment outcomes to be less or not desirable. A median from the datasets helps to avoid extreme values. Because economic data are not entirely free from outliers, a mean value would not be proper, hence taking the median would be more statistically accurate. The median would then be compared against the real values to create a data count of the total data that were below and above the median value. Real values that were below the median were designated as "0" whereas "1" were assigned to data points that were above the median. Depending on the remaining itemized national account from the data consolidation of each country, a summation of 0s' and 1s' across the data points was determined per country resulted in the itemized national accounts targets. Summations with more than half of the itemized national account was associated with "1" and summation with less than half was assigned with "0". To this point of the data preparation, it produced a classification of 0s and 1s as targets and the real value data as the inputs for the assessment using the artificial neural network approach. The data *"clean up"* was carried out on using Microsoft Excel spreadsheet. The established inputs and targets data were then fed into a neural network for pattern recognition to classify the country's economic fitness. The pattern recognition tool that was used is the process for classifying input data into classes; "*good fit*" as Class 1 and "*not a good fit*" as Class 2 based on certain key features and in this assessment, the key features are the list of the national account items that were used to classify the health status of the Central Asia countries. The assessment on China serves as reference point of the classification.

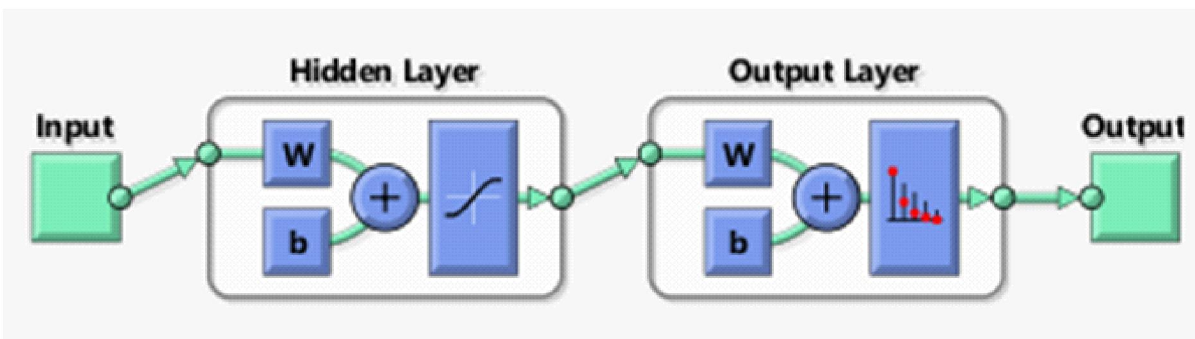

Figure No. 6: Neural Network Pattern Recognition Diagram

Source: Simulated via Matlab.

The neural network pattern recognition diagram used was a two-layer feedforward system. The hidden layer has a sigmoid "*S*" shape transfer function which limits the minimum and maximum values of the target data. A two-layer feedforward with SoftMax output neurons can perform any classification with arbitrary accuracy. The input and output data were static representing the number of samples and number of elements. The default setting recommended by the system was used in the training (70%), validation (15%), and test (15%) of the datasets. For learning (training), the data were presented and fed to the network and it was adjusted for its errors. During validation, the data measured the network's generalization and it stops learning (training) when there are no improvements to the generalization. The network testing has no effect on the network learning (training). This delivers an autonomous measure of the network's performance during and post learning (training). The default hidden neurons of 10 was used. This can be changed as and when it needs to, to obtain the optimum result. Should the network perform poorly, changing the default hidden neuron can improve the outcomes. The neural network was then created based on the given inputs, the needed hidden layers, the given output layers, and the output classification, in this case, two. The network was trained using the scaled conjugate gradient backpropagation, SCG. The training stops when the generalization stops improving as indicated by an increase in the cross-entropy error of the validation. A cross-entropy of zero is desired as it means no errors. A low cross-entropy would be ideal for optimum result. Multiple trainings to the network will generate different results due to different initial testing and sampling condition. The default settings used, and a one-time network training was sufficient to produce the needed results for this assessment. The outcome of the neural network was generated by plotting the Performance, Error Histogram, Confusion Matrix, and the Receiver Operating Characteristic. The Performance plots errors versus epochs (iterations) for the training, validation, and test performances of the network. The performance of the neural network was shown in the green validation plot line. The network stops training when the validation begins to show an incremental pattern. The best performance was taken from the epoch with the lowest validation error. The performance plot shows the mean square error, MSE, dynamics in a logarithmic scale. And when the training data starts to increase (rise), it states that the network is overfitting. The Error Histogram of a neural network provides deeper understanding to the errors of the network. The variance of errors showed that the errors can be classified into big and small in terms of the Error Value. The negative sign associated to an error for each performance index happens when the outputs are larger than its targets. Training of the dataset entails 70% of the samples. Errors were supposedly to be close to zero (small errors) while the errors in the test dataset includes 15% of the samples were far from zero (big errors). Errors of the validation dataset entails 15% of all samples were inclined to zero. This only meant that the proposed neural network setup had a high degree of generalizability. The total error from neural network ranges from the smallest number (leftmost bin) to the highest number (rightmost bin). This error range was divided into 20 smaller bins. Each vertical bar represents the number of samples from the dataset in a particular bin. A confusion matrix was the table used to describe the performance of a classification model on the test data for which the true values were known. The confusion matrix represents the performance of the proposed neural network in terms of classification accuracy. The confusion matrix exhibited the total number of observations in each cell. The rows of the confusion matrix corresponded to the true class, and the columns corresponded to the predicted class. The diagonal and off-diagonal cells corresponded accurately and erroneously classified observations. The Receiving Operating Characteristic or ROC was a metric used to check the quality of classifiers. The ROC metric was coupled with sensitivity and specificity screening test. These screening test determined whether the test fulfils the criteria or not. In this case, it is to find out the economic health condition of China and the Central Asian countries. The key thing to note about sensitivity and specificity testing are that they are both conditioning probabilities. This would mean that the outcome or the results were not be based on the entire group or data but rather a selected subset of the group or sample data, in this study, whether or not Central Asian countries are a good fit or not in becoming China's partner. A positive test result identified that the countries are indeed not a good fit. Sensitivity is the probability that the screening test was positive given that these countries are indeed unfit. This was an affirmative point of decision and specificity was the probability that the screening test was negative given that these countries were indeed fit for Chinese partnership. This too was an affirmative point decision. These screening test also incurred errors and these errors were "*false negative and false positive*". A false negative showed that the countries were fit but in fact they are not. A false positive showed that the countries were indeed unfit but showed it to be fit. Such testing and assessments were not absolute given the fact that economic testing is filled with biasness and errors starting from with the data collected. Therefore, for any results obtained from the testing would require a detailed study of the economic symptoms of the likes of policies, governance, and so on. High values were preferred for both sensitivity and specificity. High specificity meant that the countries were a fit. High sensitivity meant that the countries were unfit. The ideal testing for proper classification would see that the sensitivity and the specificity were high (at 100%). This denote that healthy economic countries were a fit and unhealthy economic country were not fit. Each class of a classifier, the ROC applied threshold values across the interval [0,1] to outputs. Two values were calculated for each threshold, the True Positive Ratio, (TPR), and the False Positive Ratio, (FPR). The ROC was the tool used to describe the discrimination accuracy of a diagnostic test or prediction model with sensitivity and specificity were the basic metrics of accuracy. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity. ROC curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds and ROC curves are appropriate when the observations are balanced between each class. The artificial neural network execution, outcome analyses, and interpretations are explained in the preceding sections. The National Account assessment for China – Central Asia were depicted, described, and delineated as follows:

China

The data used for China's assessment was an 11x18 dataset. The input data consist of a 9x18 dataset and a 2x18 target data. Of the 21 national account items, only 7 economic sectors were represented with individual data. The mining, manufacturing, electricity gas supply, and water supply sectors were consolidated as one sector. Likewise, the information and technology, professional and scientific activities, administrative and support, defence and social security, education, health, entertainment, and household and extraterritorial organization activities were consolidated as a single sector as well. The neural network diagram for China is shown in Figure No. 7.

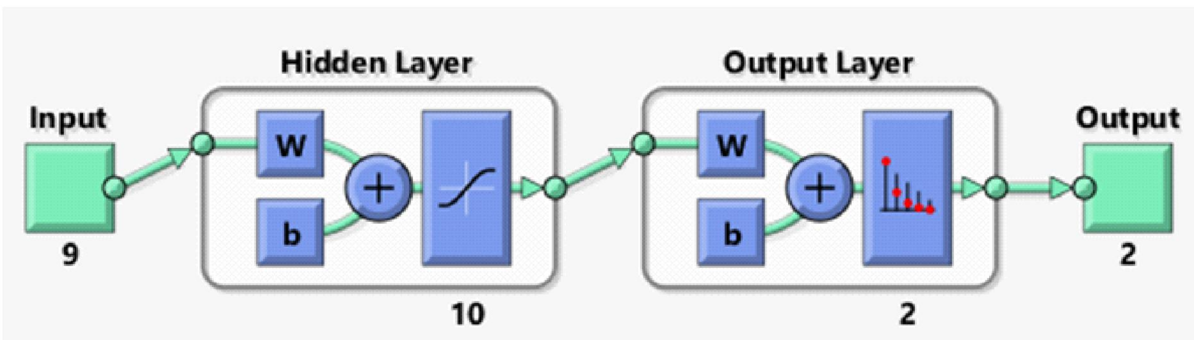

Figure No. 7: China's ANN Model

Source: Simulated via Matlab.

From the results obtained for China's assessment, the network performance validation test stopped at the 19th epoch (iteration) with an exceedingly small final score of 1.5736e-07 mean square error. Both the validation and train lines have similar characteristics indicating that the data used for the assessment had no major concerns. No significant of overfitting was presented in the network performance and analysis. In the error histogram, the variance of errors showed that the errors ranged from -0.95 to 0.95. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with exceedingly small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value, and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -0.05 and 0.05. Reflecting to the network performance against the error histogram, the error results that consist of 15% does not have a major impact to the overall analysis and can be ignored for this assessment. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 94.4%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes "*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines China as a Class 1 "*good fit*" country. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For China, the Class 1 classifier stands at 85% as its true positive rate making the country to be indeed a good fit.

Kazakhstan

The dataset used for Kazakhstan's national account assessment was a 19x18 matric. The input data consist of 17 items of the national income and the output data was a 2x18 dataset. The energy and water supply management items were consolidated as a single sector. Real estate, professional and

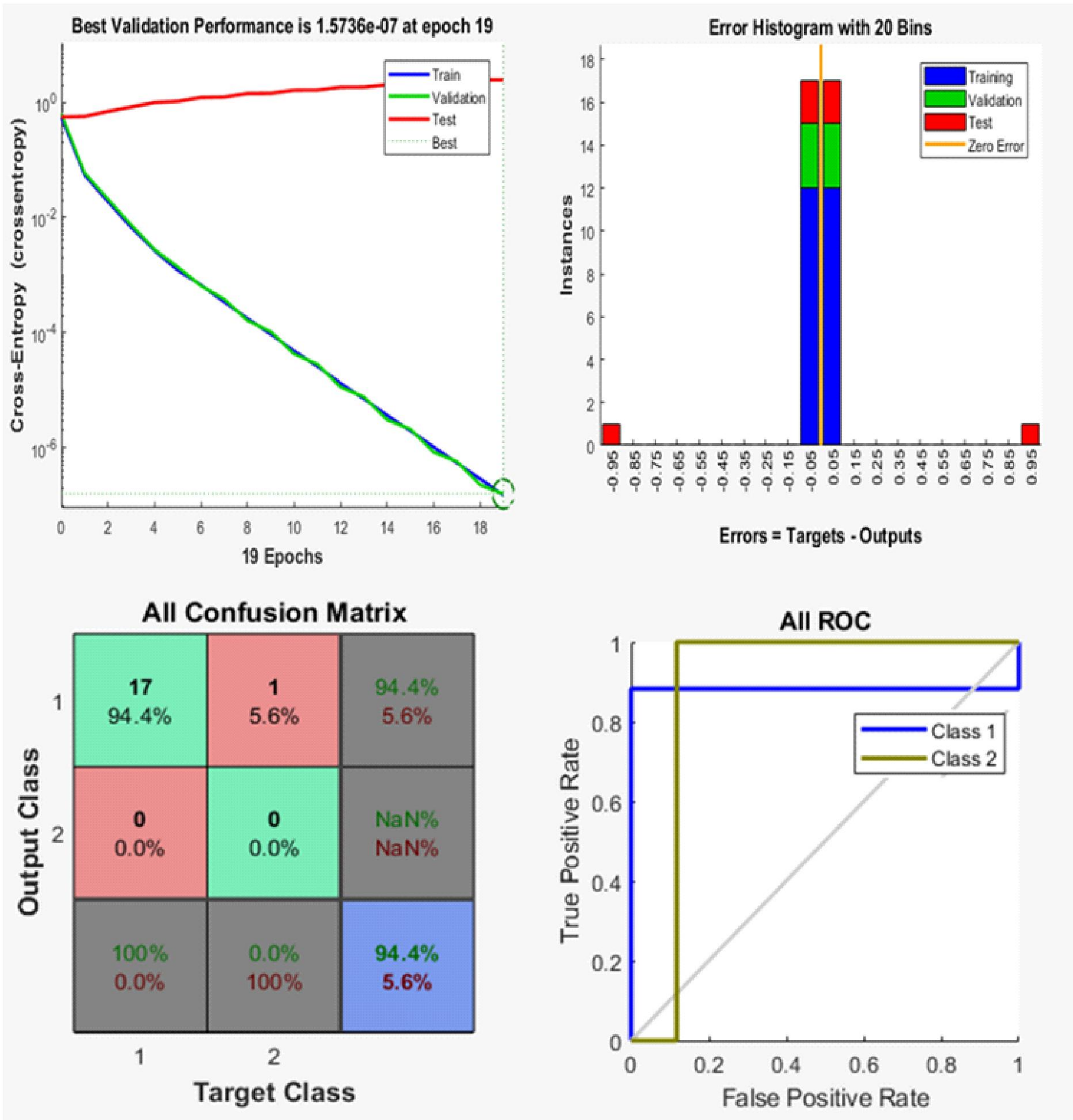

Figure No. 8: China's National Account Pattern Recognition Results

Source: Simulated via Matlab.

scientific administrative support were also consolidated so as to the households and extraterritorial organization activities. The neural network diagram for Kazakhstan is illustrated in Figure No. 9.

From the results obtained for Kazakhstan's assessment, the network performance validation test stopped at the 26th epoch (iteration) with an exceedingly small final score of 3.605e-09 mean square error. Both the validation and train lines have almost similar characteristics indicating that the data used for the assessment had no major concerns. No significant of overfitting was presented in the network performance

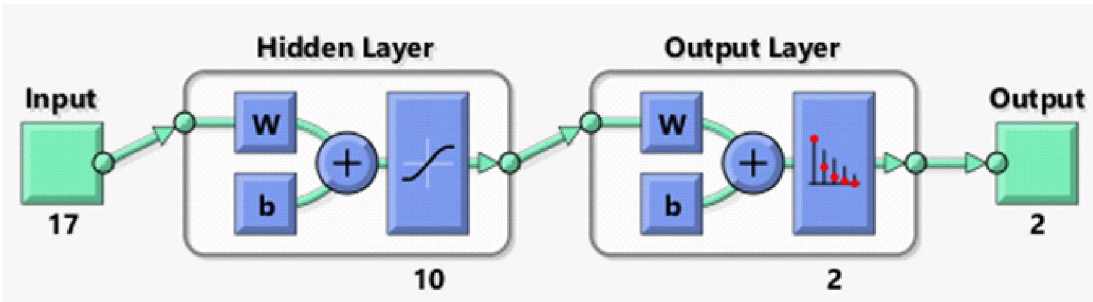

Figure No. 9: Kazakhstan's ANN Model

Source: Simulated via Matlab.

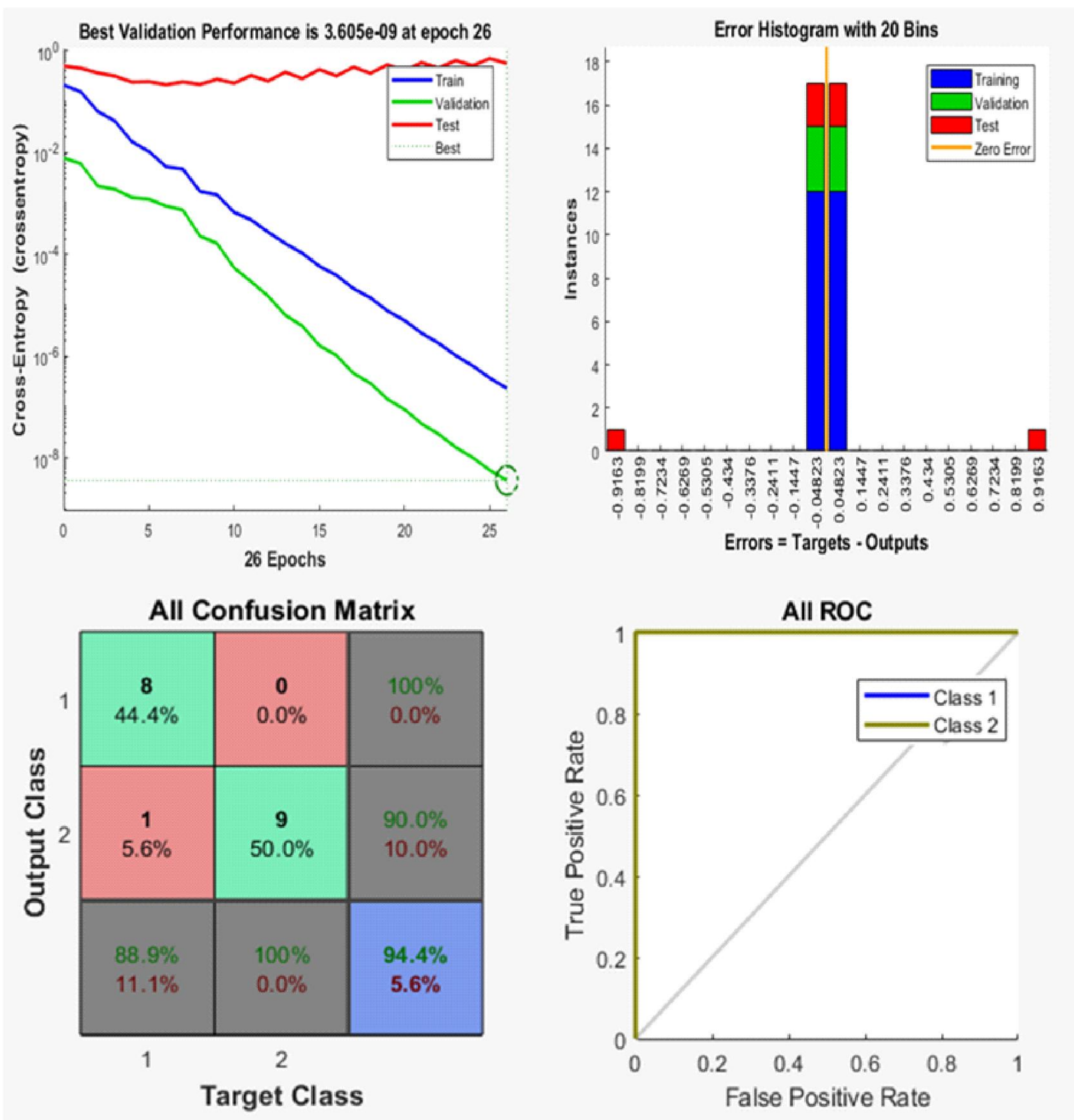

Figure No. 10: Kazakhstan's National Account Pattern Recognition Results

Source: Simulated via Matlab.

and analysis. In the error histogram, the variance of errors showed that the errors ranged from -0.9183 to 0.9183. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with very small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value, and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -0.04823 and 0.04823. Reflecting to the network performance against the error histogram, the error results that consist of 15% does not have a major impact to the overall analysis and can be ignored for this assessment. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 94.4%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes "*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines Kazakhstan as a Class 2 "*not a good fit*" country. However, there is a 44.4% classification that suggest that Kazakhstan is a Class 1 "*good fit*" country, and this coincides well with the analysis carried in the Pilot Study showing that across 18 years, Kazakhstan has indeed progress to improve its economy. Refer Chapter 4 section 4.3.4 and 4.3.5 for details. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For Kazakhstan, the Class 2 classifier is at 100% as its true positive rate classifying the country to be indeed not a good fit.

Kyrgyzstan

The data used for Kyrgyzstan's assessment was an 18x18 dataset matrix. The input data consist of a 16x18 dataset and a 2x18 target data. Of the 21 national account items, 16 economic sectors were represented with individual data and 5 was consolidated. Similar to Kazakhstan, the energy and water supply management, and household and extraterritorial organization activities were consolidated. Transportation storage, information and communication technology, and financial and insurance activities were also consolidated as one. Figure No. 11 shows the neural network setup for Kyrgyzstan.

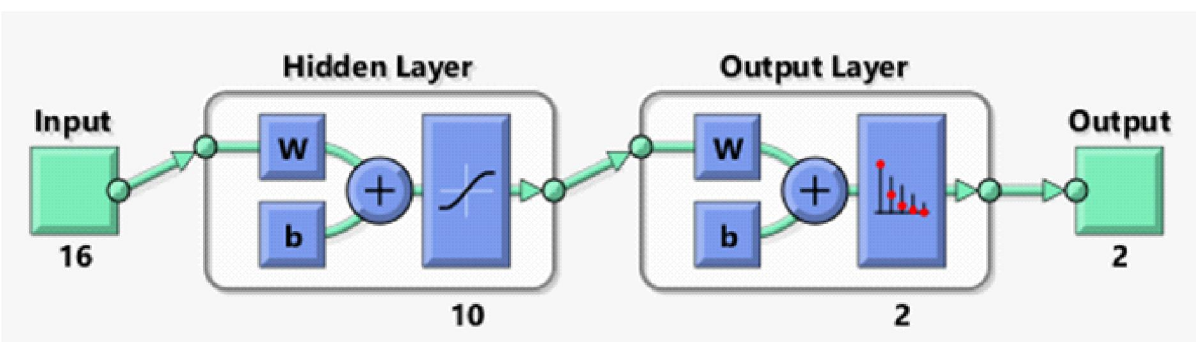

Figure No. 11: Kyrgyzstan's ANN Model

Source: Simulated via Matlab.

From the results obtained for Kyrgyzstan's assessment, the network performance validation test stopped at the 38th epoch (iteration) with an exceedingly small final score of 7.1658e-07 mean square error. The jagged validation line shows clear indication that the data underwent retraining for overfitting during the network performance and it needed higher iterations to confirm an outcome. Both the validation and train lines have almost similar characteristics in terms of movement and direction, but the data used for the assessment may had concerns. No significant of overfitting was presented but the multiple spikes on the validation line shows otherwise where the data had the tendency to over fit in the network performance and analysis. In the error histogram, the variance of errors showed that the errors ranged

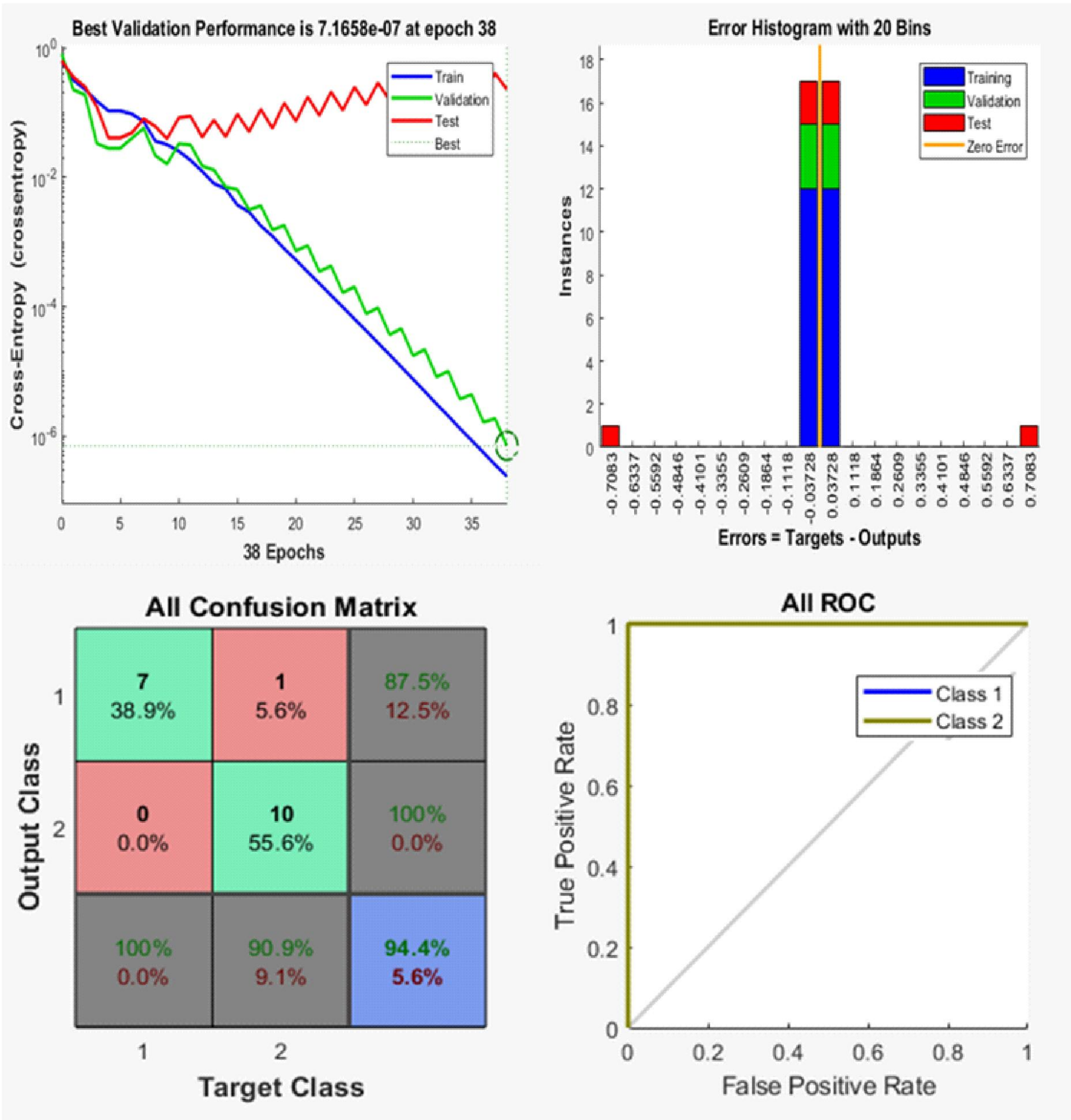

Figure No. 12: Kyrgyzstan's National Account Pattern Recognition Results

Source: Simulated via Matlab.

from -0.7083 to 0.7083. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with exceedingly small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value, and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -0.03728 and 0.03728. Reflecting to the network performance against the error histogram, the error results that consist of 15% do bring about a concern that could have an impact to the overall national account analysis. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 94.4%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes "*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines Kyrgyzstan as a Class 2 "*not a good fit*" country. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For Kyrgyzstan, the Class 2 classifier is at 100% as its true positive rate classifying the country to be indeed not a good fit.

Tajikistan

The national account assessment for Tajikistan was based on a 12x18 dataset, with 10 inputs and 2 target data. Out of the 21 items of the national account, only 7 sectors were represented properly with data. Mining, manufacturing, energy, and water supply management were consolidated as unit. Retail trade, food services, transportation, and information communication were consolidated as well. There were no data presented for real estates, professional scientific activities, administrative support, entertainment, and household, and extraterritorial organization activities. Items that were not represented was removed from the analysis to avoid unfavourable outcome. Tajikistan's neural network diagram is seen in Figure No. 13.

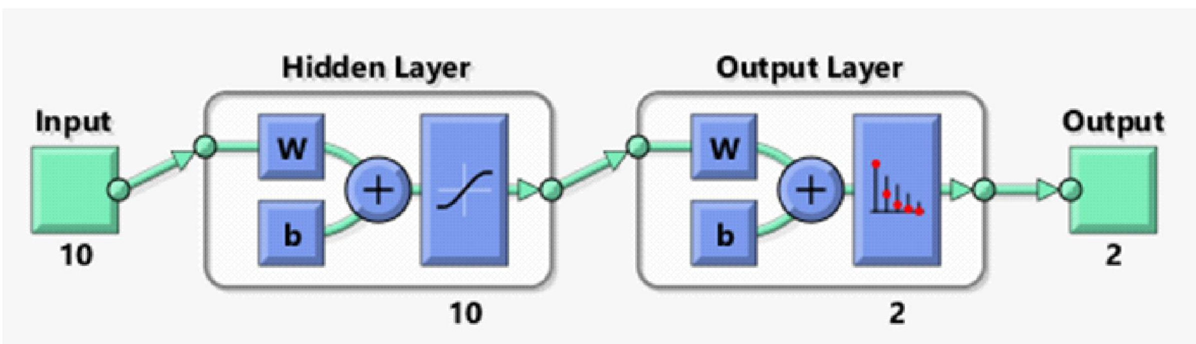

Figure No. 13: Tajikistan's ANN Model

Source: Simulated via Matlab.

From the results obtained for Tajikistan's assessment, the network performance validation test stopped at the 23rd epoch (iteration) with an exceedingly small final score of 4.9537e-08 mean square error. The jagged validation line shows clear indication that the data underwent retraining for overfitting during the network performance and it needed more iterations to confirm an outcome. Both the validation and train lines have almost similar characteristics in terms of movement and direction, but the data used for the assessment may had concerns. No significant of overfitting was presented but the multiple spikes on the validation line shows otherwise where the data had the tendency to over fit in the network performance and analysis. In the error histogram, the variance of errors showed that the errors ranged from -2.4e-05 to 2.35e-05. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with exceedingly small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -1.2e-06 and 1.24e-06. Reflecting to the network performance against the error histogram, the error results that consist of 15% do bring about a concern that could have an impact to the overall national account analysis. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 100%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes

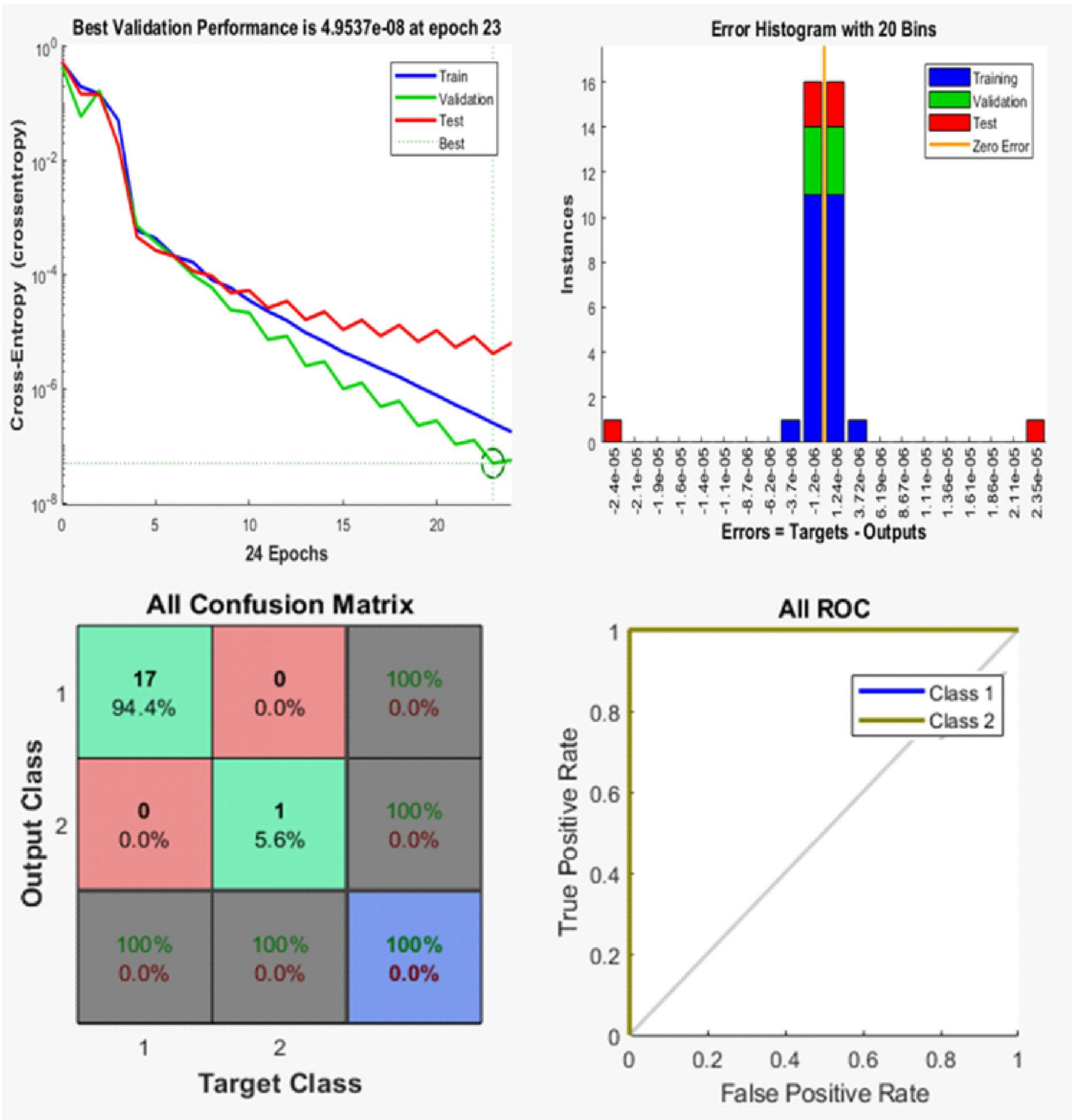

Figure No. 14: Tajikistan's National Account Pattern Recognition Results

Source: Simulated via Matlab.

"*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines Tajikistan as a Class 1 "*good fit*" country. However, the assessment here does not classify the country's status but rather the test results from the test data. As mentioned in the previous section, there are other considerations as well when classifying a country's national economic status. From the past data observations and analysis, Tajikistan is factually a country that should fall as Class 2. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For Tajikistan, the Class 2 classifier is at 100% as its true positive rate classifying the country to be indeed not a good fit.

Turkmenistan

For Turkmenistan, an 8x18 dataset was used for the assessment. Of which, 6x18 were inputs and 2x18 was the output target data. Only 2 national income items (agriculture and construction) were accurately represented with data throughout the 18-year period. Mining, manufacturing, energy, and water were consolidated as one. Retail trade and food services were consolidated as well as one. Transportation and information communication were consolidated as a single unit. Finance, real estate, professional scientific activities, administrative support, defence and social security, education, healthcare, entertainment, services, household activities, and extraterritorial organisation were all consolidated as a single entity of the national account. The neural network diagram is shown in Figure No. 15 for Turkmenistan.

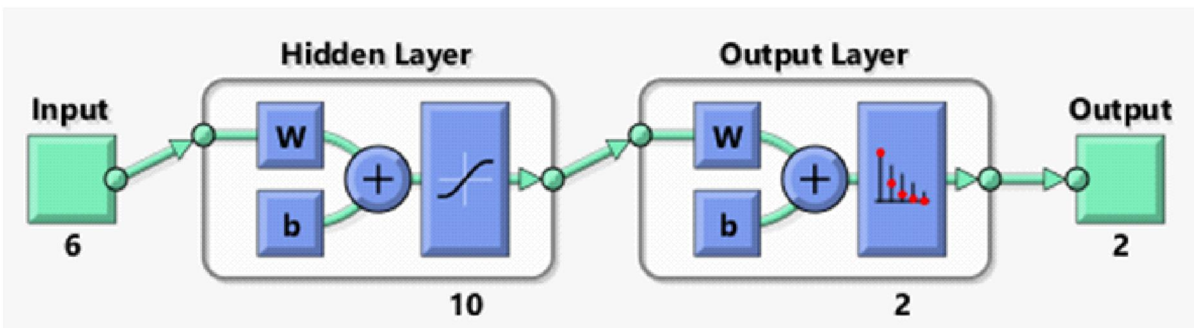

Figure No. 15: Turkmenistan's ANN Model

Source: Simulated via Matlab.

From the results obtained for Turkmenistan's assessment, the network performance validation test stopped at the 16th epoch (iteration) with an exceedingly small final score of 4.2682e-07 mean square error. Both the validation and train lines have almost similar characteristics indicating that the data used for the assessment had no major concerns. No significant of overfitting was presented in the network performance and analysis. In the error histogram, the variance of errors showed that the errors ranged from -0.95 to 0.95. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with exceedingly small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value, and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -0.05 and 0.05. Reflecting to the network performance against the error histogram, the error results that consist of 15% does not have a major impact to the overall analysis and can be ignored for this assessment. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 94.4%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes "*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines Turkmenistan as a Class 1 "*good fit*" country. However, the assessment here may be true if all attention is given and skewed toward its commodities supporting the economy. The test data classifies the country status according to the input data and the respective target data but from the past data observations and analysis, Turkmenistan should have been classified as a Class 2 "*not a good fit country*". Perhaps the demand for its commodities is making the economy health status otherwise. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For Turkmenistan, the Class 2 classifier is at 100% as its true positive rate classifying the country to be indeed not a good fit.

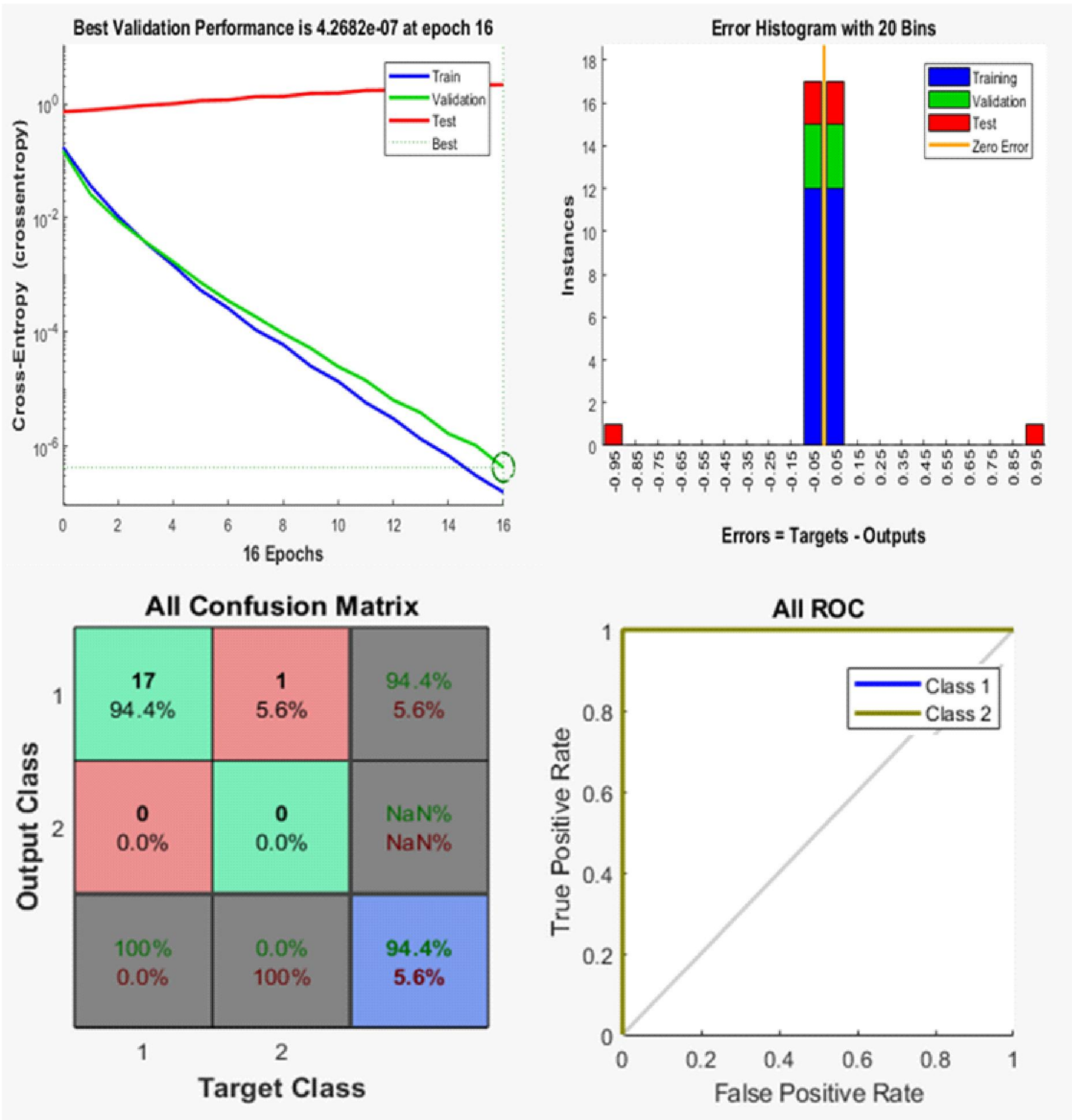

Figure No. 16: Turkmenistan's National Account Pattern Recognition Results

Source: Simulated via Matlab.

Uzbekistan

Similar to Turkmenistan, the dataset used for Uzbekistan was also consolidated. Only agriculture and construction were well represented with data. There were no data available throughout the 18-year period for household activities and extraterritorial organisation. Finance, real estate, professional scientific activities, administrative support, defence and social security, education, healthcare, entertainment, and services were grouped as a single unit. Retail trade and food services were consolidated as well as one. Transportation and information communication were consolidated as a single unit as well. Mining, manufacturing, energy, and water supply management was also grouped as a sector. The dataset used was an 8x18 matric with 6 input data and 2 output target data for Uzbekistan. Figure No. 17 displays the neural network diagram and setup for Uzbekistan.

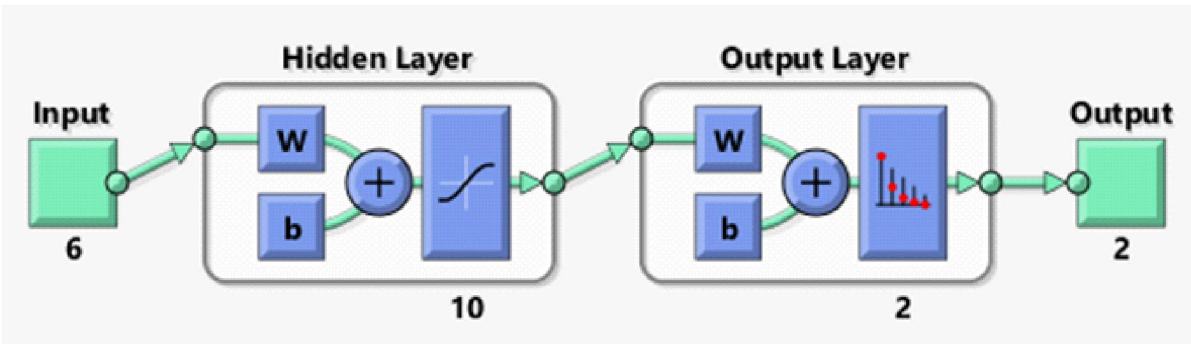

Figure No. 17: Uzbekistan's ANN Model

Source: Simulated via Matlab.

From the results obtained for Uzbekistan's assessment, the network performance validation test stopped at the 39^{th} epoch (iteration) with a much larger final score of 0.0033308 mean square error. The jagged validation lines suggest that the data had the tendency to overfit and it is definite that the data used for the assessment is a concern. No major significant of overfitting was presented in the network performance and analysis but the poor performance of the validation line when compared to the train line and the test line is a serious factor of concern. In the error histogram, the variance of errors showed that the errors ranged from -0.0188 to 0.0188. The training data entailed 70% of the samples, were close to zero. The errors of the validation data entailed 15% of the input samples were inclined to zero, meaning that the neural network has a high degree of generalizability with exceedingly small amount of errors as outliers. The middle of the error histogram graph, the corresponding error value, and the height of that error for validation dataset indicates that the samples from the validation dataset has an error that lies in the range of -0.00099 and 0.00989. Reflecting to the network performance against the error histogram, the error results that consist of 15% do bring about a concern that could have an impact to the overall national account analysis. The concern here is that the error histogram is showing that there are outliers in the validation errors as compared to the test errors. Uzbekistan's data is a definite concern. The classification precision and accuracy of the network's performance results for the data's true value is at an overall of 100%. This displays the total number of observations corresponding to the true class and the predicted class. Class 1 denotes "*good fit*" and Class 2 denotes "*not a good fit*". The diagonal cells correspond to correctly classified observations and the confusion matrix sorts the classes into their natural order as defined. This classification defines Uzbekistan as a Class 1 "*good fit*" country when in fact it is not. The Receiving Operating Characteristic metric is used to check the quality of the classifiers. For Uzbekistan, the Class 2 classifier is at 100% as its true positive rate classifying the country to be indeed not a good fit.

The focus for the national account assessment was to determine the economic health status of Central Asia and to either reject or accept the alternate hypothesis. The given analysis is summarized in the table No. 3.

From the findings of the assessment's results, it was evidently strong that Central Asia's economic health status was indeed not a good fit in becoming a partner to China. This then rejects the null and accepts the alternate hypothesis stating that - *the economic health condition of Central Asia is adversely insignificant and is not a good fit to be a partner to China*. By this, the research objective has been met and the research question has been answered. The assessment result was crucial to look and analyze

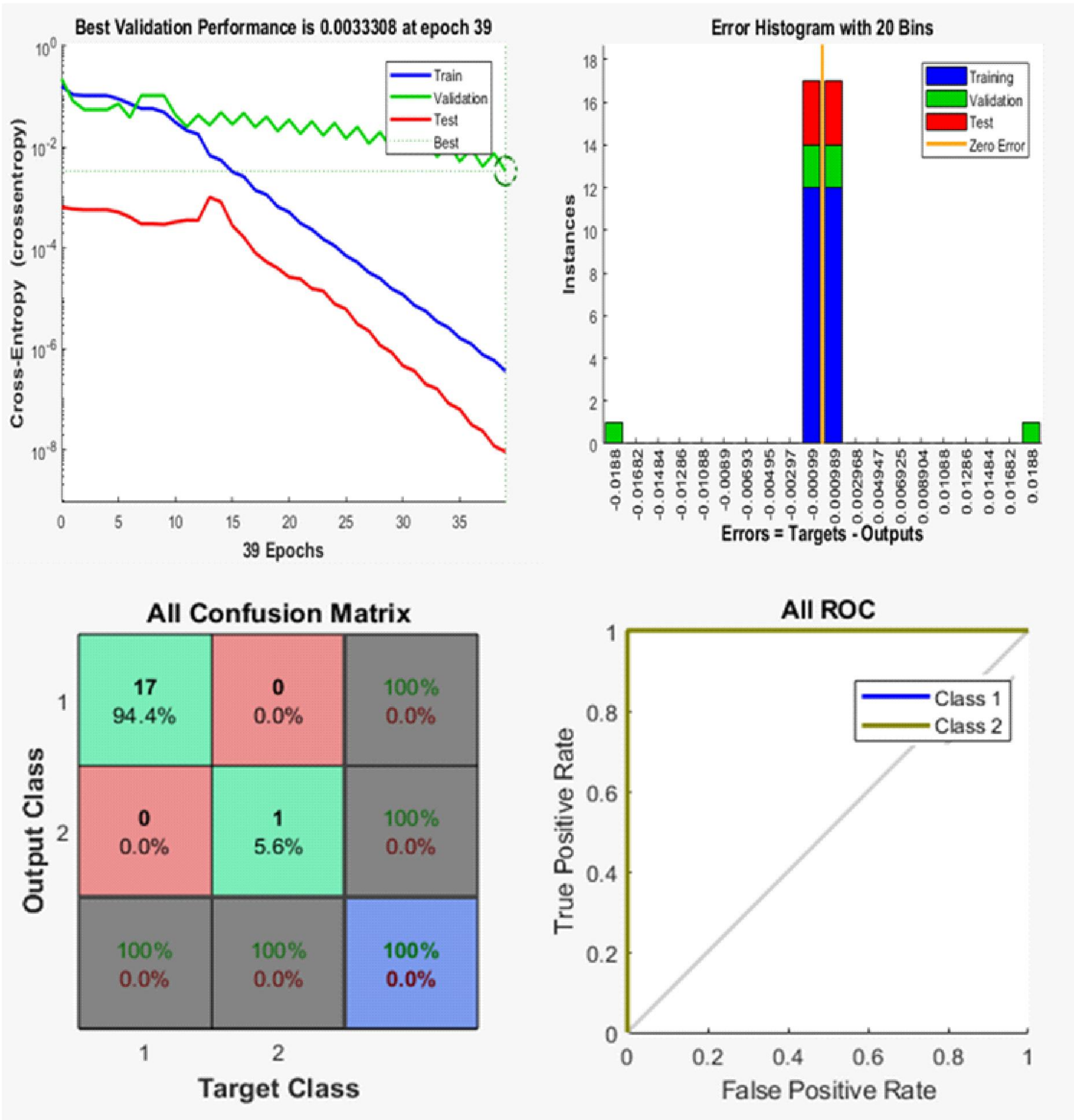

Figure No. 18: Uzbekistan's National Account Pattern Recognition Results

Source: Simulated via Matlab.

deeper into determining how the China – Central Asia Economic Corridor will eventually work. The National Account assessment was the first start of such research and it is the first step in analyzing this regional partnership. The regional integration between China and Central Asia for the purpose of the BRI is inevitable and partnership works have been agreed upon with signed billion-dollar investments. Now such results are concerning. Looking at the general economic landscape positively (superficially), it can be said that development is rather promising, however, now, the perspective could be otherwise.

Table No. 3: National Account Assessment Summary

Country	Input Data	Output Data	Assessment Result
China	9	2	Good Fit
Kazakhstan	17	2	Not a Good Fit
Kyrgyzstan	16	2	Not a Good Fit
Tajikistan	10	2	Not a Good Fit
Turkmenistan	6	2	Not a Good Fit
Uzbekistan	6	2	Not a Good Fit

Conclusion

This study has proven that the conditions of Central Asia were not inclined in becoming China's strategic economic partner. Doing so will only strain the Central Asian countries further as fundamentals and structural changes are needed. It has also been said that China has shown interest in Central Asia for a long time, and it needs Central Asia as a conduit for trade, especially to the far west of Asia. Table No. 4 summarizes the outcome of this study.

Table No. 4: Study's Assessment Summary

Study Objective	Study Question	Study Hypothesis	Study Result
Assess the economic status and standing of the Central Asian region.	What can be estimated from the condition of Central Asia's economy?	H0: *If the economic condition of Central Asia is positively significant then it is a good fit to develop the economic corridor and be a partner to China.* H1: *If the economic condition of Central Asia is adversely insignificant then is not a good fit to develop the economic corridor and be a partner to China.*	Accept Alternate

No clearer evidence was needed to justify the economic stands that Central Asia is currently taking. It needs China, badly, to grow and improve its economic condition. However, it is not China's responsibility to do so. There are various internal problems and ambiguities among the Central Asian countries and the region is one of the least unified in the world. This creates severe challenges to China, but it also offers prospects for boosting regional connectivity and integration. There has been researches and media coverages of China's Belt and Road Initiatives, but little is known about how Central Asia perceives the mega endeavour (Nurgozhayeva, 2020). China's main concern about Central Asia is its weak regulation, high corruptions, and the insufficient transparency and monitoring of Central Asia's executive branch which poses a chokehold to China's economic policy goals. The success and fall of the economic corridor of China and Central Asia could affect bilateral ties in the region and stagnates future capital inflow into Central Asia (Overland, 2019). This is something that Central Asia need to work on to not lose China as its regional and strategic economic partner.

The function of the neural network was to recognize the economic pattern of Central Asia and was to classify the countries accordingly. The confusion matrix and the ROC curve has proven to have done so correctly predicting the outcomes based on the input data. The produced result from the assessment is in no way a be all and end all situation for Central Asia. China is indeed very much interested in the region and have being investing in Central Asia even before the properly coined BRI was established. The fundamentals of this research dealt in the robustness of the Central Asia economies through the respective national account. One of the key concerns to the assessment was on the availability of data and the accuracy in the published data. The needful was carry out to ensure that the data was legitimate for the assessment. However, cleaning up the data does not prove anything when the details of the data are missing. Missing information of the national account publish by international institutions was a trigger to the economic status, but missing information of the national account by the respective countries is alarming. Data that are not disclosed by the respective national bodies could mean a few things. It can be assumed that one, the data collated was not adequate, insufficient, or not substantial for reporting. Two, it could be the inefficiency in the processing of the data. Three, it could also be that the data collected were meaningless. Four, the data was only published as a yearly annualized average and not as a periodical update of monthly, quarterly or bi-annually. Five, reasons that questions the integrity of the statistical department and also the nation's outlook of data importance. The assumptions could be of anything and in any form. At most cases, the data were actually published but it was not made publicly available and the national data were submitted for international audits. Data was then generated independently through organized fieldworks and studied, analysed, and published. There are always room to dispute these published data, but the sheer volume makes it impossible to do so. With data that are compromised in its integrity will produce wrong analytical outcomes. For any given possibilities, the data used are taken in good faith and the results generated may or may not be reflective to the actual national situation, but the results reflect the test or assessment sturdiness. The assessment that was conducted in this research shows clear evidence that was then tabulated results in Table 3. As the data generated the results, and it then produced the state of the countries, the corresponding hindsight generalized the economic state of Central Asia. A nation's economic status are made out of various economic activities. The list of 21 national account items shows that each country is indeed buzzling with many economic activities propagating development and growth. Each item of the national account contributes a certain percentage of GDP to a country. The national activity or activities that contributes the largest percentage is said to be the focus and the catalyst of economic growth. This is simply based on the Ricardian theory of comparative advantage. The biggest challenge in identifying a potential economic catalyst was due to the fact that many of the national account data items was consolidation as a single economic contributor leaving an ambiguous notion of that all the countries (including China) do not have a main catalyst. This would only mean that all the national account activities of a country are performing averagely to sustain the countries growth and development process. It could also mean that there are inadequate resources in any or all of the economic sectors for it to truly be a catalyst. This then raises a question – what is Central Asia good at? Future research studies should diagnose the various economic sectors base on efficiency rather than percentage contribution. It is hope that a true catalyst can be identified that will then become the thrust of the China – Central Asia Economic Corridor partnership.

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