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# Financial Crisis Prediction using a Hybrid ANN Model

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***Abstract*— Several economic crises have already been witnessed by the world in the past few decades. This study proposes a hybrid model combining Artificial Neural Networks (ANN) and K Nearest Neighbour (KNN) models serially in predicting financial crisis. The analysis is done using dataset of the past 15 years comprising of 13 macroeconomic indicators of the country. The macroeconomic indicators are chosen based on their relevance to the economic conditions. The crucial macroeconomic indicators used in this study include consumer price index, export prices, import prices, terms of trade, foreign direct investment, government spending, producer prices, inflation rate, unemployment rate, GDP, money supply(m1), GDP/capita and industrial production. The prediction results obtained are compared separately with the results of ANN and KNN. Overall, the hybrid model possesses a higher prognostic ability and the likeliness of financial crisis in India during 2016 and 2017 is low.**

***Keywords*— Hybrid model, Artificial Neural Networks, K Nearest Neighbour, financial crisis, macroeconomic indicators**

## I. INTRODUCTION

The global financial crisis of 2007-08 forced a lot of financial institutions to fail. Financial crisis impacts the masses and commercial enterprises, thus affecting the economic growth of the country. Hence effective prediction of financial crisis has become a hot research topic in academic as well as practical world. In developing a financial crisis prediction system, suitable indicators need to be chosen. It is possible to evaluate an economic crisis using several economic indicators but the understanding and analysis of these indicators with respect to the economy of the country is utmost important. Indicators typically include micro-indicators and macro-indicators. Selection of these indicators is based on literature survey and their relevance to the economic conditions of a country. Some indicators may be positively linked and some may be negatively linked to the level of economic risks. Macroeconomic forecasting predicts the state of economy by concentrating on some variables such as GDP, inflation rate, import prices, unemployment rate, etc. The prediction model used should be timely and accurate. Different approaches that can be used in prediction are Artificial Neural Networks, probit, logit, machine learning methods, etc. The input dataset should be normalized in order to improve the results. Artificial Neural network is a traditional prediction approach which involves the following:

***Choice of model:*** It depends on the type of application and data representation. Complex problems often make learning of the neural network difficult.

Learning Algorithm: If correct parameters are selected for training on a particular fixed data set, any algorithm will work properly. But the amount of experimentation required is more in case of unsupervised learning.

***Robustness:*** The resulting ANN can be robust if the model, learning algorithm and the cost function are selected appropriately. If the input data volume is large; training of the Neural Network is takes a longer time. Also the number of layers in the multilayer perceptron affects the predictions.

K Nearest Neighbour with gradient descent optimization is a machine learning algorithm that is used for prediction. It generates random weights which are used to obtain the class value with the help of distance metric. The accuracy of prediction matters the most.

The hybrid ANN prediction model combines the benefits of both the algorithms producing results which are much more accurate than the two algorithms applied separately.

## II. RELATED WORK

First Early Warning System model in detecting currency crisis was invented by Krugman (1979)[23] and later by Flood and Garber (1984)[24]. Krugman[23] developed a macroeconomic model to analyse the balance of payments. Other prediction approaches used in the past include signals approach by Kaminsky and Reinhart (1998)[18], logit approach by Ohlson (1980)[19] and probit model by Zmijewski (1984)[20]. Signals approach was one of the oldest and widely used prediction techniques. It is a threshold approach which is non-parametric in nature. Logit and probit models include

 

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several statistical assumptions which make it difficult to handle errors during execution.

Nor Azuana Ramli, Mohd Tahir Ismail, and Hooy Chee Wooi (2013)[10] introduced k-nearest neighbour (k-NN) method which was never applied in predicting currency crisis before with an aim of increasing the prediction accuracy. The Manhattan distance measure was used. Authors of [14] proposed a hybrid intelligent early warning system (EWS) for predicting economic crises. The EWS system combines ARIMA models for forecasting individual EWS indicators; fuzzy optimization for assessing various economic and financial risks; and ANN models for predicting the likelihood of economic crises. Authors of [15] constructed a financial distress prediction model combining artificial neural network (ANN) and data mining (DM) techniques. The financial and the non-financial ratios in the financial statement were considered and used.

Feng Kong and Wei Wang (2009) [1] used factor analysis to study the cause of China's financial risk using the model of Artificial Neural Network. Authors of [9] constructed a Back-Propagation Neural Network model and applied sequential Pattern mining inorder to gain the prediction patterns for company's operational status.

Liu Hengjun (2014) [5] presented a Rough Set Neural Network based prediction approach using financial ratios as the input. This approach shortened the overall training time producing effective prediction results. Yin Yu, Qingguo Ma, Shuqiong Fang, Baoan Yan (2008) [7] proposed the basic structure and explanatory structure for crisis forecasting. Yuhong Li, Weihua Ma (2010) [12] presented a survey on the application of Artificial Neural networks in forecasting financial markets prices. The model created was applied in predicting the exchange rates.

Lean Yu, Shouyang Wang, KinKeung Lai, Fenghua Wen (2008)[16] proposed a methodology which applies Hilbert-EMD algorithm to a frequently changing financial indicator i.e. currency exchange rate series. The Hilbert-EMD procedure obtains some intrinsic mode components (IMCs) of the currency exchange rate series, with different scales. Using these selected IMCs, a neural network learning paradigm is used to predict future financial crisis events.

## III. HYBRID ANN MODEL

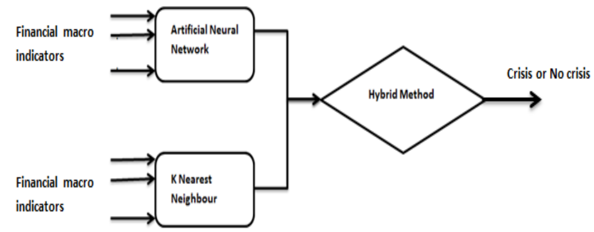


***Fig 1. Flowchart of the proposed hybrid ANN model***

The proposed hybrid prediction model comprises of the following steps:
1. Development of an Artificial Neural Network model which is trained using the feedforward Back-Propagation algorithm.
2. The output generated by ANN with the best weights is provided as an input to the KNN model which performs training with gradient descent optimization.
3. Perform financial crisis prediction using the result.

### *A. Artificial neural network architecture*

A multilayer perceptron (MLP) maps sets of macroeconomic indicators onto a set of appropriate outputs. Macroeconomic indicators are stats that signal the current condition of the economy of a country depending on related areas like trade, commerce, industry, etc. The macroeconomic indicators should be chosen based on their availability and relevancy to the economic conditions of a country. These indicators enable economic experts to estimate whether the economic condition of a country has ameliorated or deteriorated.

***Determination of parameters for Multilayer perceptron (MLP)***

Theory has proved that 3-layer network architecture is one of most common and preferred neural network architectures. The hidden layer's job is to transform the inputs into something that the output layer can use. Too many hidden layers can increase the complexity of the network. The number of neurons to be used in the hidden layer of the MLP plays a major role in predictions. Use of too few neurons in the hidden layers result in under-fitting whereas too many neurons lead to over-fitting and also an increase in the training time. Thus, the number of neurons in the hidden layer should be such that the error is minimized.

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Thumb rule for finding the correct number of neurons to be used in the hidden layer is

neuron_no= 2/3*(inp+oup) (1)

Where neuron_no represents the total number of neurons in the hidden layer; inp is the number of neurons in the input layer; oup is the number of neurons in the output layer.

***Table I. Number of neurons and the error corresponding to each of the neuron number***

| No. of Neurons(Hidden layer) | 5 | 6 | 7 |
|---|---|---|---|
| Error | 0.26 | 0.22 | 0.27 |

According to the table, error is lowest when the number of neurons in the hidden layer is 6. Hence our neural network architecture has 13, 6 and 1 neurons in the input, hidden and output layer respectively.

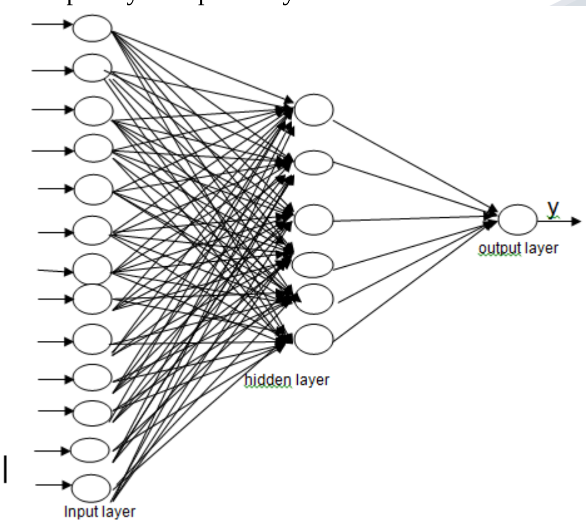


***Fig 2. Artificial Neural Network architecture***

13 macroeconomic indicators of the past 15 years are provided as an input to the 13 neurons of the input layer. The network is trained using feed forward Back-Propagation algorithm until the error in the output layer is the lowest. The final set of output generated using the best weights of ANN are provided to the KNN model in a serial fashion.

***B. KNN with gradient descent optimization***

The modified output generated using the best weights of ANN is provided as an input to the KNN model. The value of k is selected using a thumb rule. The thumb rule is given as follows:

K=(no_of_inputs)$^{0.5}$ (2)

where K represents the number of Nearest Neighbours; no_of_inputs represents the number of macroeconomic indicators used as an input.

Thus the value of k is 3. Random weights are generated and used in the training process. Distance metric used is Euclidean distance which is given by

$$D=\sum_{i=1}^{n}(Xi - Yi)^2 \qquad (3)$$

Where d is the distance; Xi is the training set and Yi is the testing set.

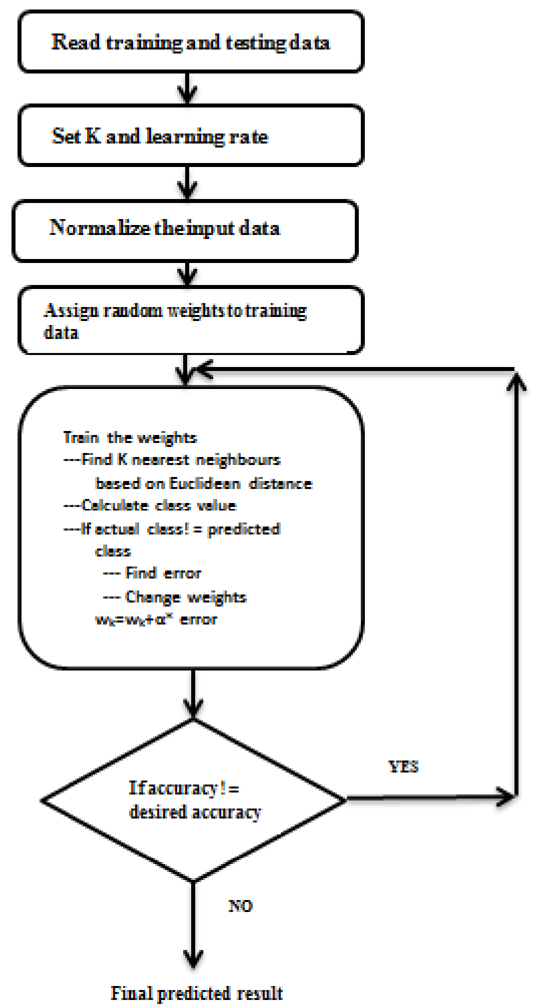


***Fig 3. Flowchart for KNN Model with gradient descent optimization***

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KNN model trains the weights till maximum accuracy is reached. The output generated at this point is considered for prediction.

***C. Prediction process***

Final step in the hybrid model is to check whether the actual output generated by KNN using gradient descent optimization matches the desired output. Accuracy of prediction is high if the number of matches are maximum. Two different values are used to depict the output class i.e. Class 0 indicates no crisis and a value of 1 indicates crisis.

## IV. EXPERIMENTAL RESULTS

The two output classes are represented using 0 and 1 values.

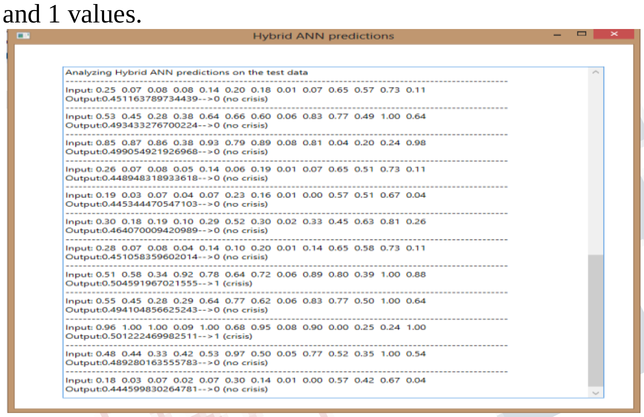


***Fig 4. C# WPF window showing results of Crisis prediction using Hybrid ANN***

The generated output is rounded up. If the calculated output value is closer to 0, it indicates no crisis period and an output closer to 1 indicates crisis period. The above window shows month wise prediction of crisis for the year 2016-17 (2nd quarter of 2016 and 1st quarter of 2017). Results indicate that likelihood of crisis in 2017 is quite low.

***Table II. Comparison of Hybrid ANN model with ANN and KNN***

| Prediction model | Accuracy (%) | Mean Squared Error | Precision (%) | Recall (%) | F-measure |
|---|---|---|---|---|---|
| Hybrid | 92 | 0.22 | 66 | 100 | 80 |
| ANN | 79 | 0.26 | 21 | 100 | 35 |
| KNN | 85 | 0.14 | 75 | 100 | 85 |

## V. CONCLUSION

In this paper we present a Hybrid Artificial Neural Network prediction model. Our approach uses the artificial neural network along with KNN model. ANN and KNN have lower accuracy when implemented separately. Our Hybrid method improved the prediction accuracy from 79% and 85% in case of ANN and KNN respectively to a high 92%. Further, the model was used to predict the likelihood of financial crisis in 2017. The results obtained indicate that the probability of financial crisis in 2017 is low. All predictions were made based on a dataset of 15 years. It was observed that with increase in the size of the dataset, accuracy of prediction decreases. Further improvement may be achieved by enhancing the Hybrid model.

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