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Stock Market Analysis and Prediction System Using Fuzzy Logic Type-2

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ABSTRACT

Stock Market can be easily seen as one of the most attractive places for investors, but it is also very complex in terms of making trading decisions. This paper presents a system which predict variable stock using historical (Open, High, Low, Close) stock prices and Fuzzy Logic. Four technical indicators were used as input variable to the fuzzy predictive system. The system programming and implementation is done using Visual Basic.Net as front end, and SQL Server as database. Data from the Nigerian Stock Exchange (NSE) was used for testing and evaluating the system. The system achieved a total of 92% accuracy in terms of making buy, hold, or sell predictions. The system when implemented can be used to draw inference in terms of making buy, hold, or sell decisions.

Keywords – Fuzzy Logic, Technical Indicators, Stock Market, Predictive System

1. INTRODUCTION

One of the most attractive place for any investor is the Stock Market, but also highly risky and complex when it comes to making predictions. Deciding on when to buy, hold, or sell is key as it can either lead to a huge profit when the right decision is made or a great loss when poor decision is made. However, no matter how risky the market is, decision-making is a very important and also a critical process which must be made correctly at the right time Ahmed (2007). It is a well-known fact that stocks fall in price nearly as often as they raise, therefore, traders seek a system which can predict the best or perfect time to buy, hold, or sell their securities precisely taking into account the nonlinearities and ambiguity of the factors which are considered to impact the market.

1.1 Statement of Problem

The most challenging task in stock trading is predicting the market itself, this is due to the difficulties and ambiguity of the overall noise coming from the market in general. Its obvious that share markets are highly dynamic, nonlinear, and complex. Therefore, predicting the market has always been a risky gamble. Although, people see stock market as good investment destination for higher profit making. However, as the expectation of profit is high, it also comes with a high-risk implication. In stock trading, most of the noise comes from forecasters and economists making market predictions about the next big boom or bust. The problems of predicting the stock market can be in the form of:

i. Perspectives of different individuals (profit perspectives, predicting the unpredictable)
ii. Ambiguity, nonlinear and dynamic nature of the market
iii. Working with big data set (Knowing how to separate market signal from noise)
iv. Uncertainties and the complexity of human behaviour in general.

1.2 Objectives

The objectives of this research paper in an attempt to analyse and predict the stock market are by conducting a survey to identify factors which affects the share market in terms of making predictions, design a predictive system for stock market using Fuzzy Logic, develop and implement the system using VB.Net and SQL Server, and also determine the effectiveness and efficiency of the system by testing the developed system using sample data.

2. RELATED WORKS

Suanu *et al.* (2012) investigated the predictive capabilities of the Fuzzy Inference System (FIS) on stock that are listed on Nigerian Stock Exchange (NSE) within the space of two-months. Their system was developed in MATLAB 7.0 using the technical indicator-based fuzzy system to provide sell, buy, or hold decision for each trading day. Their results show the FIS can be reliably serve as a decision support workbench for intelligent investments.

Peachavanish (2018) proposed a stock selection method that applies Mamdani-type fuzzy rule-based inference on dual time frame Relative Strength Index (RSI) momentum technical indicators. The rational for the approach is based on well-known phenomena of long-term trend and short-term momentum. The method was tested on the Thailand's SET100 constituents using price data of past five years, and the proposed method outperformed the index benchmark significally.

Escobar *et al.* (2013) proposed an indicator for technical analysis based Fuzzy Logic which is unlike the normal traditional technical indicators. Their method incorporates subjective investor features such as the tendency for risk. Their method uses fuzzy logic approach to represent their decision-making reasoning in a human understanding format to allow effective use for users like the non-expert investors. Their proposed indicator takes input and produces outputs which are the buy and sell signal.

Fanita & Rustam (2018) used an Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the Jakarta Composite Index (JKSE). The method gives two outputs with the intension of providing accuracy to the investor when making decisions to avoid losses. These outputs are the prediction results and the classification results. Experimental results of their method give an average of 91% accuracy in prediction and 80.2% in classification.

Pai & Kar (2019) proposed a hybrid approach of time series forecasting of stock prices with the aid of data discretization based on fuzzistics. They first order fuzzy rule generation and also performed reduction of rule set using rough set theory. Predicting of the time series data was computed from defuzzification using reduced rule base and its historical data evidences. Their method was tested on the closing price of stock index for three-time series data (BSE, NYSE, and TAIEX) as experimental dataset. Their results show more effective than others.

3. METHODOLOGY

The constructive research approach as defined by Oyegoke (2011) is adopted for this research, and the Object-Oriented Design Approach (OODA) is adopted for the system structure development.

3.1 Proposed System

The architecture of the proposed system design is shown in Fig. 1. The following are the key modules included in the proposed system architecture:

- Pre-processing Module
- Indicators Module
- Tuning Factor Module
- Fuzzy System Module

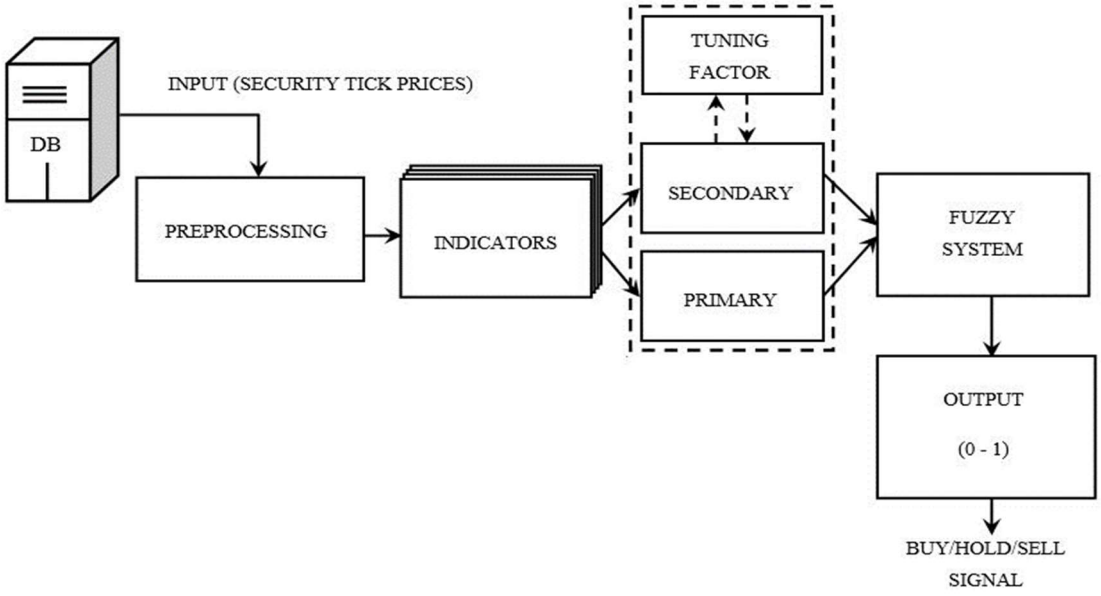

Fig.1. Architectural Design of the Proposed System

3.2 Description of the modules

The key modules used for output/results generation is described in this section.

Pre-processing Module

The inputs (security tick prices) from database are pre-processed to form the various technical indicators selected for this research which are the Moving Average Convergence/ Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator (SO), and William Average (WA).

Indicator Module

After pre-processing of the inputs (security tick prices), the selected indicators are now formed using the tick prices of the security from the companies listed on NSE. The indicators will be subdivided to form both the primary (MACD and SO) and secondary (RSI and WA) indicators. The secondary (RSI and WA) indicators will be divided by 89, and their results will be compared to the tuning factor which is the Fibonacci retracement ratios of 23.6%, 38.2%, and 61%. Both the primary and secondary indicators will form the inputs to the Fuzzy System, but first they will be compared to the various Fibonacci retracement ratios. The calculation of these indicators selected for this research is fully based on the default guideline when predicting stock market using technical analysis.

Tuning Factor Module

The tuning factor for this research paper is the Fibonacci Retracement Ratio. Fibonacci retracement is applied to the results of the secondary (RSI and WA) indicators for this research to help in identifying the support and resistance level of a given indicator (whether or not we are making the right decision before trading).

Fuzzy System Module

The input variables to the Fuzzy system are the various selected indicators which are fuzzified to linguistic (high, medium, low) variable of certain degree of membership. The Fuzzy Inference then creates the mapping between the input variables (indicators) and the outputs of prediction system. These mapping is the base for which the stock market (buy/hold/sell) decisions can be made. The output of the inference engine ranges from 0-1, with Sell signals having the membership range of 0-0.4, Hold signal is from 0.4-0.6, and Buy signal is from 0.6-1. The block diagram for the Fuzzy Inference System (FIS), and the output membership function of the proposed system is shown in Fig. 1.2.

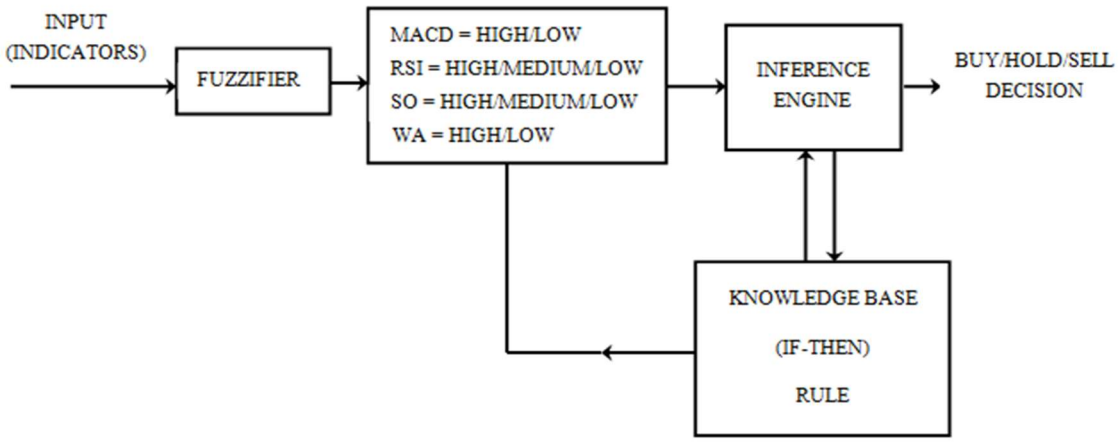

Fig.2. Fuzzy Inference of the Proposed System

Before making trading decision in the proposed system, the FIS takes input variable (indicators) and construct fuzzy stock trading rules. These rules are in the form:

> *IF countries economy is good AND the MACD is high AND the RSI is high AND SO is high THEN the output of the system will signal a Buy.*

3.3 Use Case Diagram of the Proposed System

The proposed system uses the use-case of the unified modelling language to show the various task of an actor when interacting with the system. The use case diagram for this research is shown in Fig.3.

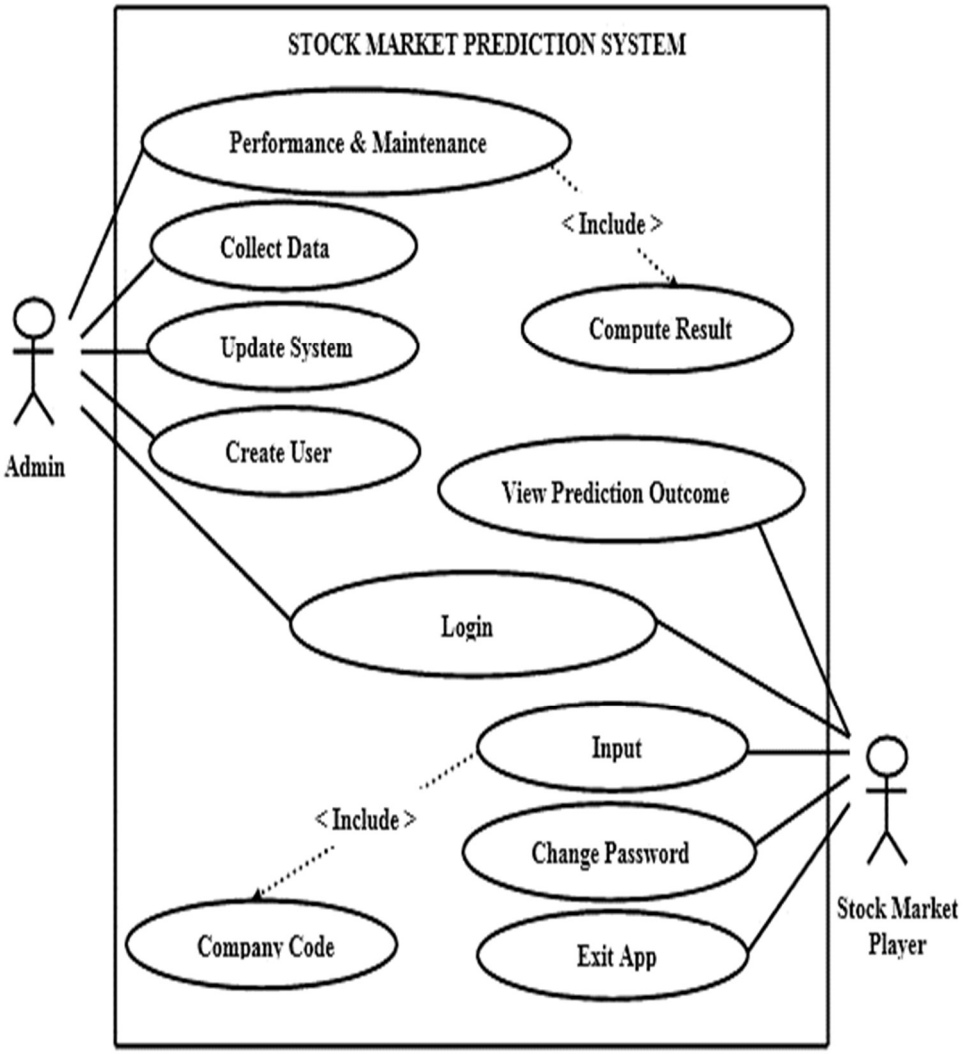

Fig.3. Use case Diagram of the proposed system

4. RESULTS AND DISCUSSIONS

4.1 Dataset Description

This research uses the historical stock prices of the Nigerian Stock Exchange (NSE) for Dangote Cement Plc, Flour Mills Nig. Plc, Access Bank Plc, Cham Plc, Guaranty Trust Bank Plc, Nigerian Brew. Plc, Julius Berger Nig. Plc, Guinness Nig. Plc, AG Leventis Nigeria Plc, and Forte Oil Plc to analyzed and test its performance in terms of accuracy in making buy, hold, or sell trading decisions. These companies present the system with stock movement for a total of 52 trading periods (15 days per period) from 3rd Jan 2017 up to 23rd March 2018, thereby generating five stock price datasets (Opening, High, Low, Closing, and Volume).

4.2 Presentation of Results

The results and its interpretation are tabulated in Table 1 and Table 2 respectively. Table 1. lists the company symbol and the fuzzy output. While Table 2. lists the name of the company, symbol of the company as listed on NSE, fuzzy output, and also the interpretation of the fuzzy output value.

Table 1. Result Presentation

S/N	Company Symbol	Fuzzy Output
1	CHAMS	0.3
2	DANGCEM	0.7
3	FLOURMILL	0.4
4	ACCESS	0.7
5	FO	0.3
6	GUARANTY	0.7
7	JBERGER	0.4
8	AGLEVENT	0.3
9	GUINNESS	0.4
10	NB	0.7

Table 2. Interpretation of Result

S/N	Company Name	Symbol	Fuzzy Output	Interpretation
1	Cham Plc	CHAMS	0.3	Sell
2	Dangote Cement Plc	DANGCEM	0.7	Buy
3	Flour Mills Nig. Plc	FLOURMILL	0.4	Hold
4	Access Bank Plc	ACCESS	0.7	Buy
5	Forte Oil Plc	FO	0.3	Sell
6	Guaranty Trust Bank	GUARANTY	0.7	Buy
7	Julius Berger Nig. Plc	JBERGER	0.4	Hold
8	AG Leventis Nig. Plc	AGLEVENT	0.3	Sell
9	Guinness Nig. Plc	GUINNESS	0.4	Hold
10	Nigerian Brew. Plc	NB	0.7	Buy

The line graph in Fig.4. was plotted using the interpreted results shown in Table 2. The y-axis represents the fuzzy out membership, while the x-axis represents the names of the ten companies. Four (Dangote Cement Plc, Access Bank Plc, Guaranty Trust Bank, and Nigerian Brew. Plc) have a Fuzzy Output Membership of 0.7, three companies (Flour Mills Nig. Plc, Julius Berger Nig. Plc, and Guinness Nig. Plc) have 0.4, and also three companies (Cham Plc, Forte Oil Plc, and AG Leventis Nig. Plc) have Fuzzy Output Membership of 0.3.

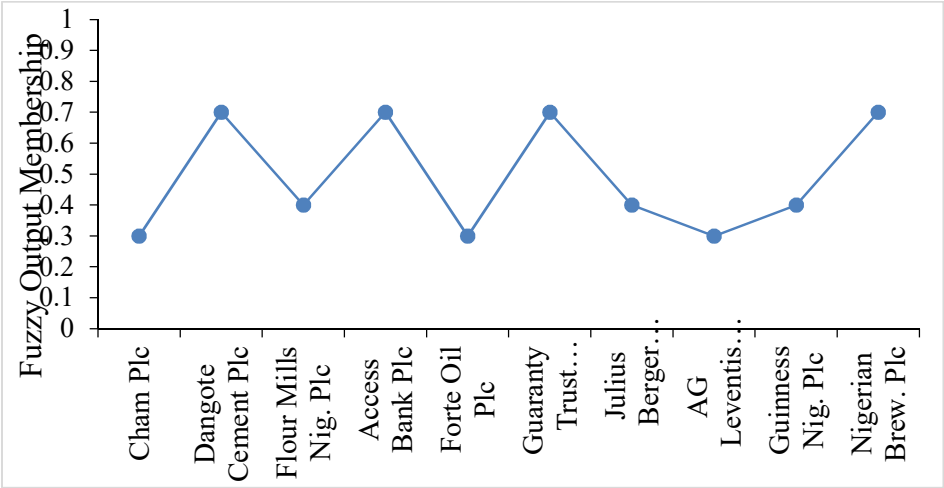

Fig. 4: Line Graph Representation of the Interpreted Results in Table 2.

4.3 Prediction Error Rate

Using Root Mean Square Error (RMSE) metric, an approximate error of 0.03 was achieved. This means that with the sample dataset collected, the proposed system can serve as a good buy, hold, or sell trading decision making aid to stock traders. The line graph in Fig.5. is plotted using the predicted values and the forecasted values of this research (See Appendix A). Note a three day Moving Average (MA3) was used to get the forecasted values for this research. The red and blue lines indicate the actual and forecasted values respectively as shown in the graph legend.

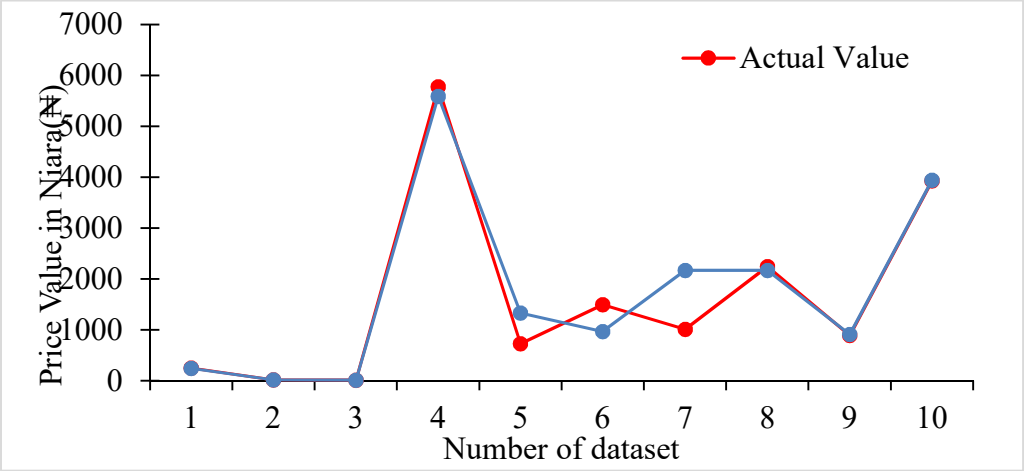

Fig. 5: Line Graph Representation of Actual and Forecasted Values of the Dataset

4.4 Comparative Analysis

A comparative analysis was carried out for the purpose of effectiveness of the proposed system on the basis of accuracy in making buy/hold/sell prediction as compared to other. By slitting the indicators into primary and secondary, and also applying the Fibonacci retracement to the secondary, the proposed system achieved 92% accuracy when equated with the actual data from NSE. This outperformed other existing system. Note; the accuracy of the proposed system was computed using the Mean Average Deviation (MAD).

5. CONCLUSION

A system that predicts the stock market in terms of making buy, hold, or sell trading decisions has been developed using technical analysis and fuzzy logic. The performance of the system was tested using historical stock price dataset from the Nigerian Stock Exchange for ten companies. The dataset collected were pre-processed to for the input variables (indicators) to the FIS. The developed system achieved a buy/hold/sell prediction accuracy of 92% and therefore the output of the system can serve as guide to traders when making stock buy, hold, or sell trading decisions.

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APPENDIX A

Table A3: Summation of actual and forecast values of the various securities

COMPANY NAMES	Price Value		Prediction Error	
	Actual $\sum_{tp=1}^{n} AV_{tp}$	Forecast $\sum_{tp=1}^{n} FV_{tp}$	Error $\frac{FV_{tp} - AV_{tp}}{n}$	Error Square $(\frac{FV_{tp} - AV_{tp}}{n})^2$
Access Bank Plc	255.46	244.68	-0.29	0.08
AG Leventis Nig. Plc	18.25	18.70	0.16	0.03
Cham Plc	13.46	13.49	0.01	0.01
Dangote Cement Plc	5780.76	5590.89	-7.03	49.4
Flour Mills Nig. Plc	730.70	696.73	-1.25	1.56
Forte Oil Plc	1499.29	1332.50	-6.17	38.1
Guaranty Trust Bank	1015.62	969.84	-1.69	2.86
Guinness Nig. Plc	2248.14	2170.64	-2.87	8.24
Julius Berger Nig. Plc	893.85	914.01	0.74	0.55
Nigerian Brew. Plc	3931.87	3944.62	0.47	0.22
				Total = 92.81

APPENDIX B (USER INTERFACES)

Fig.B5. Interface for Security Price Collection

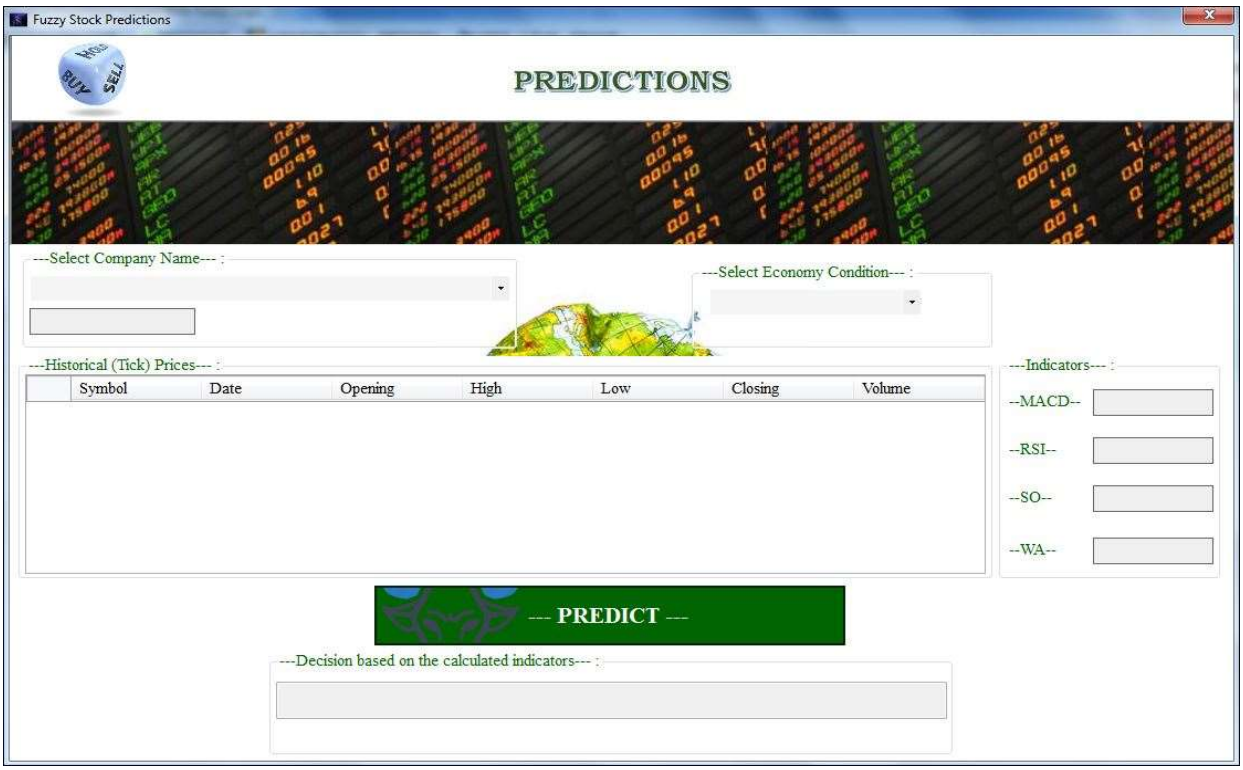

Fig.B6. Interface for Stock Predictions