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Prediction of Automated Stock Trading Auditing Opinion of Listed Securities Using Type 2 Fuzzy Neural Network

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Abstract: **In this research we developed a technique that is robust and invariant to the underlined statistics of the input data. It is an integrated system that combines the Hierarchical Decision Making Model (HDM) capability of an interval type-2 fuzzy logic and the predictive abilities of an adaptive and continual learning machine intelligent neural network. The dataset used in this research is based on readily available financial statements provided by stock brokers authorized by the Nigerian Stock Exchange (NSE). It was useful for audit opinion mining and decision making in a continual auditing framework using a Type-2 Fuzzy Neural Network. The data is categorized into three main criteria (Balance Sheet, Operation Statement and Operation Statistics) which identify the key factors needed in this research.**

This technique has been applied to the automated auditing of securities listed in Nigeria Stock Exchange (NSE). Performance simulations have been conducted using the MATLAB software.

The Results show that the listed securities are vulnerable as further indicated by the reported centroid values max similarities values and mean absolute percentage error rate.

Keywords: **Type2 fuzzy Neural Network, Financial Data, Model Base Engineering.**

1. INTRODUCTION

Intelligent systems including fuzzy logic system and neural networks have been successfully used in various applications in machine learning. Machine learning as a discipline attempts to predict an outcome and reduce prediction error overtime by analyzing more and more data to generate more accurate results. Andrew,(2016).The fuzzy logic and neural network systems combine the advantages of becoming a very active subject in scientific and engineering areas.

Type 1 fuzzy logic was first introduced by Zadeh (1965). Type-1 fuzzy logic has been used successfully in a wide range of problems such as control system design, decision making, classification, system modeling and information retrieval. However, the type-1 approach is not able to directly model all uncertainties and minimize their effect, therefore, the existence of uncertainties in the majority of real-world applications makes the use of type-1 fuzzy logic inappropriate in many cases especially with problems related to inefficiency of performance in fuzzy logic control. Problems related to modeling uncertainty using membership functions of type-1 fuzzy sets. Due to uncertainty associated with information type 2 fuzzy system are used. Type 2 fuzzy minimizes the effect of uncertainties in rule base fuzzy system. Type-2 fuzzy logic systems have many advantages compared with type-1 fuzzy logic systems, including the ability to handle different types of uncertainties and the ability to model problems with fewer rule..M.Almaraashi ,et al.(2016) .Type-2 fuzzy logic systems are now well established as both a research topic and an application tool. The motivation for the use of type-2 fuzzy sets is that type-1 fuzzy logic has problems when faced with environments that contain uncertainties that are typical in a large number of real-world applications. However, recent advances in general type-2 fuzzy logic systems research, including new representations, optimized operations and faster type-reduction methods, indicate an expected growth in applications. Despite the larger number of computations associated with general type-2 fuzzy sets, there may well be benefits compared to interval type-2 fuzzy sets. This ability can be unveiled using automated designing methods rather than being chosen by the designer manually. Automated methods can fine-tune initial fuzzy logic system designs due to the lack of a rational basis for choosing secondary membership functions for general type-2 fuzzy sets. This issue enforces the need for using automated methods in such problem. M.Almaraashi ,et al.(2016) .

1.2 Aim and Objectives of Study

The aim of this research is to develop a type 2 Fuzzy Neural Network System that automates the audit of listed companies in a stock exchange. The objectives include to:

i) Identify factors affecting audit of listed companies in a stock exchange.

ii) Design architecture of automated stock trading system for evaluating the financial indexes of listed securities in stock exchange.

iii) Validate the effectiveness of type 2 fuzzy Neural Network for the task of continual auditing of financial statements of listed securities in a stock exchange.

iv) Compare with existing technique.

2. RELATED WORKS

Fuzzy logic is an artificial intelligent technique has been use for various ranges of application. For example, fuzzy time series prediction is a prudent avenue in the areas where information is inexplicit, approximate and unclear. Also, fuzzy logic is capable of handling problems in vague statement, to imprecise data and also in decision making system (DMS). Fuzzy time series model for forecasting production values and their work provide a more accurate result than the methods that already exist. For the prediction, interval-based partitioning was use as the partition of discourse and actual production (Shubham et al, 2017).

Takagi-Sugeno (TS) Fuzzy Logic Neural Network (TS-FNN). This system is based on a Type-1 Fuzzy Logic technique using traditional back-propagation trained neural network, the data used in their model are audit opinions from financial indexes obtained from listed companies in the Shenzhen and Shanghai stock market (Hengshu et al., 2017).

Financial data was collected from Nigerian Stock Exchange for 3 years, which was used as training set of 2016 financial data of listed companies. The result shows that prediction model is accurate and will enable investors know the right company that makes profit or loss to invest in (Itari & Anireh,2019).

A fuzzy logic based decision support system was proposed to help investors of the stock market to make the correct *buy/sell/hold* decisions. Experimental simulation using actual price data from NASDAQ index was carried out to demonstrate the power of their proposed model. They state that the result were satisfactory and outperformed better than other models (Ahmed et al ,2007). Takagi-Sugeno-Kang (TSK) type fuzzy rule based system for stock prediction. The model developed, applied the technical index of the Taiwan stock market as the input variables. They tested the model on the Taiwan electronic shares from the Taiwan Stock Exchange; the model successfully forecasted the price variation for stocks from different sectors (Chang and Liu, 2008).

Fuzzy inference systems for recognizing fuzzy rules of stock market trends and predict upward and downward directions of the stock market. The proposed system was tested and the results were good. They tested the result using data from National Stock Exchange (NSE) (Gunasekaran et al,2009).

Fuzzy inference was deployed to stock market, with four indicators used in technical analysis to aid in the decision-making process in order to deal with probability. The four technical indicators are the Moving Average convergence/Divergence (MACD), Relative strength index (RSI), Stochastic Oscillator (SO) and On-Balance Volume. The result was a recommendation for buy, sell or hold (Acheme et al,2014).

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Type-2 fuzzy rule based expert system was developed for stock price analysis. Interval type-2 fuzzy logic system permitted to model rule uncertainties and every membership value of an element was interval itself. The proposed type-2 fuzzy model applied the technical and fundamental indexes as the input variables. The model was tested on stock price prediction of an automotive manufactory in Asia. Through the intensive experimental tests, the model had successfully forecasted the price variation for stocks from different sectors. The results were very encouraging and implemented in a real-time trading system for stock price prediction during the trading period (Fazel *et al*, 2009).

Predictive capability of the fuzzy inference system (FIS) was investigated on stocks listed on the Nigerian Stock Exchange using data within a two-month window for each selected stock, the technical indicator-based fuzzy expert system provides the buy, sell, or hold decision for each trading day .The result shows that the FIS can reliably serve a decision support workbench for intelligent investments (Neenwi et al,2012.

3. METHODOLOGY

The software development methodology employed in this research is two-fold: The first method uses a recursive and object-oriented development method for which the entire system is broken down into subsystems and modules. (Ramirez et al, 2011). The second method is based on the Model-Based Software Engineering/Development approach. This approach is particularly well suited for implementing dynamic systems model software which is very suitable in real-time applications.

3.1 Proposed System

The proposed (present) system overcomes the limitations of the existing system. The present system uses neural techniques that are closer to biological neural networks than existing system that are online capable i.e. It can make predictions into the future and automatically identify trends that may indicate an anomaly an important feature of data analytics. The present system also uses a Hierarchical Decision Making (HDM) fuzzy technique based on the Interval Type-2 (IT-2) Fuzzy Logic (FL) which can infer rules and conditions almost automatically.

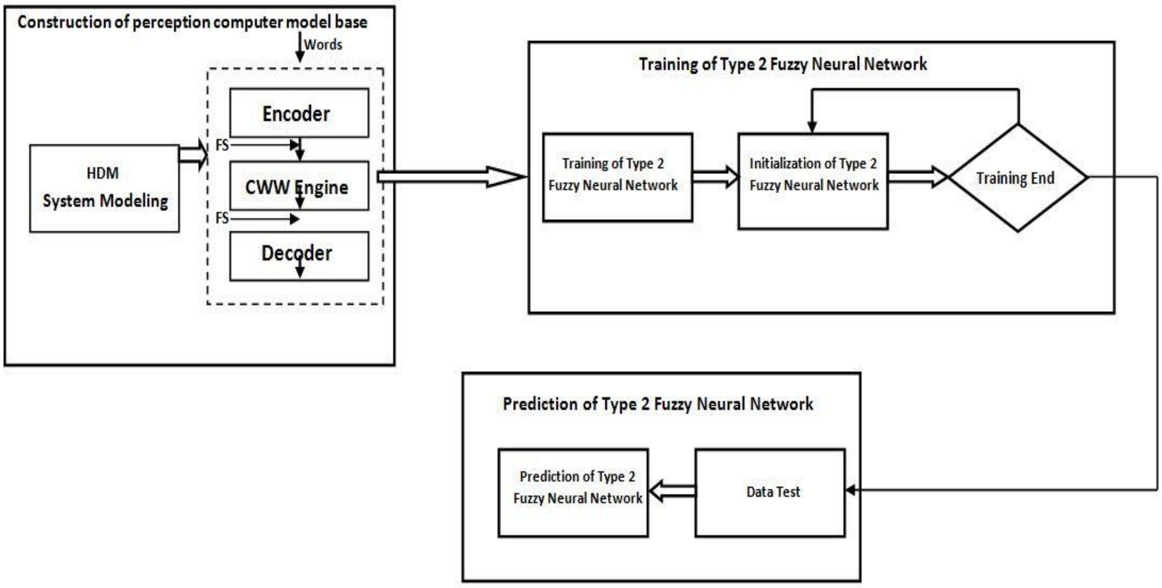

Figure 1: The architecture flow diagram of the proposed

It includes the following primary phase;

- Entity Phase
- Criterion Phase
- Interval Type-2 (IT-2) Fuzzy Logic System Phase
- Neural Network (NN) Phase

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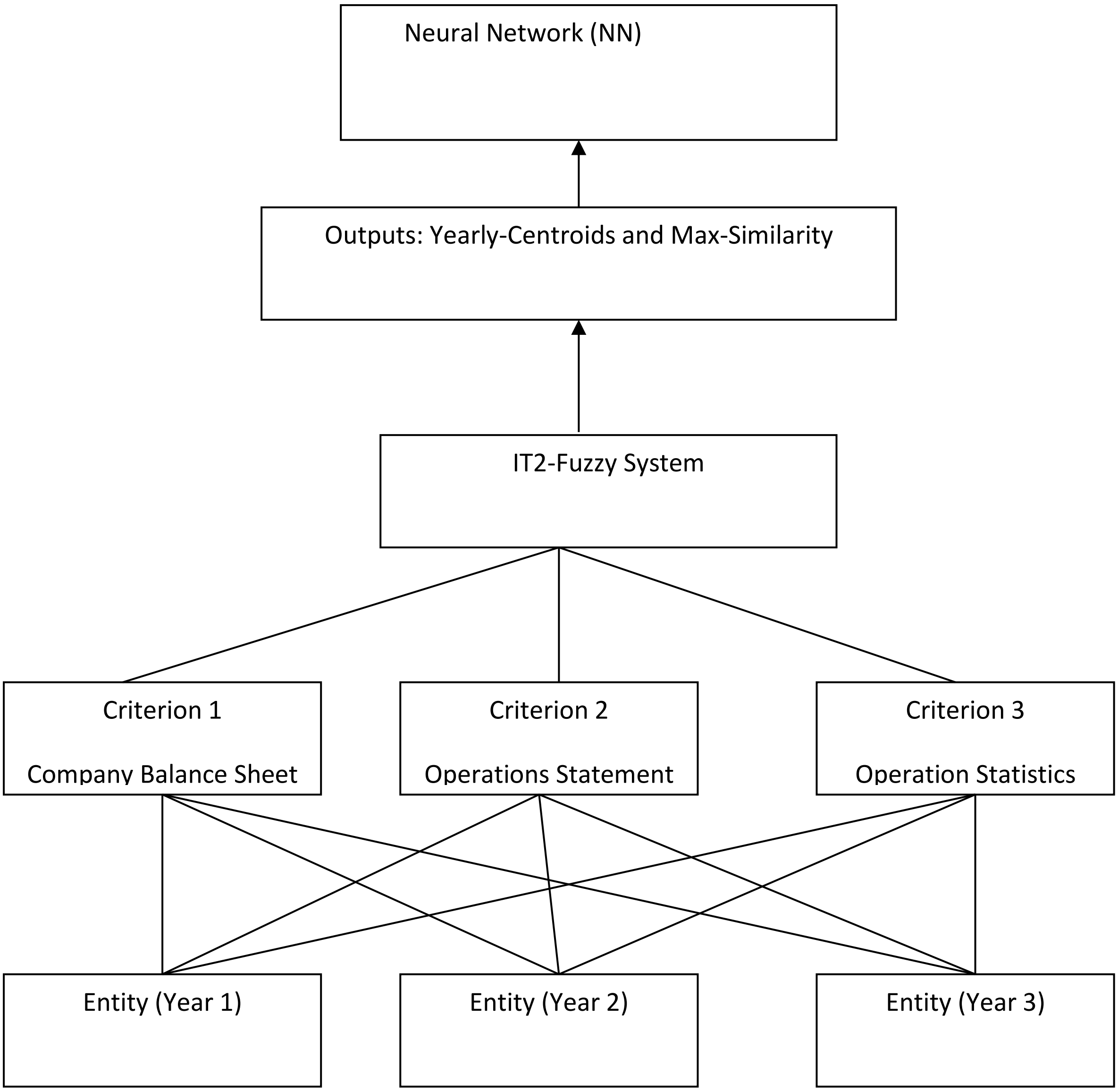

Figure 2. Architectural flow diagram of Proposed System

Entity Phase

This phase describes a system, a process or any object that is required as a basis for making decision. For instance, in Fig.2, a Year entity is used to identify if the companies (also called securities) listed in the Nigerian Stock Exchange (NSE) will perform well for the considered year(s); patterns can also be inferred about the state of the listed NSE securities and also about the health of the listed companies. At this phase, performance evaluations are indicated by using lines that interact with a higher (Criterion) phase.

Criterion Blocks

These blocks handle information describing the processes that occur in an entity. In a criterion block, there are sub-criteria that handle some other related functions with associated sub-criteria. A weighted aggregation of all sub-criteria is performed at this stage. The criteria and sub-criteria used in this study are provided in the Appendix (Appendix A).

Interval Type-2 (IT-2) Fuzzy Logic System Phase

This phase performs the inference rule generation using the Interval Type 2 (IT-2) fuzzy logic (IT-2-FL) used by the Hierarchical Decision Making (HDM) phase. Thus the IT-2-FL represents the HDM phase.

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The phase generalizes the synthesis of mean centroids and appropriate similarity constructs from a weighted aggregation of input data which is necessary for informed decision making.

The weighted aggregation process is a technique that uses a multiplying factor on the input data prior to computing the average; this typical results to an amplification or attenuation of the input data as desired by the fuzzy expert developer.

The mathematical formulations for this type of fuzzy system are presented thus as follows (Wu & Mendel., 2010):

Step 1: Normalization

Data numbers are scaled to a usable level using the model:

$$x_i \rightarrow x_i^* = 1/x_i \qquad (3.1)$$

where,

x_i = data input numbers

x_i^* = large value of the set of input numbers

Step 2: Encoding

Here a set of system raw numbers (audit financial data) for each case (Year) is mapped to a fuzzy range say 0 to 10 using the relation of Eqn(3.2) :

$$x_i \rightarrow x_i^* = \frac{10x_i}{\max(x_1, x_2, x_3)} \qquad (3.2)$$

Step 3: Computing With Word (CWW) Engine

In this step, a Novel Weighted Average (NWA) which is a Fuzzy Weighted Average (FWA) is computed according to the following equation:

$$Y_{crit(1)} = \frac{\sum_{i=1}^{\bar{n}crit} X_{crit(1)} W_i}{\sum_{i=1}^{\bar{n}crit} W_i} \qquad (3.3)$$

Step 4: Decoding

This involves the computation of ranking, similarity and centroids. Ranking is done by a sorting algorithm provided in the Appendix. The centroid may be computed from relations in Eqn(3.4-3.6):

$$C_{\tilde{A}}(x) = \bigcup_{\forall A_e} c(A_e) = \{c_l(\tilde{A}), \ldots, c_r(\tilde{A})\} \equiv [c_l(\tilde{A}), c_r(\tilde{A})] \qquad (3.4)$$

$$c_l(\tilde{A}) = \min_{\forall A_e} c_{\tilde{A}}(A_e) = \min_{\forall \theta_i \in [\underline{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{A}}(x_i)]} \frac{\sum_{i=1}^{N} x_i \theta_i}{\sum_{i=1}^{N} \theta_i} \qquad (3.5)$$

$$c_r(\tilde{A}) = \max_{\forall A_e} c_{\tilde{A}}(A_e) = \max_{\forall \theta_i \in [\underline{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{A}}(x_i)]} \frac{\sum_{i=1}^{N} x_i \theta_i}{\sum_{i=1}^{N} \theta_i} \qquad (3.5)$$

The Jaccard Similarity (JS) is used. It is described as:

$$sm_J(A, B) = \frac{\sum_{i=1}^{N} \min(\mu_A(x_i), \mu_B(x_i))}{\sum_{i=1}^{N} \max(\mu_A(x_i), \mu_B(x_i))} \tag{3.6}$$

Note that the output of the IT-2-FL is fed to the Cortical Learning Neural Network (CLNN) phase for post predictions.

Cortical Learning Neural Network (CLNN) Phase

This phase performs online data capture to decipher the continual hidden causes that occur in the information generated by the fuzzy HDM model. This is done using a biological machine intelligence neural network (BAMI-NN) called the Hierarchical Temporal Memory currently developed in (Hawkins et al., 2016). In this research study, the HTM spatial pooler is applied to the task of predicting the audit inferences from the Interval Type-2 Fuzzy Logic (IT-2-FL) phase. The mathematical details involved in the neural processing are as follows (Cui et al., 2017; Anireh & Osegi., 2018):

Step 1: Form the set of Generative Mini-columns

A set of Spatial Pooler (SP) generative mini-columns comprising cortical neurons is initialized according to the rule in Eqn(3.1):

$$\Pi_i = \{ j \mid \mathrm{I}(x_j; x_i^c, \gamma) \ \& \ Z_{ij} < \rho \} \tag{3.1}$$

where,

j = HTM neuron location index in the mini-column

i = mini-column index

x_j = location of the jth input neuron (synapses) in the input space

x_i^c = location centre of potential neurons (synapses) of ith mini-column in a hypercube of input space

γ = edge length of x_j

ρ = fraction of inputs within the hypercube of input space that are potential connections

Z_{ij} = represents a uniformly distributed random number between 0 and 1

I = an indicator function

The indicator function I in Eqn(3.1) is described by Eqn(3.2):

$$\mathrm{I}(x_j; x_i^c, \gamma) = \begin{cases} 1, & if \ x_j \subset x_i^c \\ 0, & otherwise \end{cases} \tag{3.2}$$

Step 2: Form the binary synapses

A set of binary synapses W_{ij} is formed by conditioning using a permanence activation rule as in Eqn(3.3):

$$W_{ij} = \begin{cases} 1, & if \ D_{ij} \geq \theta_c \\ 0, & otherwise \end{cases} \tag{3.3}$$

where,

D_{ij} = independent and identically distributed (i.i.d) dendrite synaptic permanence values from the jth input to the ith mini-column

θ_c = synaptic permanence threshold

The synaptic permanence values are conditioned by Eqn(3.4):

$$D_{ij} = \begin{cases} U(0,\ 1), & if\ \ j \in \Pi_i \\ 0, & otherwise \end{cases} \tag{3.4}$$

Step 3: Overlap computation

Associations with input patterns (features) are created by computing feed-forward inputs to each generative spatial mini-columns using a matching approach called the "overlap" - see Eqn(3.5):

$$o_i = b_i \sum_j W_{ij} z_j \tag{3.5}$$

Step 4: Compute the activations

Using Eqn(3.5) the activations of each SP mini-column is computed as:

$$a_i = \begin{cases} 1, & if\ \ o_i \geq Z(V_i, 100 - s)\ \&\, o_i \geq \theta_{stim} \\ 0, & otherwise \end{cases} \tag{3.6}$$

Also,

$$V_i = \{o_i \mid j \in N_i\} \tag{3.7}$$

where,

s = target activation density (sparsity)

Z = a percentile function

θ_{stim} = a stimulus threshold

Step 5: Learning

Learning is done by activating, deactivating and updating the permanence values via the synaptic connections:

$$\Delta D_{ij} = p^+ D_{ij} \circ A^{t-1} - p^- D_{ij} \circ (1 - A^{t-1}) \tag{3.8}$$

where,

p^+ = positive permanence value increment

p^- = negative permanence value increment

A^{t-1} = activation state at time step, t

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Step 6: Classification

Classification may done in a temporal manner using a temporal version of Eqn(3.6) as below:

$$o_{j_t} = \sum_{j_t} W_{j_t}^{sp} W_{(k-N_c):j_t}^{sp}, \quad N_c < k \le j_t, \qquad (3.9)$$

where,

N_c = Number of past sample SDRs used as context

k = size of the temporal aggregated (bivariate) sequence through time

j_t = a temporal aggregation index number

$W_{j_t}^{sp}$ = a bivariate SDRs after a temporal aggregate

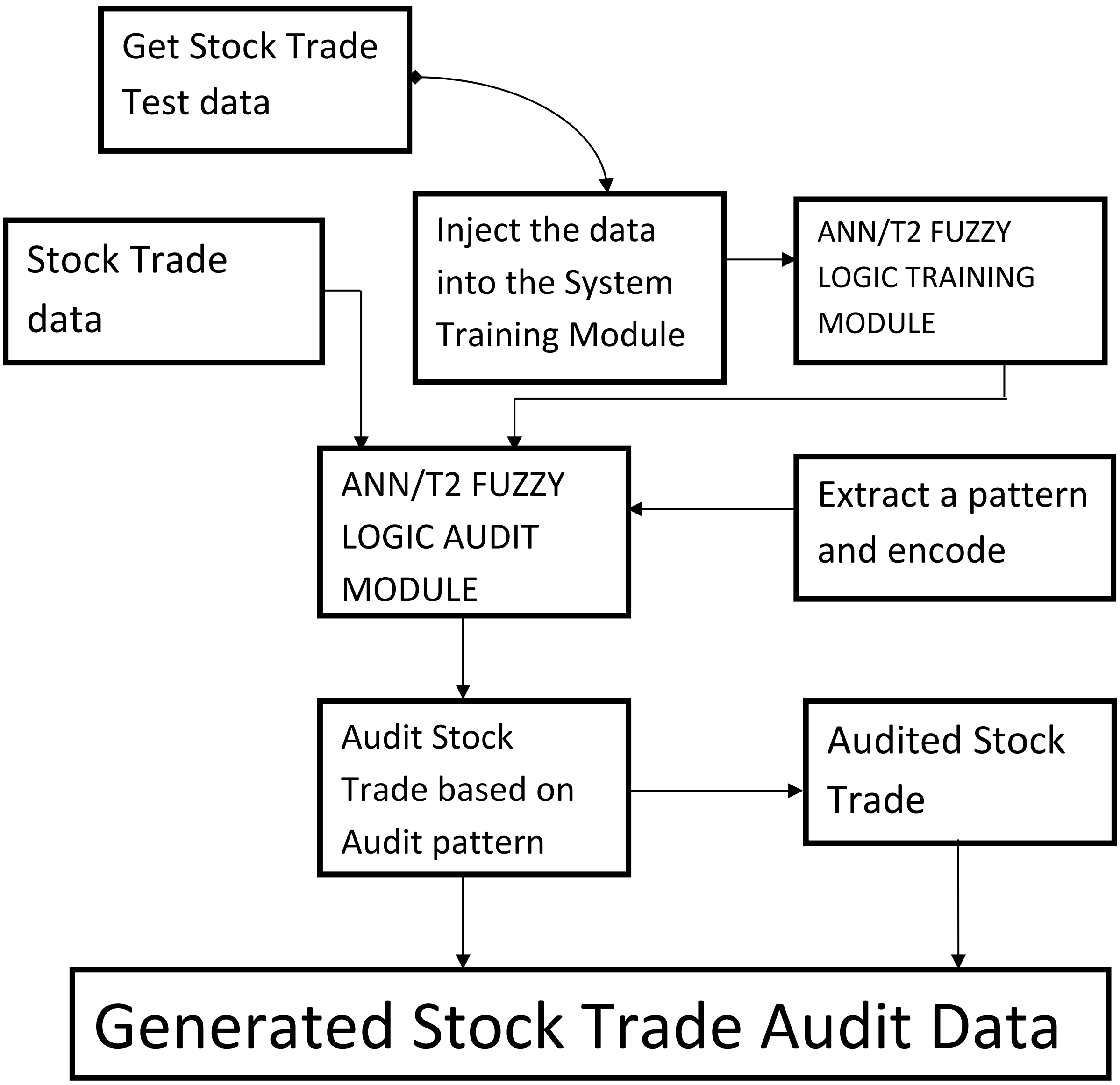

Figure 3: Design of the Proposed System

The design of the propose system uses hybrid techniques, type 2 fuzzy and neural network. Stock trade data also called financial indexes are gotten from Nigeria Stock exchange (NSE), the data is been tested and train to check the performance of the system against trained data. The audit modules are extracted to generate the stock trade data, which shows the performance of listed securities, which can be unhealthy or healthy.

Table 1: Financial Indexes table

S/NO	NAME OF ATTRIBUTE	DATA TYPE	DESCRIPTION
1.	Fixed Assets	Double	Long term tangible asset used in the company
2.	Depreciation	Double	Reduction of recorded cost of fixed asset
3.	Profit Before Tax margin	Double	Earnings before taxes
4.	Profit After Tax margin	Double	Total revenue remaining after deducting expenses
5.	Dividend	Double	Distribution of reward from a portion of the company earning
6	Number of Employees	Double	No of staff for the given year

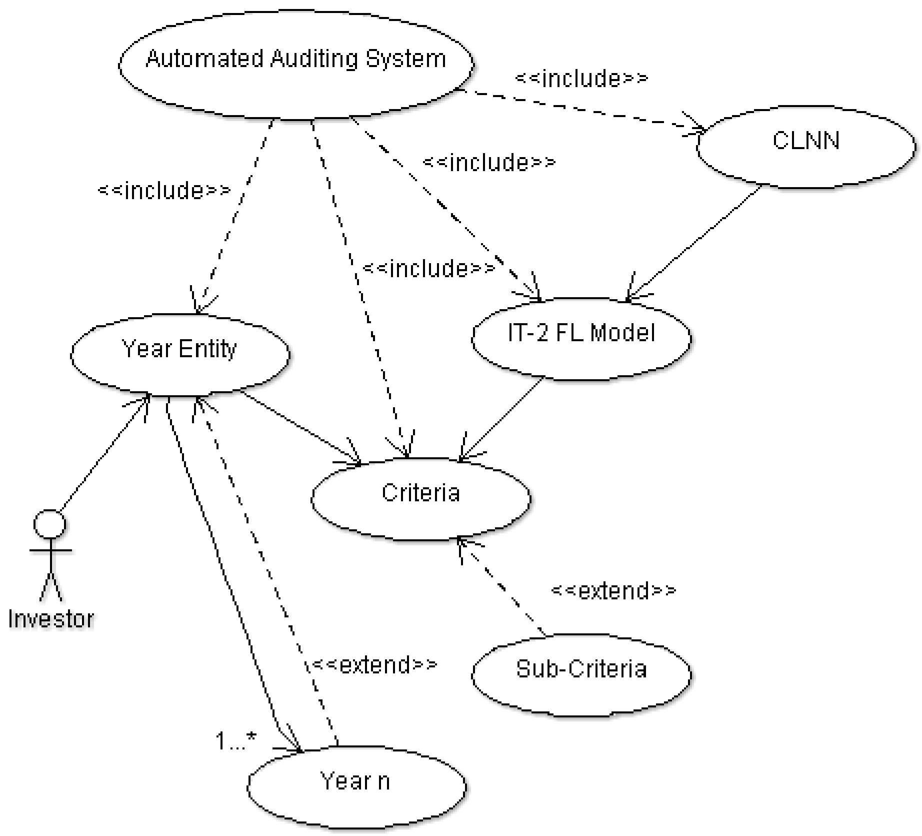

Figure 4: Use case diagram

Use-case modeling of the Proposed System

The use case diagram is used to gain understanding on how the proposed Automated Fuzzy Neural Stock-Exchange Auditing tool may operate in reality. It shows how an investor (actor) interact with several cases from a base use case (Year Entity) to derive useful information from a result use case (e.g. Investment Option) from the Automated Auditing System.

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In this diagram, the Year Entity (YE) use case defines a state variable (which could be a system, process, or time entity). The YE use case is then extended to two or more states such that a Hierarchical Model (HM) may be built. This YE use case has a dependency on a Criteria use case which in turn is extended by the Sub-Criteria use case. The criteria and sub-criteria use cases define the input to the system which are usually numerical quantities.

4. RESULTS

Performance simulations of the automated auditing system have been conducted using codes adapted from HTM-MAT tool developed in (Anireh & Osegi, 2016) and adapted Interval Type-2 code base from the book by Mendel and Wu (Mendel & Wu, 2010). Scoring are based on the mean centroids and max-similarity; the mean centroid computation can be found in (Mendel & Wu, 2010) while the max-similarity is computed using the source-code listing in Appendix C. Results of tests have been analyzed on the basis of the considered Year and corresponding mean centroids and max-similarity values as reported by the Interval Type-2 Fuzzy Logic (IT-2FL) phase; this is shown in Tables 2 and 3 respectively with the securities indicated by code labels – for complete details please refer to Appendix E. The mean-centroids is needed to compute the max-similarity values. A max-similarity close to 1 is indicative of a healthy security. From Table5.2, the max-similarity values indicate that a7 (UBN), a8 (Unity) and a9 (WEMA) securities are perfectly healthy; a1 (ACCESS), a4 (Fidelity), a6 (UBA) and a10 (Zenith) are moderately healthy and the rest are unhealthy to invest in.

Also the Hierarchical Temporal Memory Spatial Pooler (HTM-SP) based on the Cortical Learning Algorithm (CLA) is used to model the Cortical Learning Neural Network (CLNN) used in the Automated Auditing System. The mathematical treatment of the HTM-SP can be found in (Cui et al., 2017) and has already been discussed in Section 3. Source code listing is provided in Appendix D. The results showing varying context i.e. when the HTM-SP context parameter is set to 1 and 3 have been reported (see Figures 5.1 and 5.2). This shows the performance of the automated auditing system in terms of a moving Mean Absolute Percentage Error (MAPE). At a context of 1, the results (Figure 5.1) indicate that the performance of the listed securities are largely variable and investing in these securities are largely risky; this is further validated by the results of Figure 5.2 but with a somewhat moderate variability.

Table 2: Mean centroids of the Automated Auditing System for Year 2015

Security	Per-C1	Per-C2	Per-C3
a1 (ACCESS)	8.5163	7.9826	7.9954
a2 (Diamond)	0.0047	0.0043	0.0044
a3 (FCMB)	0.0009	0.0009	0.0009
a4 (Fidelity)	9.4766	8.7476	8.4146
a5 (GTB)	2.0361	1.8930	1.7714
a6 (UBA)	4.3630	4.0776	4.2553
a7 (UBN)	9.8173	9.0916	8.3765
a8 (Unity)	0.0000	9.1533	8.4338
a9 (WEMA)	0.0000	9.0909	8.3333
a10 (Zenith)	7.1587	7.1610	6.9109

Table 3: Max-Similarity of the Automated Auditing System for Year 2015

Security	Max-Similarity Values
a1 (ACCESS)	0.6077
a2 (Diamond)	0.0000
a3 (FCMB)	0.0000
a4 (Fidelity)	0.7364
a5 (GTB)	0.3775
a6 (UBA)	0.8604
a7 (UBN)	1.0000
a8 (Unity)	1.0000
a9 (WEMA)	1.0000
a10 (Zenith)	0.6140

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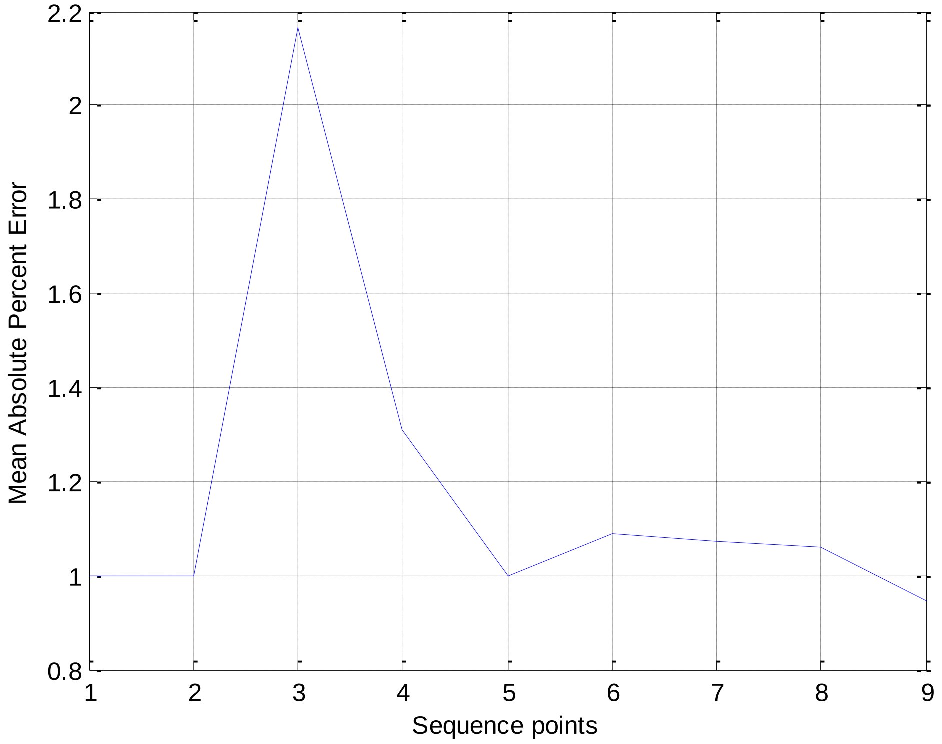

Fig 5.1. HTM-SP moving average MAPE response for listed securities in Year 2015 at a context = 1

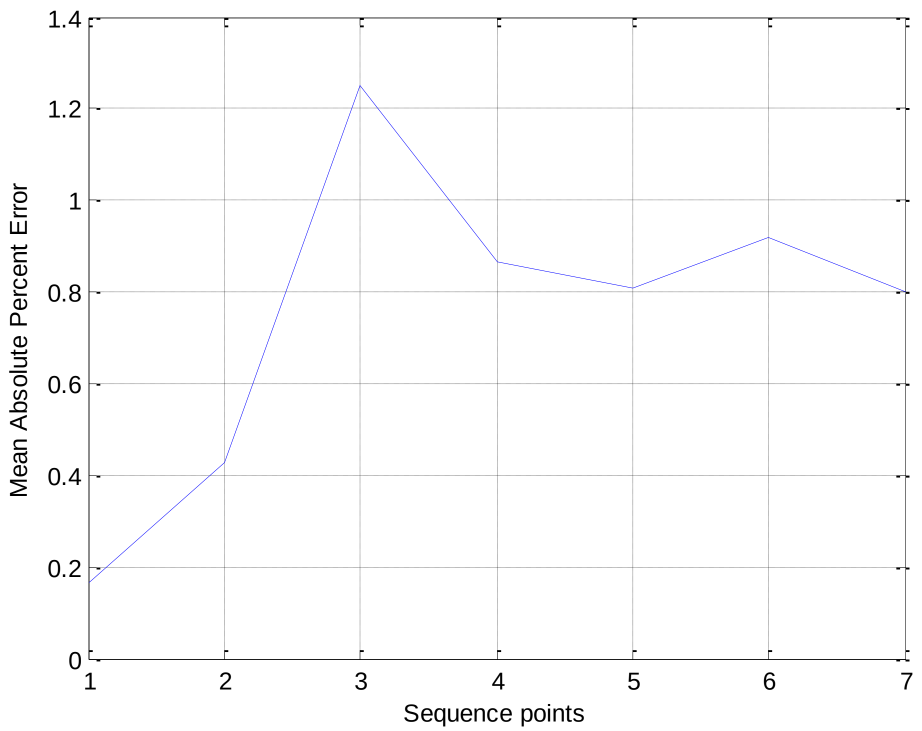

Fig 5.2. HTM-SP moving average MAPE response for listed securities in Year 2015 at a context = 3

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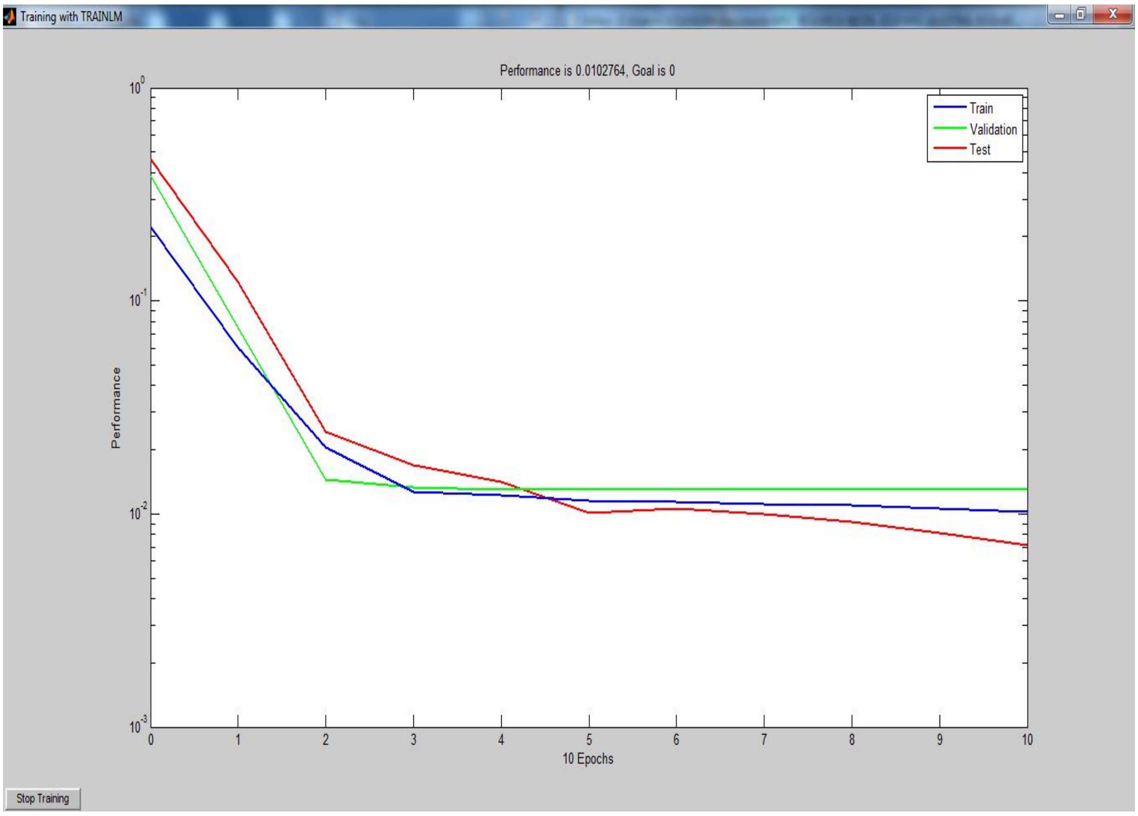

Fig 5.3 Simulation Plots Using the NN System for Max-Similarity Prediction for a given simulation run: Epochs = 50; Neurons = 5;

Table 4: Predicted Vs Actual Max-Similarity Values for a given simulation run

id	Prediction (Max-Similarity)	Actual (Max-Similarity)
1	0.798	0.608
2	0.003	0.000
3	0.002	0.000
4	0.806	0.737
5	0.525	0.378
6	0.857	0.860
7	0.809	1.000
8	0.986	1.000
9	1.022	1.000
10	0.782	0.614

4.1 Comparison Evaluation

The existing system is a Takagi-Sugeno (TS) Fuzzy Logic Neural Network (TS-FNN). This system is based on a Type-1 Fuzzy Logic technique using traditional back-propagation trained neural network (Hengshu et al., 2017). Limited Footprint-of-Uncertainty (FOU) of the Takagi-Sugeno (TK) Type-1 Fuzzy Logic (TK-T1-FL) leading to reduced inference capability.

The proposed system overcomes the limitations of the existing system. It uses neural techniques that are closer to biological neural networks system that are online capable i.e. it can learn continually which is very desirable for continual auditing of listed securities in the Nigerian Stock Exchange (NSE). It can make predictions into the future and automatically identify trends that may indicate an anomaly an important feature of data analytics. The present system also uses a Hierarchical Decision Making (HDM) fuzzy technique based on the Interval Type-2 (IT-2) Fuzzy Logic (FL) which can infer rules and conditions automatically.

5. CONCLUSION

The develop technique has been applied in the listed securities of NSE, however, it is also possible that other securities from other stock exchanges can as well be analyze with the develop technique. The primary challenge is in the aspect of integrating system modeling using the propose type-2 fuzzy neural network due to inherent complexity that arise when developing sophisticated mathematical model. However with a careful structure constructive methodology, it is possible to overcome partially, this obvious challenge.

It is believed that the combination of extended more fuzzy logic capable techniques in addition to neural network with much closer biological root remain a promising direction for computer science and artificial network expert to follow.

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