

## PERFORMANCE OF MUTUAL FUNDS ON SUSTAINABLE MICRO-HEALTH INSURANCE SCHEMES IN GHANA: The Role of Fast Adaptive Neural Network Classifier


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### Abstract

Micro-health insurance models have emerged (in different forms) as a more reliable source of seeking financial protection for a significant proportion of Ghanaians against the downside of medical cost. Most micro-health insurance contributions end up with mutual funds hence the performance of the mutual fund determines to a large extent the sustainability of the scheme. This makes the mutual fund market an indispensable factor in stimulating or stifling healthcare access in Ghana with health equity implications. Recently, machine learning performance evaluation approaches such as *Artificial Neural Networks* (ANN) have proven valuable in evaluating the performance of mutual funds due to superior forecasting and calculating abilities relative to native algorithms. We applied a novel *Fast Adaptive Neural Network Classifier* (FANNC) to publicly available historical financial performance data from the Ghana Stock Exchange. We benchmarked our results against the outcome of a backpropagation neural network model (BPN) and measured speed of processing performance information for micro-health insurance managers looking for high earning but less risky investment destination for their vulnerable funds. The FANNC tool proved superior in terms of prediction error and processing time to existing robust models such as the Backpropagation neural network. Employing effective tools such as FANNC tools can quicken the pace of investment performance assessment, rank a hierarchy of desirable investment options for micro-health insurance schemes to explore. This can guarantee fast processing time and accurate investment decision of micro-health insurance to enable it play the essential role of enhancing health risk management of the members of the general public especially the poor and vulnerable that are often the victims of catastrophic healthcare expenditure.

**Keywords:** Performance, Micro Health Fast Adaptive, Neural Network Classifier, Mutual fund, Ghana.

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## I. Introduction

Typical of most developing countries, health inequity has become endemic in Ghana over time. Despite its resource potential, several Ghanaians (especially those in rural areas) live under high financial catastrophe and impoverishment and are unable to meet the constantly rising cost of an “unreliable” healthcare service (Nishtar et al., 2013). According to the World Health Organization 55% of total healthcare cost in Ghana is financed through Out of Pocket (OOP) even though an estimated 64% of the population are enrolled in the National Health Insurance Scheme started in 2004 hence have their healthcare cost partially funded by the scheme (Abbas et al., 2015). In 2016, the gross total OOP expenditure incurred by households in Ghana exceeded \$1.9 million dollars. In the midst of escalating healthcare cost among the majority low-income households, expenses associated with sudden illness, are managed through adopting several coping strategies such as drawing on savings, borrowing and selling productive assets such as poultry, cattle and land (Jakovljevic et al., 2016). The significance of health systems in governing access to health care services is emphasized in contemporary thinking. Indeed, there is a growing awareness of the critical importance of health system development as a foundation for enhancing population health.

Because health funding is such an important part of health systems, many nations have attempted major reforms in health system financing in the last decade or so, with the goal of making health care more accessible and equitable to their people (Axelson et al., 2009). The concept of universal coverage, as confirmed by health leaders in a resolution at the World Health Assembly in 2005, is at the heart of equitable and accessible health systems. Out-of-pocket expenses (OOP) for health care are not always easy to manage. As a result, households may face financial difficulty and poverty. In fact, every year, over 150 million individuals confront catastrophic health costs, and 100 million people fall into poverty as a result of paying for health care. Many other families choose to forego care because it is too costly and many families find it difficult or impossible to access health care due to financial constraints (Damrongplasit & Melnick, 2009; WHO, 2005). As a result, we believe that universal coverage and access to health insurance, with a significant amount of prepayment, is a critical policy goal that might increase financial security for many people. Increasing payments and achieving universal coverage can be accomplished in a variety of ways. In most affluent countries that have achieved universal coverage, tax-based systems, social health insurance systems, or combination systems are common. Transition strategies, on the other hand, are frequently required in emerging countries. These initiatives include various prepayment structures, such as mutual health insurance, to reduce OOP and improve access to care (MHI). Many African countries have MHI, or community-based health insurance. Only a few applications, however, have been significantly scaled up when compared to national systems, these schemes' sustainability and financial risk pooling capacities are regarded weak. They could, however, be a first step toward universal coverage. In terms of expanding population coverage in a relatively short period of time, as a result, there is a lot of interest in looking into the Ghanaian model as a strategy for achieving universal coverage quickly (Kagubare, 2006). Yet these coping strategies have become frequently inadequate to fully cover the cost of healthcare leading to unexpected consequential debts that exacerbated the precarious financial situation of an already impoverished family (Boddam-Whetham et al., 2016). Even though the social health insurance system has gained some mileage in Ghana due to swift learning from advanced countries, its intervention as a healthcare financial protection mechanism against excessive healthcare cost is still an adventure in transition (Lulin et al., 2016). In 2004, an elementary district mutual health insurance scheme was launched across the 110 districts at the time. This formed the foundation for the current national health insurance scheme that requires individuals to voluntarily enroll. However nearly a decade and half of its introduction, the system is on the verge of collapsed under managerial crisis, accumulated debt owed to service providers, accusations of corruption against managers hence dampening public confidence in the system to deliver the desired affordable and quality healthcare to the citizens (Khatib et al., 2016).

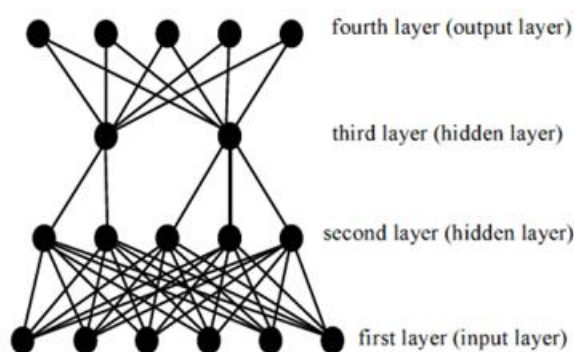
## II. Literature Review

As reported by (Landmann & Frolich, 2015), privately organized micro-health insurance models have emerged as a more reliable source of seeking financial protection for a significant proportion of Ghanaians (especially those in rural areas) against the downside of medical cost. They exist in different parts of the country in different models namely partner agent model (10%), full service model (44%), provider-driven model (4%) and community-based/mutual model (42%) (Nishtar et al., 2013) yet the underlining principles are the same i.e. to protect low income people against financial risk, in exchange of payment of premiums, according to the probability and the cost of the risk (Rehman et al., 2016). Despite the important role played by micro-health insurance schemes in ameliorating the predicaments of a large population of Ghanaians, micro-health insurance schemes have their own challenges. Dubby Mahalanobis as

reported in (Tischer, 2012) reveals that in developing countries with weak regulatory regimes such as Ghana, Nigeria, Ghana, Bangladesh, etc., many micro-health insurance schemes (and micro-credit schemes in general) have become instruments to defraud unsuspecting clients. To that extent one must be thorough and careful when making policies, otherwise micro-insurance could do more harm than good (Nishtar et al., 2013). In Ghana, pioneering micro health insurance schemes such as the Nationwide, GLICO health etc. have grown to become fully fledged alternative health insurance platforms yet, a sizeable number of nearly 302 registered and unregistered micro insurance schemes have not survived beyond their first five years thereby depriving many poor citizens of contributions intended to safeguard their future health expenditure (Ghaffar et al., 2013). Specifically, (Malik & Syed, 2012) shows that 60% of micro health insurance schemes operating in different parts of the country between 2000 and 2010 as in 2007 are no longer functional and 43% of all those registered did not survive beyond the first five years of operation. This leaves many contributors distraught and misled largely because of poor investment options pursued by these schemes. Unlike the partner agent model which constitutes only 10% of all registered micro health insurance schemes in Ghana (where micro-health insurance schemes only act as agents or partners of major insurance companies), the full-service model (44%) and community-based/mutual model (42%) are autonomous (Ali & Wajidi, 2013). In the latter, the micro-insurance scheme, or the policyholders or clients are in charge of everything; both the design, delivery of products to the clients, managing and owning the operations and working with external healthcare providers to provide the services (Sax & Marx, 2013). Most of the premiums or contributions paid by the members or clients are invested in less risky but high yielding mutual funds operated in Ghana. As micro-health insurance, contribution end up with mutual funds, the performance of the mutual fund then determines the sustainability of the scheme. This makes the mutual fund market an indispensable factor in stimulating or stifling healthcare access in Ghana with health equity implications (Aslam et al., 2016). As more and more micro-health insurance invests in non-performing mutual funds to their detriment (Aftab, 2016), the need to effectively measure the performance of mutual funds is essential to consolidating the attainment of health equity in Ghana and beyond. However, in less developed economies like Ghana, industry players usually present the raw returns in their financial statements but these often fails to reveal the underlining risks in performance as unskilled persons can increase raw returns by undertaking highly risky investment. To date, the most frequently used measure of mutual fund performance is the Jensen Alpha Index, Sharpe and Treynor as well as Capital Asset Pricing Model (CAPM) (Sriram et al., 2016). For investments intended to safeguard the health of poor people through micro-health insurance schemes, it is necessary to go beyond the accounting techniques and draw on more robust techniques to evaluate the risk-adjusted returns of the mutual fund investment where volatility and variability is of interest (Afza & Rauf, 2009). Further, a key weakness in the traditional models used in evaluating mutual fund performance is that it evaluates the funds on periodic basis either in weeks, months or quarterly making it only important to compare past performances (Iqbal & Molyneux, 2016). In order to meet the fast-changing trends, dimensions and market conditions, performance evaluation aerobics must update repetitively and anytime at the request of the user (Lobe & Walkshausl, 2016). This is essential for managers of micro-health insurance firms and advisors to evaluate the performance of these instruments in real time to make timely decision to safeguard the wellbeing of their contributors.

Moreover, the traditional mutual fund performance measurement tools do not normally provide predictive variables and as such makes it difficult to be used in forecasting superior funds which provide insight into a hierarchy of funds from which micro-health insurance managers in Ghana can choose from to minimize their risk (Gil- Bazo & Ruiz-Verdú, 2009). To be able to deal with such situation, interested researchers have adopted and employed various approaches to get predictive variables in order to make forecasting of superior mutual funds more evident for would be investors such as micro-health insurance companies that hold funds for the most vulnerable in society. Recently, machine learning evaluation approaches such as Artificial Neural Networks (ANN) have proven valuable due to superior forecasting and calculating abilities relative to native algorithms in several dimensions (Eakins & Stansell, 2003). For example, Backpropagation Neural Networks (BPN) has been widely used with a supervised neural network to analyze continuous financial data and determine investment performance (Malhotra & Malhotra, 2003). Among the often-cited studies that have deployed Backpropagation Neural Networks (BPN) to model the performance of financial instruments includes (Davalos et al., 2010; Surkan & Singleton, 1990; Udo, 1993) etc. In the work of (Udo, 1993) the BPN model proved superior in evaluating bankruptcy classification than other statistical instruments. Similarly, (Davalos et al., 2010) used BPN to predict the bankruptcy risk of major US carriers while (Surkan & Singleton, 1990) used the BPN to improve bond rating in the stock market. On another hand, Multi-Layer perceptron (MLP) has also been used to evaluate the performance of securities and mutual funds in different countries. The MLP is a feedforward neural network with one or more layers between input and output layer. Feed-forward means that data flows in one direction from input to output layer. This type of network is trained with the back-propagation learning algorithm. The extant literature is replete with studies that have adopted different configurations of MLPs for

pattern classification, recognition, prediction and approximation. In the field of mutual investment performance, the MLP has been applied by (Indro et al., 1999) to predict mutual fund performance. This study returned a good forecasting result in blended funds, but not for growth funds. Oh et al. 2010 suggested a hybrid intelligent system to predict the failure of firms based on past financial performance. This can be done through the combination of a rough set approach with MLP. Lam (Oh et al., 2010) tested the positivity of backpropagation neural networks to integrate technical and fundamental analysis to predict financial performance. This notwithstanding, neural networks such as BPN and MLP commonly applied in financial literatures have their own limitations including the high training cost and effect of extraneous factors. These weaknesses can be ameliorated or eliminated using other forms of Artificial Neural Network models designs such as the Self Organization Map (SOM) (Wang & Huang, 2010) and Adaptive Resonance Theory (ART) (Ferson & Kim, 2012) families etc. These types of neural model unlike the BPN, can be trained quickly and be put in an unknown pattern without accurate information. However, most of these neural models are unsupervised models, features which limit their application in financial fields. But in a constantly changing financial market conditions where fast and instant response to financial queries is imminent (Chen et al., 2008), fast adaptive neural network classifier (FANNC) is more suitable in its algorithm to provide real time financial information response to investors especially managers of micro-health insurance contributions looking for high earning but less risky investment destination for their vulnerable funds. The fast-adaptive neural network classifier method is developed based on adaptive resonance theory and field theory (Chen & Lu, 2019). This enables the FANNC to carry out online learning, perform real-time data analysis and classification. As in field theory, the fast-adaptive neural networks classifier uses Coulomb potential model for electrostatic forces. This allows the feedback connections to transfers active signals to each successive layer in a structured neural network to stimulate resonance and competition (Tkáč & Verner, 2016) as illustrated in figure 1.



**Figure 1:** The Structure of Fast Adaptive Neural Network Classifier

The extant literature provides several instances of application of neural networks to health sector problem analysis. To date the most common areas of application of neural networks includes ANN applications in clinical diagnosis (Dayhoff & DeLeo 2001), image interpretation (Zhou et al; 2002), signal interpretation (Altman & Royston, 2000) and drug development (Amato et al., 2013) and emergency management (Lee & Chen, 2005). We contribute to the current literature by empaneling and testing an ensemble of more sophisticated analytical neural network models (BPN and FANNC) to evaluate the investment options of micro-health insurance firms which is at the core of sustainable, affordable and equitable healthcare in a developing country. Next, we outline the materials and methods, sources of data and the calibration of the fast-adaptive neural networks model used in our study. After presenting our results, we provide emerging issues for future research.

### III. Methodology

#### Data Source

To establish the healthcare implication of mutual fund performance, a two-staged inclusion and exclusion criteria was used to select input and output variables. Detailed questionnaires were first administered to managers of 103 registered and non-registered community micro-health insurance schemes in the ten regional capitals in Ghana namely Accra, Cape Coast, Takoradi, Ho, Koforidua, Kumasi, Sunyani, Wa, Tamale and Bolgatanga to identify the top mutual funds where contributions of members and clients are invested. Further, a structured interview with mutual fund managers

of mutual funds helped to the top 10 mutual funds micro-schemes invest into in Ghana. Six continuous historical years' performance of these mutual funds were collated and validated using the publicly available performance data by the Ghana Stock Exchange of (2011-2012, 2013- 2014 and 2015-2016).

### Input Variables

Following (Wang & Huang, 2010) the herding behavior and momentum strategies of the mutual fund manager were designated as input for the FANNC and BPN. These variables are used because many factors that affect mutual fund performance such as the size of the fund and other features of the fund managers have been studied in earlier researches (Wang & Huang, 2010). A momentum strategy is used as it is the best-known anomaly in equities. It assumes that past winners will continue to have a strong return in future, while past losers will also continue to have a weak return in the future. Thus, it is always better to pick the future best performing mutual funds. Momentum investors buy assets that were past winners and sell those stocks that were past losers (Dreiseitl et al., 2001). As in (Grinblatt et al., 1995) we measure momentum strategies as follows:

$$M = \frac{1}{T} \sum_{t=1}^T \sum_{s=1}^N (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) \tilde{R}_{s,t-k+1} \quad (1)$$

where  $\tilde{\omega}_{s,t}$  is the portfolio weight on security  $s$  at time  $t$ ,

$\tilde{R}_{s,t-k+1}$  is the return of security  $s$  ( $s = 1, \dots, N$ ) from time  $t-k$  to time  $t-k+1$ , with  $k$  as the lag index. The two benchmarks that are most used in recent times are represented by  $k=1$  and  $k=2$ . They may be the major facts that affect the momentum of the mutual fund. The study refers  $M_1$  as lag-1 momentum (L1M) and  $M_2$  as lag-2 momentum (L2M). Again, the study crumbles the L1M into "buy" and "sell" parts. The equation is expressed as:

$$M_{1\ B} = \frac{1}{T} \sum_{s=1}^T \sum_{s=1}^N \sum_{\tilde{\omega}_{s,t} > \tilde{\omega}_{s,t-1}} (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) (\tilde{R}_{s,t} - \bar{R}_s) \quad (2)$$

$$M_{1\ S} = \frac{1}{T} \sum_{s=1}^T \sum_{s=1}^N \sum_{\tilde{\omega}_{s,t} < \tilde{\omega}_{s,t-1}} (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) (\tilde{R}_{s,t} - \bar{R}_s) \quad (3)$$

The mean is then subtracted from the return so as to have measures that will be close to zero under no momentum investing. Closely to the lag-1 momentum measures, the 'buy' and 'sell' parts of the lag-2 momentum measure are:

$$M_{2\ B} = \frac{1}{T} \sum_{s=1}^T \sum_{s=1}^N \sum_{\tilde{\omega}_{s,t} > \tilde{\omega}_{s,t-1}} (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) (\tilde{R}_{s,t} - \bar{R}_s) \quad (4)$$

$$M_{2\ S} = \frac{1}{T} \sum_{s=1}^T \sum_{s=1}^N \sum_{\tilde{\omega}_{s,t} < \tilde{\omega}_{s,t-1}} (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) (\tilde{R}_{s,t} - \bar{R}_s) \quad (5)$$

On the other hand, we measured herding behaviour (tendency of fund managers to follow the crowd to buy or sell assets in the same period) using Grinblatt, Sheridan and Wemers' (Daniel et al., 1997) Signed Herding Measure (SHM). This is expressed mathematically as:

$$SHM_{st} = I_{st} \times UHM_{s,t} - E[I_{st} \times UHM_{s,t}] \quad (6)$$

Where  $I_{st}$  is an indicator for 'buy' or 'sell' herding.  $I_{st}$  is defined as follows:

$$I_{st} = 0 \quad \text{If } |P_{s,t} - \bar{P}_t| < E|P_{s,t} - \bar{P}_t|$$

$$I_{st} = 0 \quad \text{If } |P_{s,t} - \bar{P}_t| > E|P_{s,t} - \bar{P}_t| \quad \text{and the mutual fund is a buyer of stock } s \text{ during quarter } t, \text{ or if}$$

$$-(P_{s,t} - \bar{P}_t) > E|P_{s,t} - \bar{P}_t| \quad \text{and the fund is a seller of stock } s.$$

$I_{st} = -1$  If  $P_{s,t} - \bar{P}_t < E|P_{s,t} - \bar{P}_t|$  and the mutual fund is a seller of stock  $s$  during quarter  $t$ , Or If  $-(P_{s,t} - \bar{P}_t) > E|P_{s,t} - \bar{P}_t|$  and the fund is a buyer.

SHM<sub>s,t</sub> is set to be zero if fewer than 10 funds trade stock  $s$  during time  $t$ . If the number of funds trading stock  $s$  is small, no meaningful way can indicate whether the fund is herding or not. Finally, the herding measure of a mutual fund (FHM) is then calculated by substituting the signed herding measure in place of the stock return in equation (1).

$$FHM = \frac{1}{T} \sum_{s=1}^T \sum_{t=1}^n (\tilde{\omega}_{s,t} - \tilde{\omega}_{s,t-1}) SHM_{s,t} \quad (7)$$

where  $\tilde{\omega}_{s,t}$  is the proportion of the funds trading stock  $s$  during quarter  $t$ .

### Output Variables

Two sets of output cases were designated as performance evaluation models to identify the classification capability and the predictive power of FANNC. Sharpe Index was first used to calculate the output for the same period where the momentum and herding measures are resolute. This is denoted as the “classification case”. The second instance used the Sharpe Index to calculate the output for the next month right after the period for momentum and herding measures. It is named the “prediction case”. The output instances are calculated as follows:

$$Sharpe\ Index = \frac{\bar{Q}_s - \bar{Q}_f}{\sigma_s} \quad (8)$$

Predictive Sharpe Index

$$Sharpe\ Index = \frac{Q_s^+ - \bar{Q}_f}{\sigma_s} \quad (9)$$

Where:

$\bar{Q}_s$ : The average monthly return for fund  $s$  in the calculation period.

$Q_s^+$ : The return of fund  $s$  for the month after the calculation period.

$\bar{Q}_f$ : The average monthly risk-free rate represented by the 1-year CD rate of commercial bank.

$\sigma_s$ : The standard deviation of the return of the fund  $s$  over the calculation period.

## IV. Data Analysis

### Model 1: Backpropagation Neural Network (BPN)

The input and output instance combined were divided into training and testing parts. Four-fifth of the data was classified for training while one-fifth was classified for testing. Neural Connection by SPSS was applied to implement the backpropagation neural networks (BPN) algorithm with designated momentum coefficient, learning coefficient and stop criterion before the network training. The maximum epochs were limited to 3000 times for the stop criterion under the assumption that the root mean square (RMS) will be stabilized at this time. To determine the learning and momentum coefficients, a number of pairs were tested and the software spontaneously chose the most effective and efficient pairs (learning coefficient optimization value of 0.1, momentum coefficient value 0.9). To decide the activation function, two choices were offered the software (the sigmoid function or hyperbolic tangent function) but no significant differences was found between the two functions after training and testing. We decided on the sigmoid function since the extant literature on BPN significantly provides concrete result for their discussions. Normalization of the input and output instances through normalization method was done to improve the accuracy of BPN.

$$f(X_s) = \frac{X_s - \mu}{\sigma} \quad (10)$$

where

$X_s$ : is the normalized variable,  $\mu$  is the mean of  $x$ , and  $\sigma$  is the standard deviation of  $x$ .

Similar to the application of the learning and momentum coefficients, the software decided on the number of layers and nodes systematically. Then again, the software fine-tunes the network structure based on the input and output nodes. The architecture obtained in this study is a 7-4-1 network. As soon as the instances are inputted into the network,



the feeding sequence and the selection of testing instances are arranged randomly and just after the training, the software then reports the RMS which is computed from the instances.

### Model 2: Fast Adaptive Neural Network Classifier (FANNC)

The extant literature does not offer any specific, robust and agreeable commercial package to model FANNC due the distinctiveness of every research variable, its parameterisation and country or industry context. Following earlier works of (Tkáč & Verner, 2016; Daniel et al., 1997; Zhou et al., 2017) (that shares closer relationship with the objectives of this research), we used C++ to program the FANNC variables. Next, we determined and denoted the seven desirable FANNC variables as follows:

- $\theta_{sj}$  - denotes responsive centre,
- $\alpha_{sj}$  - denotes responsive characteristic width
- $\delta$ , -denotes responsive centre adjustment step
- $Err$  - denotes bias, the leakage competition threshold in the second layer, the outer layer similarity control coefficient
- $Errc_u$  - denotes the inner layer similarity control coefficient

As soon as there is a new node generation in the second layer, its related responsive centre is agreed to input component value in current instance beneath training, and the responsive feature measurement is set to be the default value, 0.25. Immediately there is a slight increase in the value, there will also be an increase in the predictive ability of the network; however, excessive increase in the responsive feature measurements will decrease the predictive ability. The responsive centre adjustment value step,  $\delta$ , touches the learning speed of the network and normally adopts a value between 0 and 1.0. We decided to choose the value to be 0.01 for this study.

The second layer which has the leakage competition thresholds,  $Err$  and  $Errc_u$  has a similar role played by them, as they all set to determine the number of new nodes that has to be generated in a trained network. When there is an increase in  $Err$ , the network tends to adjust its  $\theta_{sj}$  and  $\alpha_{sj}$  when rather, it's supposed to generate new nodes in the second and the third layers. An increase in  $Errc_u$  will increase the probability that only one new node is appended to the second layer and decrease the probability that two new nodes are appended to the second and the third layers simultaneously. The predictability of the model with its ability to have in mind the trained instances is determine by the number of the nodes in the second and the third layers. The predictability in general will decrease and the error from memorizing increases when the node number increases. Zhou et al. (2017) suggests that the leakage competition threshold be 0.8 and the maximum permissible error 0.11. The composition of FANNC is made of seven input units and one output unit. The hidden layer units are generated energetically. The study then utilizes the regression function of FANNC to evaluate the performance of the mutual fund. Just as in BPN, input and output instances are regularized by the standard procedure. In the interim, the selection of testing instances and feeding sequence are randomly arranged.

## V. Results

The tables below, thus table 1 and table 2 shows the comparison of Root Mean Square (RMS) and the processing time that exist between the FANNC approach and the BPN approach. The classification case and the prediction case, FANNC indicate a clear superiority to BPN.

**Table 1:** Output of Classification Test

PERIOD	Sample Number		FANNC		BPN	
	Training	Testing	RMS	Time*	RMS	Time*
2011-2012	23	7	0.078785	<1	0.175665	15
2013-2014	34	10	0.010678	<1	0.112255	18
2015-2016	50	16	0.075512	<1	0.111401	20

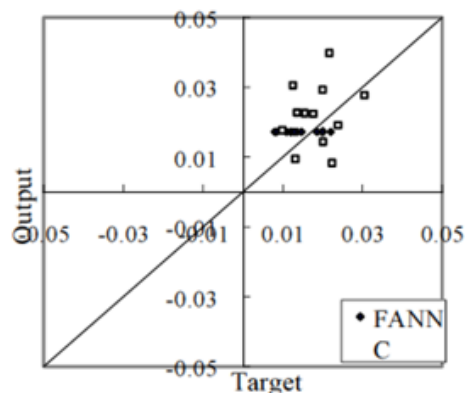
\*Including training time and testing time. Units are in seconds.

**Table 2:** Output of Prediction Test

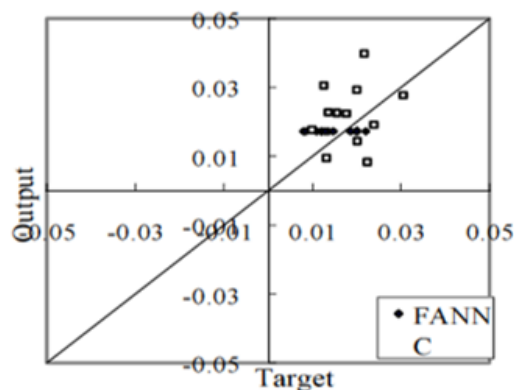
PERIOD	Sample Number		FANNC		BPN	
	Training	Testing	RMS	Time*	RMS	Time*
2011-2012	23	7	0.004062	<1	0.007121	15
2013-2014	34	10	0.004188	<1	0.011241	18
2015-2016	50	16	0.004204	<1	0.010145	20

\*Including training time and testing time. Units are in seconds.

From tables 1, it is observed that the RMS from FANNC is significantly lower than those from BPN, indicating the significant difference by a factor of two or three. FANNC consume less than one second in terms of processing time, whereas BPN in terms of processing time requires at least a minimum of 15 seconds. The difference in process time will only become more significant if only there will be an increase in the number of samples. Figure 2 shows a scatter diagram of classification RMS. The points are mostly distributed around the 45-degree line. On the other hand, the points from FANNC are more focus and closer to 45-degree line comparatively to the results generated by BPN. This means that the FANNC approach is highly accurate within the Sharpe Index classification than the BPN approach. The results prove similar to the one in the prediction case, as shown in figure 3. As already indicated, points from FANNC are highly focused and closer to 45-degree line. Adding to the benefits in time consumption and RMS accuracy, FANNC mostly shows superiority to BPN for financial presentations in other facets as well. Primarily, FANNC is highly equipped with a real-time learning capability. When a new instance is obtained, re-training becomes unnecessary, so in practical terms, algorithm can be used to monitor a dynamic database. As soon as there is a change in the database, the network has to monitor if the new instance can be classified by any of the existing attraction basin otherwise it will has to manufacture a new one. However, as soon as the trained network fails to classify a new input, it will then memorize and reclassify it later after more instances are available.



**Figure 2:** RMS in Classification case 2015-2016



**Figure 3:** RMS in Prediction case 2014-2015



## VI. Conclusion

We sought to evaluate the performance of mutual funds base on its flexibility and responsiveness utilizing fast adaptive neural network classifier, after which the results are compared with those from Backpropagation Neural Network based model. This is necessary because the survival of most micro-health insurance schemes in Ghana is based on the performance of mutual health schemes which is the preferred investment instrument for their funds collected to safeguard the health of mostly vulnerable people. Our results indicate that FANNC is superior to the BPN in evaluating mutual funds' performance in terms of the time utilised to evaluate performance and the Root Mean Square (prediction error).

The result has a number of implications for health equity in Ghana. Even though there is yet to be determined a model or group of models of healthcare financing that perfectly leverages the healthcare needs of vulnerable people, in the case of Ghana, the overriding importance of the micro health insurance scheme is not in doubt. But for wrongful investment choices of many well thought micro health insurance schemes, the health perils of a significant number of low-income Ghanaians would have been hedged against the severe economic constraints, political instability, and lack of good governance that significantly derails access to quality and affordable healthcare. That notwithstanding evidence from successful micro-health insurance companies that have invested in high earning but less risky mutual funds to sustain their operations is highly recognized in the extant literature (Lulin et al., 2016; Tischer, 2012; Ferson & Kim, 2012; Amato et al., 2013; Zhou et al., 2017) and international health forums (WHO, 2016). Employing effective tools such as FANNC tools can quicken the pace of investment performance assessment, rank a hierarchy of desirable investment options for micro-health insurance schemes to explore. This can guarantee fast processing time for investment decision of micro-health insurance to enable it play the essential role of enhancing health risk management of the members of the general public especially the poor and vulnerable that are often the victims of catastrophic healthcare expenditure.

## VII. Implications

Nonetheless, the benefit of Performance of Mutual Funds on Sustainable Micro-Health Insurance Schemes fit package may need to be improved further, as some members may still be having difficulty getting care. More research is needed to determine whether the Performance of Mutual Funds on Sustainable Micro-Health Insurance scheme's subsequent evolution has been able to address these coverage gaps. The findings of this study, on the other hand, show that continues to Performance of Mutual Funds on Sustainable Micro-Health Insurance Schemes benefit its members. Indeed, our findings strongly justify the Performance of Mutual Funds on Sustainable Micro-Health Insurance Schemes scheme's continued expansion. Ghana's experience with in expanding coverage can undoubtedly be useful to other countries. We leave this task for our ongoing project and future study

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## Conflict of interest statement

Nothing declared.

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