Forecasting the Financial Soundness of Indonesia's National Board of Zakat (BAZNAS) Using Artificial Neural Network Models

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Abstract **– The potential value of zakat in Indonesia in 2021 was estimated at RP 13.529 trillion; however, the actual amount of zakat collected was only RP 571 billion. Thus, this study aims to develop a precise financial soundness forecasting model for the National Board of Zakat (BAZNAS) in Indonesia using multiple linear regression (MLR) and artificial neural networks (ANN) with three algorithms to investigate, compare, and interpret the obtained results for better forecasting. The information was extracted from the financial statements of six BAZNAS for the period spanning year 2017 to 2021. The study determined unique and best models for each current ratio, cash ratio, and quick ratio. The results highlighted two models deemed best for forecasting Indonesia's BAZNAS financial soundness: MLR and ANN with Scaled Conjugate Gradient (SCG) training algorithm and MLR and ANN with Bayesian Regularization (BR). The research implications could help decision-makers strategise for the financial health of other Zakat organisations accordingly.**

Keywords **– Forecasting model, financial soundness, BAZNAS, multiple linear regression, artificial neural network.**

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1. Introduction

Islam strongly emphasises socioeconomic growth, and zakat is one of its pillars of faith. Delving into the subject of zakat within the realm of worship inevitably intertwines with socio-economic deliberations, particularly in extending assistance to those facing adversity. This connection becomes more profound when viewed through the lens of the Maslahat principle, emphasising the inherent societal benefits derived from charitable acts. The discourse underscores the inseparable link between religious obligations and the broader responsibility to address economic disparities, thereby highlighting the harmonious integration of spiritual devotion and compassionate societal engagement [1].

Zakat is essential in establishing economic justice and social welfare for all citizens [2]. It is a community-driven economic stimulus that considerably boosts the accumulation of local businesses to strengthen the state's economic cycle. From a macro perspective, zakat could increase demand by motivating more people to purchase items, especially those with low incomes and those in need. It automatically catalyses the lowering of unemployment and poverty [3].

The prospective scope of zakat in Indonesia is estimated at Rp. 13.529 trillion in 2021, encompasses potential contributions from diverse sectors, including households, private enterprises, state-run entities, deposits, and savings. Despite this considerable potential, a substantial disparity persists between the realised and potential zakat funds in the country. In the fiscal year 2021, the total Zakat, Infaq, and Sadaqah (ZIS) collection by all zakat institutions amounted to a mere Rp. 571 billion, falling significantly short of the anticipated amount. This incongruity underscores the untapped potential within the realm of zakat, signifying an area where concerted efforts could substantially bridge the existing gap and maximise the societal impact of these charitable contributions [4].

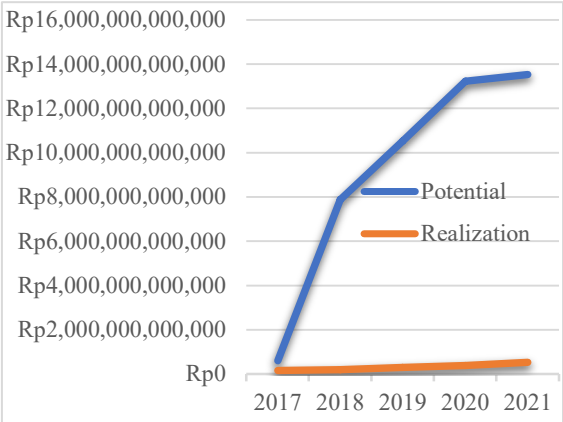

Figure 1. Potential and realisation of zakat collection

2. Research Methodology

This study incorporated secondary data from various Indonesian BAZNAS institutes. The ancillary data utilised in this study were extracted from the financial statements of the Indonesian BAZNAS provinces spanning the period from 2017 to 2021, encompassing comprehensive quantitative details [5].

The technique used in collecting the sample data was cluster sampling. Cluster sampling entails a bifurcated methodology wherein the entirety of the population is subdivided into clusters or groups, often delineated by geographic parameters such as villages, schools, wards or blocks. This approach facilitates a systematic and structured means of data collection, providing a representative cross-section of the population's diversity within each identified cluster. The use of clusters aids in managing logistical challenges and ensures a more efficient sampling strategy, particularly when the population is extensive and geographically dispersed. It is the most practical technique to be used in an extensive national survey. Cluster sampling is beneficial when the population is widely scattered.

However, it is impractical to sample and select a representative sample of all the elements [6].

The study population consists of 34 BAZNAS Provinces in Indonesia. The cluster sampling technique employed in this investigation guarantees that a comprehensive set of observations is acquired, amounting to 6 data points selected from 34 BAZNAS entities. This methodology strategically organises the sampling process by grouping BAZNAS units into clusters before selecting representative samples. This not only simplifies the data collection process but also enhances the efficiency of the study by capturing a diverse yet manageable subset of observations from the larger BAZNAS population., which from five big islands in Indonesia: Sumatera,Jawa, Kalimantan, Sulawesi, and Papua. BAZNAS West Java, BAZNAS Riau, BAZNAS Papua, BAZNAS North Sumatera, BAZNAS Southeast Sulawesi, BAZNAS South Kalimantan as the sampling [7].

The data analysis in this study utilised a hybrid approach, employing Multiple Linear Regression and Artificial Neural Network (ANN) methods to examine and model the relationships within the dataset comprehensively. This combination of statistical and machine learning techniques enhances the analytical depth, allowing for a more nuanced understanding of the intricate patterns and dependencies present in the data. Integrating multiple linear regression (MLR) offers interpretability and insights into linear relationships while incorporating ANN methods, enables the model to capture non-linear complexities, collectively contributing to a more robust and accurate dataset analysis. The data was processed using Matlab R2022b and MS Excel. ANNs are mathematical constructs inspired by biological neurons' structural and functional attributes, enabling them to simulate and comprehend non-stationary, non-linear, and exceedingly intricate datasets. Drawing inspiration from the intricacies of the human brain, ANN possess the capacity to adapt and learn from diverse patterns, making them particularly adept at capturing the complexities inherent in datasets that exhibit non-linear relationships or dynamic variations. This inherent flexibility and adaptability empower ANN to excel in scenarios where traditional methods may fall short, offering a valuable tool for comprehending and modelling intricate data patterns in various fields of study.

In finance, neural networks have gained widespread popularity as a preferred choice among practitioners and academics for capturing non-linear patterns and complexities. The adoption of neural networks in financial modelling reflects a recognition of their effectiveness in handling intricate relationships within data sets, particularly those that exhibit non-linear behaviour.

The increasing popularity of neural networks highlights their adaptability in effectively handling financial data's complex and dynamic characteristics. This adaptability led to the widespread utilisation as a powerful tool for analysing and predicting financial trends. Neural networks demonstrate a remarkable ability to discern complex patterns and relationships within financial datasets, making them invaluable in decision-making processes within the financial domain [8].

The expansion of the financial sector and the delivery of financial services have rendered neural networks and other machine learning algorithms indispensable for fraud detection, information extraction, and credit risk assessment. This inherent capability, coupled with advancements in computational power, has propelled ANN to the forefront of research in scientific domains. The integration of ANN in financial applications is driven by its capacity to discern intricate patterns in data, contributing significantly to the enhancement of security measures, insightful data extraction, and the accurate evaluation of credit risks within the financial landscape. This pivotal role solidifies ANN as a cornerstone technology in the ongoing evolution of scientific inquiry and financial advancements [9].

Parisi [10] evaluated the finances of the Zakat Management organisation using the Data Envelopment Analysis (DEA) approach. Harto *et al.* [11] evaluated the performance of Zakat Institutions using the International Standard of Zakat Management (ISZM) based on the efficiency and capacity of the Zakat Institutions. According to the findings of both studies,the management of donation funds could be done arbitrarily without any basis for evaluating operational performance or financial health. Anwar *et al.* [12] revealed that the five Zakat Institutions studied were not optimal in utilising the existing resources economically and were inefficient in managing the output. Additionally, Prayogi [13] indicated that the performance of BAZNAS in South Tangerang city with an index approach national zakat aimed at the government and community was in bad condition.

However, Lubis dan Budiman [14] revealed that BAZNAS Yogyakarta performed considerably well in its management. Previous studies [15], [16] partially analysed the ratio of activity and efficiency as no studies measured the influence of financial factors such as activity ratios, efficiency ratios, liquidity ratios, and growth ratios on the health or financial performance of Zakat Institutions in Indonesia.

2.1. Data Collection Technique

Data collection is an essential step in research because the data collected will be used to solve problems that are being researched and test hypotheses that have been formulated [17].

In this study, data was collected from secondary data, for example, from institutions' annual reports. The official annual reports were sufficient to support this study. The methodology employed for gathering secondary data in this research encompassed systematic exploration and analysis of pertinent information obtained from various sources. These sources predominantly comprised statistical data, agenda activities, policies, and other relevant materials germane to the research. Documentation methods were chosen for their inherent benefits, which include the accessibility of readily available data, cost-effectiveness, and operational efficiency in terms of labour. Leveraging documentation techniques allows the utilisation of existing data repositories and underscores the pragmatic advantages of efficiency and economic feasibility in the research process [18].

2.2. Data Analysis Technique

This type of experimental research determines the effects of specific treatments. This model involves basic processes like literature study, research data, research data analysis, and forecasting process.

2.2.1. ANN

The neural network employed in this context emulates the intricate workings of the brain. Just as the brain is a complex network of interconnected neurons, the neural network is structured with nodes that mirror the neurons in the brain. This emulation involves replicating the associations among neurons, a critical mechanism in the brain, by assigning weight values within the neural network. This weight-based representation captures the essence of how neurons communicate and interact, enabling the neural network to model and process information in a manner akin to the neural connectivity observed in the brain [19].

An archetypal structure of the ANN encompasses three fundamental strata: input, hidden, and output layers, each comprising nodes or neurons. In the configuration of any neural network, the inaugural layer is the input layer, its node count aligning with the number of explanatory variables or inputs. Conversely, the culminating layer is the output layer, with its node count mirroring the number of response variables or forecasted outcomes.

The hidden layer is interposed between the input and output layers, a pivotal component that imparts intricacy to the model's fitting. The nodes within this layer play a defining role in capturing nuanced patterns within the dataset, contributing to the network's ability to comprehend complex relationships. Notably, a prevalent feature in the topologies of most neural networks, especially within the input and the first hidden layer, is the inclusion of an additional node referred to as the bias node. This bias node, characterised by a constant value of one, serves a role analogous to the intercept in traditional regression models. Concerning inter-layer connectivity, each node within one layer establishes connections, represented by weights, with either all or a subset of nodes in the subsequent layer. This intricate web of connections facilitates the neural network's capacity to adapt and learn from the data, making accurate predictions or classifications based on the input variables. Including these structural elements and the nuanced interactions among nodes and layers underscores the sophisticated nature of neural networks in modelling complex relationships within datasets [19].

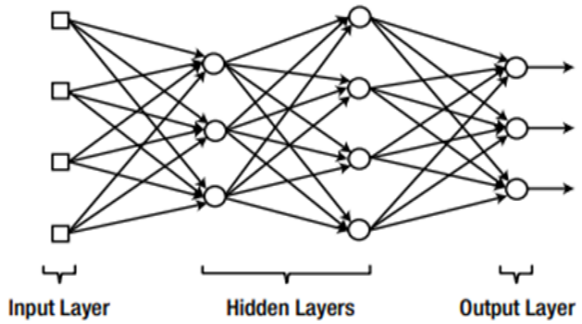

Figure 2. A layered structure of the nodes

3. Analysis

Training ANN with Levenberg-Marquardt (LM) Algorithm

This study executed the network training process using the LM backpropagation algorithm, denoted as "trainlm," within the Matlab software. This algorithm, "trainlm," is a specific method employed to adjust the network's parameters during the training phase. Matlab, a programming environment, facilitated the implementation of this algorithm to enhance the network's performance effectively through iterative learning and adjustment based on the provided data.

1. Current Ratio

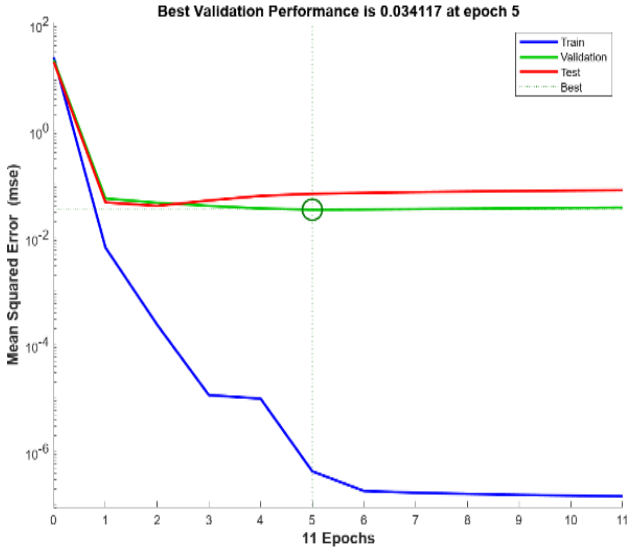

Figure 3. Architectural performance with the best raining result

Figure 3 illustrates the training of ANN with Levenberg-Marquardt, which stopped after n =11 epochs as the training error remained within the performance index (goal) set 10^{-6}. The best validation performance yielded during the training was 0.034117 epoch as depicted in Figure 5.

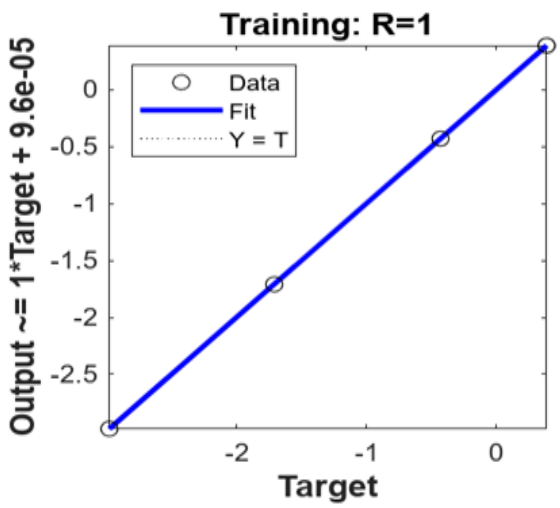

Figure 4. Regression plot

The regression plot indicated the regression between the network output and network target. Based on the regression plot, we validated the network performance by assessing whether the output results were far from the target. The blue line in Figure 4 represents the precise results of the training data to the target and regressionvalue of 1.

2. Quick Ratio

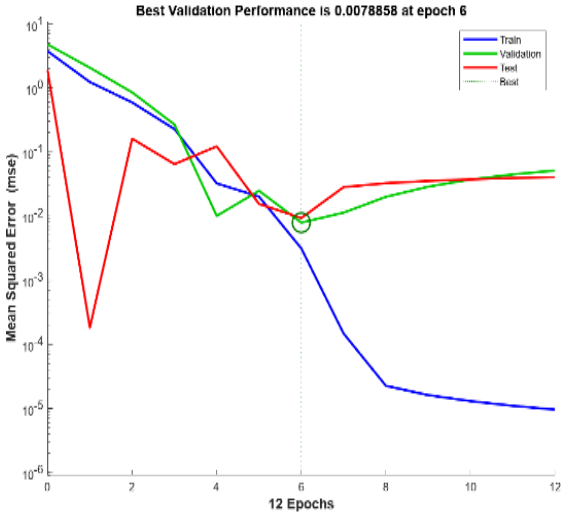

Figure 5. Architectural performance with the best training result

Figure 5 illustrates the ANN training with LM, which stopped after n = 12 epochs when the training error remained within the performance index (goal) set 10^6. Based on the training, we determined the best validation performance of the training dataset at 0.0078858 for epoch 6.

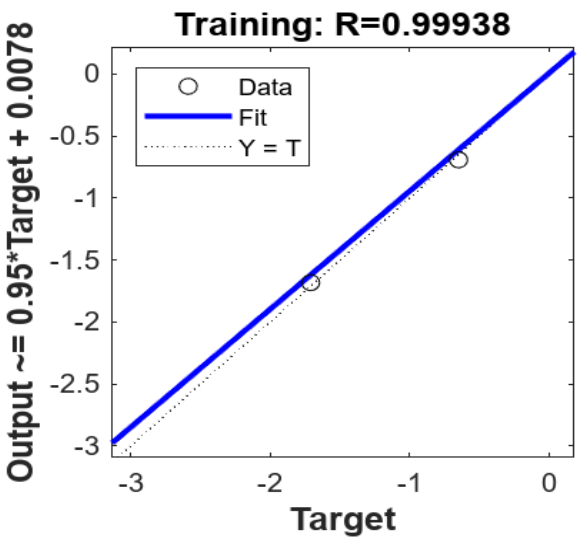

Figure 6. Regression plot

The regression plot indicates the regression between the network output and network target. The network performance can be validated based on this regression plot, by determining whether the output results are far from the target. According to Figure 6, the blue line represents the training data results being very close to the target with a regression value of 0.99938, approaching the value of 1.

3. Cash Ratio

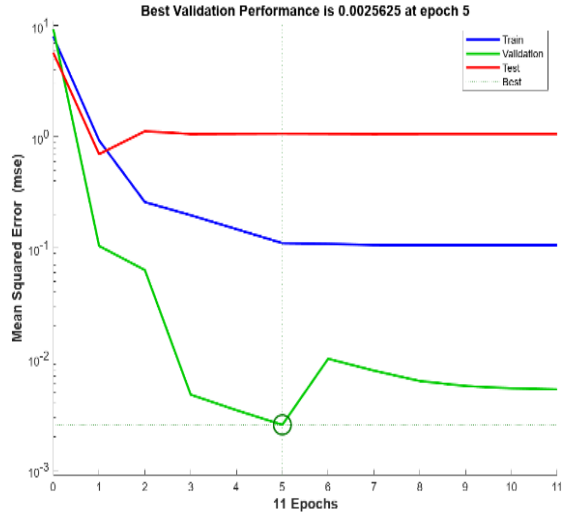

Figure 7. Architectural performance with the best training result

The ANN training with LM is depicted in Figure 7, and it was terminated after n = 11 epochs when the training error stayed within the performance index (goal) set 10^{-3}. The best validation performance was predicted by training to be 0.0025625 for epoch 5.

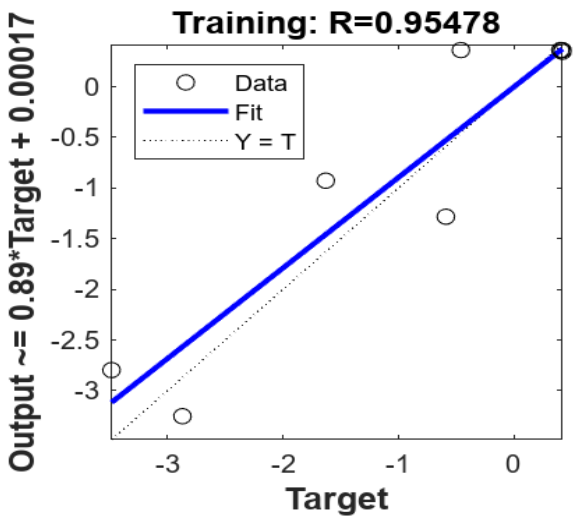

Figure 8. Regression plot

The network output and network target were correlated based on the regression plot. The regression plot was used to validate the network performance by evaluating the placement of the output far from the target. Figure 8 indicates that, with a regression value of 0.95478, the training data (the blue lines) results were extremely near to the desired outcome.

Training ANN with Bayesian Regularization (BR)

The following study was performed using Matlab Environment. The command employed for the training network was the BR backpropagation algorithm, "trainbr".

1. Current Ratio

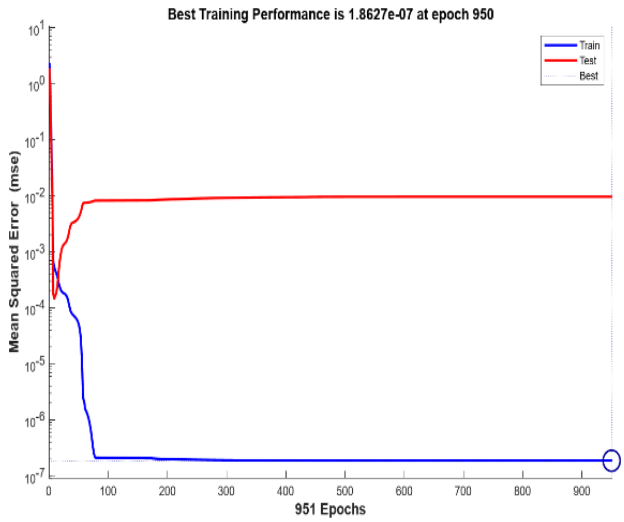

Figure 9. Architectural performance with the best training result

Figure 9 indicates the ANN training with BR, which stopped after n = 951 epochs when the training error remained within the performance index (goal) set10^{-7}. The best validation performance was estimated at 1,8627e-07 at epoch 950.

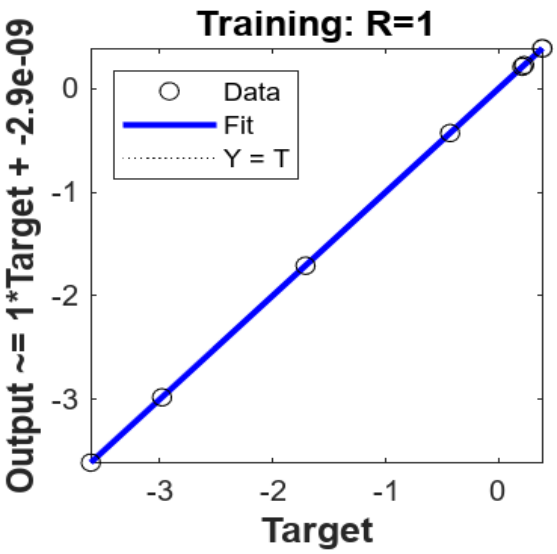

Figure 10. Regression plot calculation result

The regression plot represents the regression between the network output and network target. Figure 10 indicates that the blue line of training data depicts the precise value to the target and regression with a value of close to 1.

2. Quick Ratio

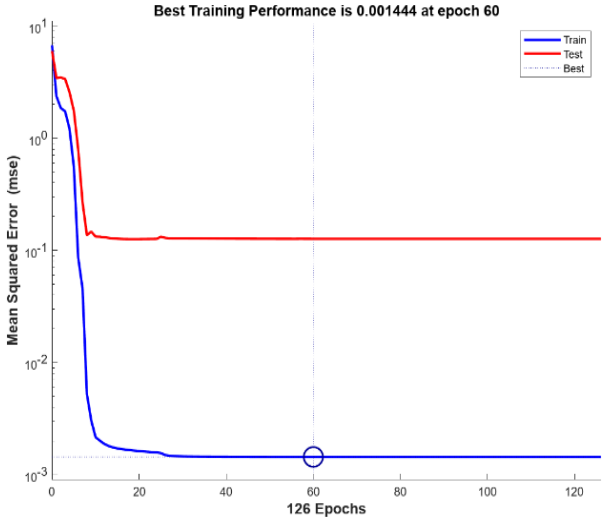

Figure 11. Architectural performance with the best training result

According to Figure 11, the ANN training with BR stopped after n = 126 epochs when the training error remained within the performance index (goal) set at 10^{-3}. The best performance validation was estimated at 0.001444 for epoch 60.

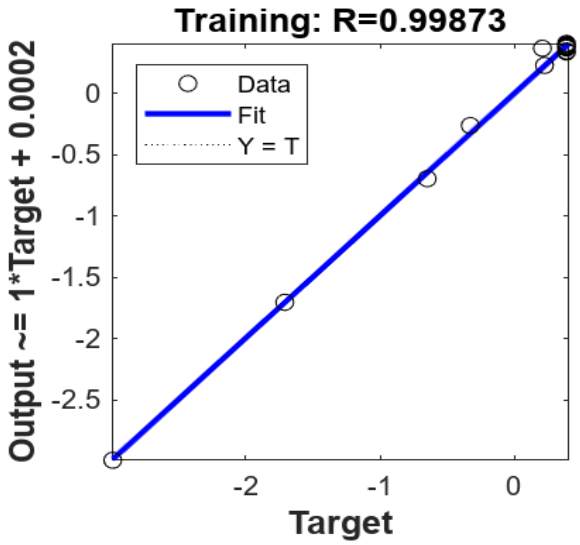

Figure 12. Regression plot calculation result

The regression plot validates the network performance by determining whether the output results are far from the target. The blue line in the figure indicated that the training data results were very close to the target and regression value of 0.99873.

3. Cash Ratio

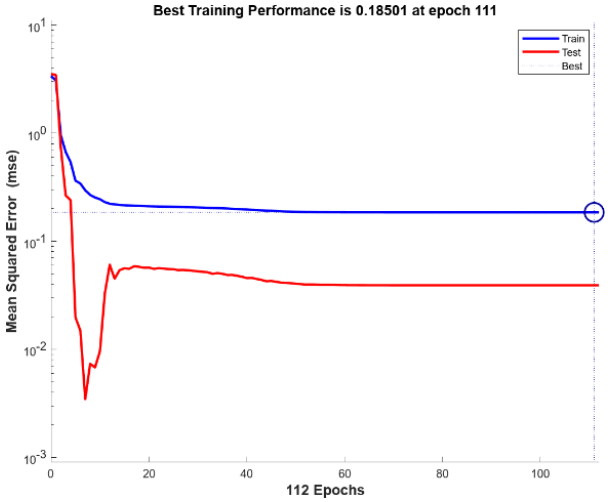

Figure 13. Architectural performance best training result

The training ANN with BR is depicted in Figure 13 and was terminated at n = 112 epochs with training error within the performance index (goal) set to 10^{-2}. At epoch 112 the training found the best validation performance to be 0.18501.

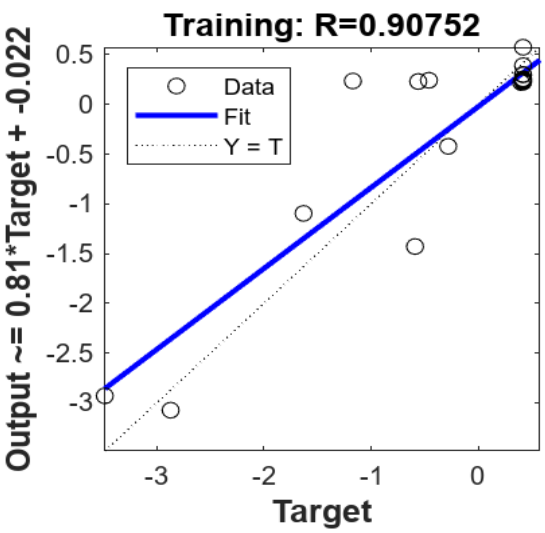

Figure 14. Regression plot calculation result

Regression plots demonstrate the relationship between the network target and output. Using this regression figure, we can check to see if the output results are close to the target, which will validate the network performance. Figure 14 demonstrates that the regression value of 0.90752, which is near to value 1, and the blue line, which depicts training data outcomes, are both extremely close to the target.

Training ANN with Scaled Conjugate Gradient (SCG)

This research is conducted within the Matlab environment. In Matlab, the directive employed to train the network through the SCG backpropagation algorithm is the "trains" command. This command serves as a key interface for initiating the training process, facilitating the optimisation of neural network parameters using the SCG backpropagation algorithm. Matlab provides a versatile and efficient platform for neural network implementation, and the "trains" command encapsulates the functionality crucial for the iterative refinement of network weights and biases. Leveraging the SCG backpropagation algorithm within Matlab underscores the commitment to precision and adaptability in optimising the neural network's performance, ensuring a robust and effective training process for the specific objectives of this study.

1. Current Ratio

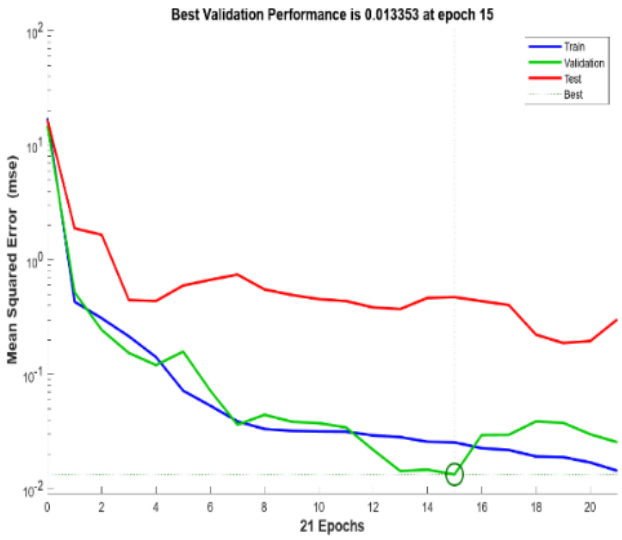

Figure 15. Architectural performance best training result

When the training error stays within the performance index (target) set at 10^{-2}, the training of the ANN with SCG stopped after n = 21 epochs. The training discovered that 0.013353 at epoch 15 yielded the best validation performance.

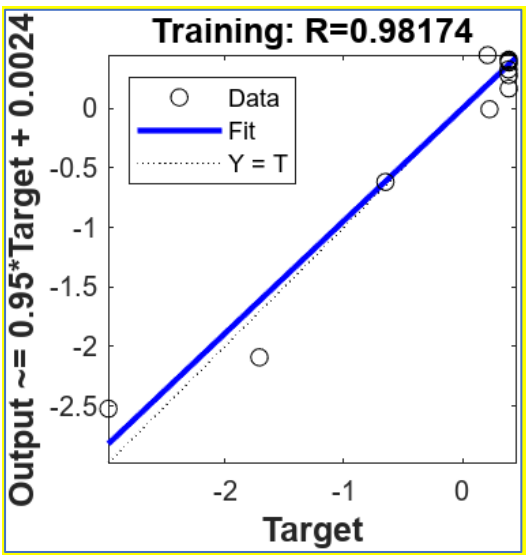

Figure 16. Regression plot calculation result

Regression plots demonstrate the relationship between network target and output. Based on this regression plot, we could deduce whether the output results are close to the target, to validate the network performance. The illustration above demonstrates that the regression value of 0.98174 and the blue line, representing training data results, are extremely close to the target.

2. Quick Ratio

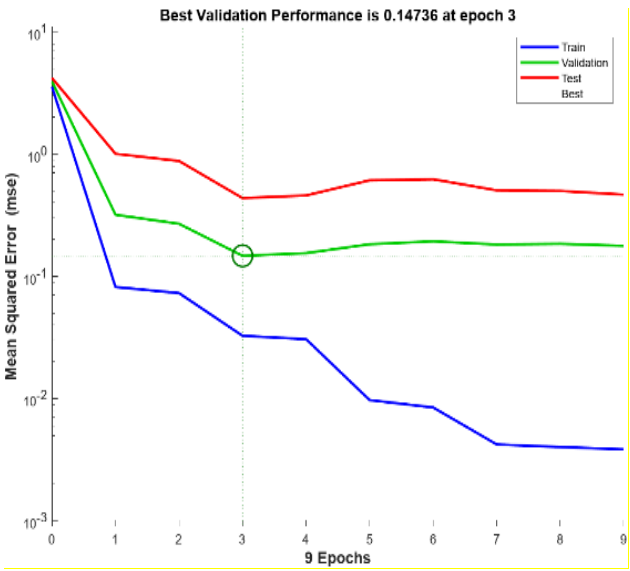

Figure 17. Architectural performance best training result

As depicted in Figure 17, when the training error is within the performance index (target) set at 10^{-2}, the training of the ANN with SCG stopped after n = 9 epochs. The training discovered that at epoch 3, 0.14736 yielded the best validation performance.

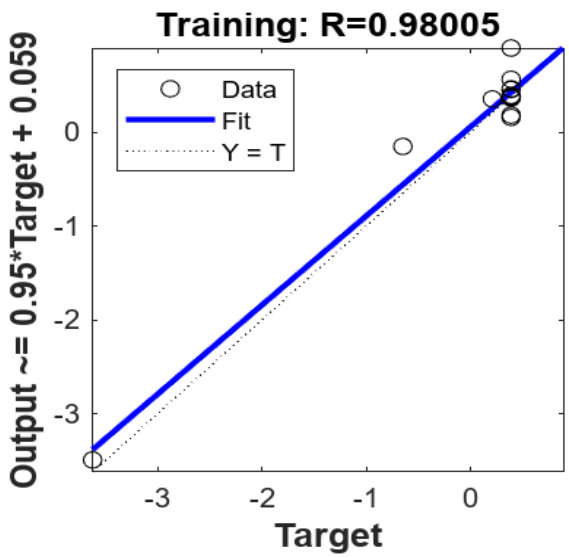

Figure 18. Regression plot calculation results

The network output and network target are correlated through regression plots. Using this regression plot, we can verify the network performance by determining whether the output results are close to the target. Figure 18 demonstrates that the regression value of 0.98005, near the target, is represented by the blue line, is extremely close to value 1.

3. Cash Ratio

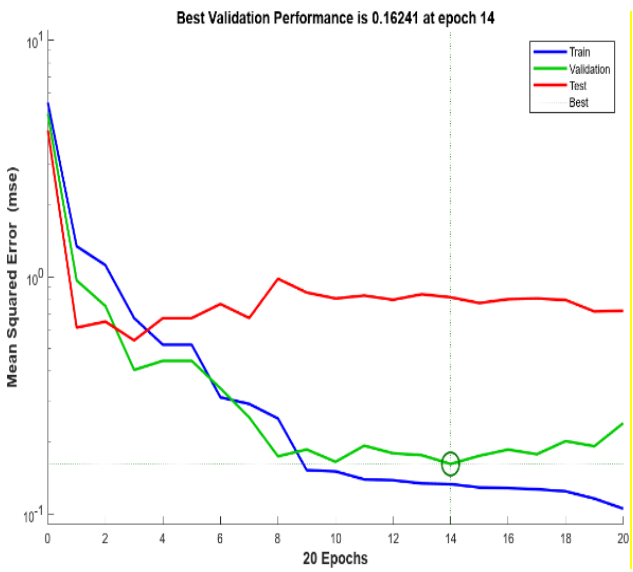

Figure 19. Architectural performance best training result

When the training error stays within the performance index (target) set at 10^{-1}, the training of the ANN with SCG stopped after n = 20 epochs. At epoch 14, the training discovered the best validation performance at 0.016241.

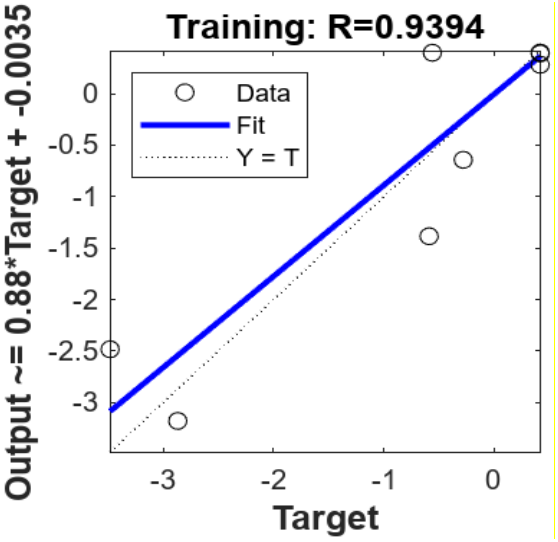

Figure 20. Regression plot calculation results

Regression plots illustrate the connection between the networks desired outcome and its actual output. Analysing this regression chart closely with the desired target confirms the network's effectiveness. As depicted in Figure 20 above, the regression value is 0.9394, which is close proximity to 1, and the blue line, representing the training data results, closely aligns with the target. Based on Table 3, the LM method was selected as the best method for forecasting cash ratio, yielding the smallest mean squared error (MSE) value of 0.0025625.

4. Discussion

The optimal performance in forecasting the current ratio, a metric assessing the financial stability of BAZNAS, was achieved by utilising MLR-ANN. The inclusion of the SCG training algorithm and fine-tuning network configuration parameters resulted in the most favourable outcomes among all models. The MSE for this MLR-ANN model with SCG training was notably low, measuring at 0.001444, the lowest across all considered models. Furthermore, the coefficient of determination, a measure of the model's explanatory power, reached 0.98174, the highest among the models considered. This underscores the effectiveness of the MLR-ANN approach, especially when paired with the SCG training algorithm and optimised network configuration parameters, in providing precise and reliable forecasts for the current ratio of BAZNAS, thereby offering valuable insights into its financial soundness. This result is also supported by Oyewale [20] who forecasted the inflation rates for Nigerians and Americans.The findings revealed that, across the board, ANN models incorporating the SCG algorithm exhibited superior performance compared to the auto regressive integrated moving average (ARIMA) models.

This discernible outperformance suggests that the ANN with SCG has the potential to serve as a foundational model for accurate and reliable rate forecasts within market structures. The study's conclusion underscores the viability of adopting the ANN with SCG as a benchmark model, showcasing its efficacy in surpassing traditional ARIMA models. By positioning the ANN with SCG as a foundational framework, there is a strategic implication for enhancing forecasting precision in diverse market scenarios. This recognition further underscores the adaptability and potential impact of advanced neural network models, particularly when integrated with sophisticated training algorithms like SCG, in refining predictions and understanding the dynamics of market structures more effectively. Similarly, other studies also revealed that SCG optimisation-based ANN model yielded the best forecasting results [21], [22], [23].

Conversely, the most effective forecasting outcomes for the quick ratio, a critical metric in evaluating the financial robustness of BAZNAS, were achieved through the application of MLR-ANN with the Broyden-Fletcher-Goldfarb-Shanno training agorithm and meticulously optimised network configuration parameters. This specific MLR-ANN model demonstrated unparalleled performance, as evidenced by its remarkably low MSE of 0.0013353—the lowest among all models considered. Additionally, the coefficient of determination for this model reached 1, representing the highest level among the various models evaluated. These results signify the exceptional accuracy and reliability of the MLR-ANN framework with BR training algorithm, emphasising its proficiency in providing precise forecasts for the quick ratio and offering invaluable insights into the financial stability of BAZNAS.

Similarly, Khan [24] compared the performance analysis of LM, BR, and SCG terms to predict flash floods. The study outcomes revealed that the BR learning algorithm exhibited superior performance compared to other algorithms. This superiority was evident through enhanced fitness, higher regression values, and reduced MSE achieved within a significantly lower number of training epochs.

The emphasis here is on the efficiency and effectiveness of the BR learning algorithm, as it demonstrated a quicker convergence to optimal results with fewer training iterations. The improved fitness and regression values underscore its capacity to fine-tune model parameters efficiently, resulting in a more accurate and robust learning process. The reduced MSE further substantiates the algorithm's proficiency in minimising prediction errors, ultimately contributing to the overall enhanced performance in comparison to alternative learning algorithms.

The findings were in line with previous studies revealing that BR served as the best forecasting ANN model. As for the cash ratio, the optimal forecasting results were achieved by applying MLR-ANN with the LM training algorithm and finely tuned network configuration parameters. This model demonstrated unparalleled accuracy, as reflected in its exceptionally low MSE of 0.0025625, representing the lowest among all models considered. Additionally, it attained a coefficient of determination of 1, signifying the highest level of predictive precision across the various models evaluated.

In a parallel context, Garoosiha [25] explored the application of the LM and Bayesian framework training algorithms in predicting concrete shrinkage using ANN. Their findings corroborated the superiority of the LM algorithm, as the neural network-based method employing LM exhibited more accurate shrinkage strain data than the Bayesian Framework algorithm. This aligns with the LM training algorithm's observed excellence in forecasting the cash ratio. It further reinforces its efficacy across diverse applications and highlights its potential as a preferred choice for neural network training in various predictive modelling scenarios.

5. Conclusion

This study utilised multilayer feedforward neural networks trained with LM, BR, and SCG backpropagation algorithms to measure and develop the best forecasting models for the financial soundness of BAZNAS in Indonesia. These models were trained by optimising the MSE and coefficient of correlation. The formulation of the ANN forecasting models was grounded in experimental data amalgamated from both literature reviews and dedicated laboratory experiments. Drawing insights from the outcomes, the following propositions can be asserted:

1. MLR-ANN with SCG training algorithm and optimise network configuration parameters produced the best result for forecasting the current ratio measuring the financial soundness of BAZNAS with an error rate of 0.001444.
2. MLR-ANN with BR training algorithm and optimise network configuration parameter yielded the best result for forecasting quick ratio measuring the financial soundness of BAZNAS with an error rate of 0.0013353.
3. BAZNAS should suggest a precise model as part of its strategic approach to ensure the forecasting model is efficient and effective.

Conversely, this study includes several gaps that need to be filled by additional research using information from various voluntary sectors. Comparisons based on multiple experiences and nations could produce precise and significant results in the near future.

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References:

[1]. Johari, F., AF, M. A., Ab Aziz, M. R., & Ahmad, N. (2014). The importance of zakat distribution and urban-rural poverty incidence among Muallaf (new convert). *Asian Social Science, 10*(21), 42–53. Doi: 10.5539/ass.v10n21p42.

[2]. Ibrahim, S. M. (2015). The role of zakat in establishing social welfare and economic sustainability. *International Journal of Management and Commerce Innovations*, *3*(1), 437-441.

[3]. Rusydiana, A. S., & Al Farisi, S. (2016). The efficiency of zakah institutions using data envelopment analysis. *Al-Iqtishad: Jurnal Ilmu Ekonomi Syariah*, *8*(2), 213-226. Doi: 10.15408/aiq.v8i2.2876.

[4]. Baznas, P. (2020). *Outlook Zakat Indonesia 2020.* Jakarta: Pusat Kajian Strategis (Puskas) Badan Amil Zakat Nasional (BAZNAS).

[5]. Hox, J. J. & Boeije H. R. (2005). Data Collection, Primary vs. Secondary. In *Encyclopedia of Social Measurement*, *1,* 593–598. Esevier.

[6]. Acharya, A. S., Prakash, A., Saxena, P., & Nigam, A. (2013). Sampling: Why and how of it. *Indian Journal of Medical Specialties*, *4*(2), 330-333.

[7]. Cohen, G. R. (1992). Review of *Sampling of Populations: Methods and Applications.; Design and Inference in Finite Population Sampling.*, by P. S. Levy, S. Lemeshow, A. S. Hedayat, & B. K. Sinha. *Biometrics*, *48*(4), 1299–1300. Doi: 10.2307/2532723.

[8]. Kim, P. (2017). Matlab deep learning. *With machine learning, neural networks and artificial intelligence*, *130*(21).

[9]. Aggarwal, C. C. (2018). Neural networks and deep learning. *Springer*, *10*(978), 3.

[10]. Al Parisi, S. (2017). Overview of forecasting zakat collection in indonesia using multiplicative decomposition. *International Journal of Zakat*, *2*(1), 45-59.

[11]. Harto, P. P., Anggraeni, V. S., & Bayinah, A. (2018). Komparasi Kinerja Keuangan Lembaga Amil Zakat. *Jurnal Akuntansi Dan Keuangan Islam*, *6*(1), 19-33.

[12]. Anwar, M. S., Itang, I., & Risyanto, H. (2019). Analisis Efisiensi Lembaga Pengelola Zakat (LPZ) dalam Mengelola Potensi Zakat di Indonesia. *Tazkiya*, *20*(02), 145-180.

[13]. Prayogi, A. (2019). *Analisis Kinerja Baznas Kota Tangerang Selatan Dengan Pendekatan Indeks Zakat Nasional* (Bachelor's thesis, Fak. Ekonomi dan Bisnis Uin Jakarta).

[14]. Lubis, D., Hakim, D. B., & Putri, Y. H. (2018). Mengukur kinerja pengelolaan zakat di badan amil zakat nasional (baznas). *JEBI (Jurnal Ekonomi dan Bisnis Islam)*, *3*(1), 1-16.

[15]. Lestari, A. (2015). Efisiensi Kinerja Keuangan Badan Amil Zakat Daerah (BAZDA): Pendekatan Data Envelopment Analysis (DEA). *Jurnal Ekonomi & Studi Pembangunan*, *16*(2), 177-187.

[16]. Handayani, L., Ainun, B., & Fahmi, M. Y. (2020). Analisis Aktivitas Amil Pada Organisasi Pengelola Zakat. *Jurnal INTEKNA: Informasi Teknik Dan Niaga*, *20*(2), 100-110.

[17]. Peersman, G. (2014). *Overview: Data collection and analysis methods in impact evaluation*. UNICEF Office of Research-Innocenti.

[18]. Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative research journal*, *9*(2), 27-40.

[19]. Ebrahimi, N. (2017). An analysis of the relationship of imports and economic growth in Iran (Comparison of systematic and unsystematic cointegration methods with neural network). *International journal of economics and financial issues*, *7*(2), 338-347.

[20]. Oyewale, A. M., Kasali, A. O., Phazamile, K., Abiodun, M. V., & Adeyinka, A. I. (2019). Forecasting Inflation Rates Using Artificial Neural Networks. *International Journal of Statistics and Applications*, *9*(6), 201-207.

[21]. P Rodríguez Miranda, J., A Zafra Mejía, C., & Feria Díaz, J. J. (2019). Neuronal Artificial Network (Algorithm Scaled Conjugate Gradient): Prediction of Forest Fires in the Eastern Area of the Cundinamarca Department, Colombia. *International Journal of Civil Engineering and Technology*, *10*(07).

[22]. Selvamuthu, D., Kumar, V., & Mishra, A. (2019). Indian stock market prediction using artificial neural networks on tick data. *Financial Innovation*, *5*(1), 1-12. doi: 10.1186/s40854-019-0131-7.

[23]. SSuantai, S., Sabir, Z., Umar, M., & Cholamjiak, W. (2023). Scaled Conjugate Gradient for the Numerical Simulations of the Mathematical Model-Based Monkeypox Transmission. *Fractal and Fractional*, *7*(1), 63.

[24]. Khan, T. A., Alam, M., Shahid, Z., & Mazliham, M. S. (2019). Comparative performance analysis of Levenberg-Marquardt, Bayesian regularization and scaled conjugate gradient for the prediction of flash floods. *Journal of Information Communication Technologies and Robotic Applications*, 52-58.

[25]. Garoosiha, H., Ahmadi, J., & Bayat, H. (2019). The assessment of Levenberg–Marquardt and Bayesian Framework training algorithm for prediction of concrete shrinkage by the artificial neural network. *Cogent Engineering*, *6*(1), 1609179.