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Neural Network Model in Forecasting Malaysia's Unemployment Rates

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Neural networks (NN) have been widely applied in time series forecasting. This study aims to develop basic NN models for forecasting the unemployment rate in Malaysia by gender. The yearly unemployment rate of thirty-eight years from the year 1982 to 2019 was obtained from the Department of Statistics Malaysia. In addition, datasets of gross domestic product, inflation and population rates extracted from the World Bank Data website were used as input variables in developing the NN models. Several NN models with different number of hidden nodes were developed and evaluated. Results showed that the best model for the male population was the NN model with four hidden nodes in one hidden layer whereas the NN model with two hidden nodes in one hidden layer was the best for the female population. Additionally, it can be concluded that the trend for the future unemployment rate in Malaysia for male and female population in the next ten years will be gradually constant throughout the year starting from 2020 to 2030.

Keywords: forecasting; gender; unemployment rate; neural network

I. INTRODUCTION

Nowadays, the issue related to unemployment rate is a common thing in all countries. Ramli *et al.* (2018) stated that unemployment gives negative government, community, and individual impacts. The unemployment rate can be defined as the percentage of the labour force that is currently unemployed but willing and able to work as well as actively seeking a job (Tsvetinov, 1999). The unemployment rate is an indicator of the prevalence of unemployment and it is measured by a percentage which is calculated by the number of unemployed individuals divided by all individuals currently in the labour force and multiplied by 100% (Huang, 2015). In economic status analysis, unemployment rate is an important predictor that has become an essential measure in planning risk management of most fields such as education, tax, agricultural, finance and industrial policies (Mahipan *et al.*, 2013).

International Labour Organisation (2018) stated that global unemployment rate decreased in 2018 and this scenario remained unchanged in 2019. However, in 2020, 8.8 percent of global working hours were lost and this was equal to hours worked in a year by 255 million permanent workers in the world (International Labour Organisation, 2021). This summary indicator captured the current global scenario due to the COVID-19 pandemic which has affected labour markets.

Xu *et al.* (2012) stated that the forecasting of the unemployment rate has pulled a lot of debates from governments, industries, practitioners, and researchers. With the assistance of unemployment rate prediction, the government may implement an appropriate control strategy in sustaining economic development and social stability (Cheng *et al.*, 2017). According to Dritsakis and Klazoglou (2018), future unemployment predictions are critical for economic policymakers to track, prepare and avoid any sustained increase of unemployment in a country. In addition, Chakraborty *et al.* (2021) highlighted that unemployment rate prediction is an important element for economic and financial growth planning and a challenging job for policymakers of the country in most countries of the

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world. Additionally, several researchers (Shabbir *et. al.,* 2021; Ziberi & Avdiu, 2020; Dalmar *et. al.*, 2017; Furuoka & Munir, 2014; Aqil *et. al.*, 2014; Asif, 2013) found that inflation, exchange rate, gross domestic product (GDP) and a number of the population are important factors that have impact on unemployment rate. In addition, Ramli *et al.* (2018) also considered these factors in predicting the unemployment rate of Malaysia using a linear regression method.

Previously, several studies regarding forecasting of unemployment rate have been conducted globally by previous researchers (Huang, 2015; Dumicic *et. al.*, 2017; Dritsakis & Klazoglou, 2018; Claveria, 2019; Didiharyono & Syukri, 2020; Chakraborty *et al.*, 2021). In the case of Malaysia, there were also several studies (Ramli *et. al.,* 2018, Islam & Kamarudin, 2017; Nor *et al.*, 2018) conducted in forecasting the country's unemployment rate. However, to the researcher's knowledge, those studies did not use Neural Network (NN) model in forecasting the unemployment rate of Malaysia. Currently, the Box-Jenkins method and NN are among the popular methods in predicting and forecasting. Both techniques are flexible when it comes to complex non-linear data. However, additional advantages of applying the NN technique are high potential in approximation and fast time processing with the mathematical formulae and prior information about the relationship between inputs and outputs is uncertain (Mahipan *et al.,* 2013).

Therefore, this study was conducted to fill the gap by establishing the NN model in considering inflation, exchange rate, gross domestic product (GDP) and the population as input factors in forecasting the unemployment rate of Malaysia. In addition, this study also investigated the future trend of unemployment rate in Malaysia by gender-base on forecast values of the year 2020 to 2030. It is aligned with goal number 8 in Sustainable Development Goal (SDG) which strives to achieve full-time and suitable employment for men and women, including young people and those with impairment by 2030 (Department of Statistics Malaysia, 2021). Hence, examining the trend and forecasting the future of unemployment rate are essential.

II. DATA DESCRIPTION

Unemployment rate data available from 1982 to 2019 were extracted from the Department of Statistics Malaysia (DOSM). The data consisted of annual unemployment and unemployment rate separated by gender. The input variables (GDP, number population, and inflation rate) were extracted from The World Bank Data (2020). This study focused on forecasting the unemployment rate by gender and identifying the significance of independent variables toward the unemployment rate by gender. Hence, it cannot be generalised to research that does not take into account the gender aspect.

III. NEURAL NETWORK METHODOLOGY

NN is an approach of forecasting based on the brain's basic mathematical models to map outputs according to the input variables. It is a series of algorithms designed to recognise patterns and allow for complex and nonlinear relationships between the response variable (output) and its predictors (input factors) (Hyndman & Athanasopoulos, 2018).

A. Data Normalisation

Normalisation of data is useful for modelling applications where the inputs are based on wide varying scales. Following Gholami *et al.* (2011), data normalisation has been used in scaling data within the same range value for each input feature in minimising bias. This process may increase the speed of training time by starting the training process within the same scale for each feature. The NN training has become more efficient which leads to a better predictor of the data by normalising the input variables under study which are GDP, inflation rate, and population. If not, the predicted values of the unemployment rate in Malaysia by gender could remain the same for all observations regardless of input values. This process has made the data calibrated into a specific scale. Consequently, the predicted gender-based unemployment rate in Malaysia and its actual values have been accurately compared (McCaffrey, 2014).

According to Aksu *et al.* (2019), there are five ways in data normalisation process which are statistical (z-score) normalisation, max-min normalisation, sigmoid normalisation, median normalisation and statistical column normalisation. However, this study only focused on max-min normalisation.

B. Cross-validation

A cross-validation is an approach whereby the data set under study is divided into a training dataset subset and a testing dataset subset. Then, the developed model is trained using the training dataset and tested using the testing data set. Model evaluation is very beneficial because it allows us to determine the consistency of the model. Then, it chooses the model that best performs with unseen data and prevents overfitting patterns that do not generalise well to the unseen data. This study used the holdout method as the cross-validation approach. Hold-out is the simplest type of cross-validation technique in which the data set is separated into a set of trains and tests. The training set is what the model is being trained on to learn patterns from the results, and the test set is being used to understand how the model is doing in real-world scenarios. Following Tashman (2000), the training set for this study was 75 percent of the data while the balance of 25 percent was the test set.

C. Multilayer Perceptron Neural Network

Multilayer Perceptron (MLP) is a standard NN structure. MLP is composed of three layers which are input layer, intermediate layer and output layer as shown in Figure 1.

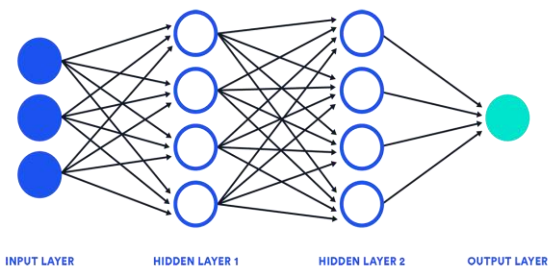

Figure 1. Neural Network Structure

The first layer is an input layer consisting of independent variables which are GDP, inflation rate and population number. Later, all the data reach the network and all inputs are standardised with similar input ranges. The outputs then become inputs to the second layer in the sequence layer. The second layer is the intermediate layer which is between the input and output layers. The intermediate layer contains hidden neurons in which each receives multiple inputs from the input layer. This layer is made up of artificial neurons with each receiving multiple inputs from the input layer. The neurons perform intermediate calculations in the hidden layer and transfer the result to the next layer with the number of hidden layers being identified using the rule of thumb (Salaan *et al.*, 2013). A various number of hidden layer has been employed in improving NN performance. The result is modified by the non-linear activation functions that contain in the hidden layer before becoming the output in the output layer. A hyperbolic tangent is preferred as it spans positive as well as negative values. This modification helps to reduce the impact of extreme input values and renders outliers more robust in the network.

The third layer is a layer in which the artificial neurons summarise the results. This layer is called the output layer. The neurons in the output layer perform the combination and activation operations where there are combination and activation functions between the hidden layer and output layer. This operation becomes the key element of the NN model. The formulae used in the combination of outputs are called target layer combination functions, while for activation or transformation of the variable, it is called target layer activation functions. A distinct NN model is produced differently in the number of combinations of hidden layer combination function, hidden layer activation function, output layer combination function and output layer activation function.

D. Selection of Hidden Layer and Hidden Neurons

According to Panchal (2011), two decisions have to be taken regarding the hidden layers which are the number of hidden layers the NN should have and the number of neurons in each of these hidden layers. Hence, in this study, both the numbers of hidden layers and the number of neurons used in each of the hidden layers have been carefully identified to avoid overfitting and underfitting problem. In addition, in many real cases, it is more sufficient to use only one hidden layer

(Panchal *et al.*, 2011). Based on the rule-of-thumb, the number of hidden neurons in the hidden layer should be less than twice of the input layer size. Therefore, NN models with one hidden layer and a maximum of six hidden neurons were used in this study and ultimately it was based on the result of trial and error in choosing the best NN architecture.

E. Activation Function

A NN without activation function is just a linear regression model. An activation function adds a further step at each layer during the forward propagation. This step increases the network's complexity and becomes more efficient, thus enabling the network to learn from the data, compute and provide accurate predictions about the complex patterns. Forward propagation is a process of multiplying the input values ($x_1, x_{2,\ldots,}x_n$) of a neuron by their associated weights ($w_1, w_{2,\ldots,}w_n$) and summing the results as in Equation (1) (Olawoyin & Chen, 2018).

$$I = f(x) = \sum_{i=1}^{n}((x_i w_i) \quad (1)$$

where;

x_i= the input, i=1,2,...,n

w_i=the weight, i=1,2,...,n

The input represents the raw data and this raw data is computed into the hidden layer network together with the weight (Olawoyin & Chen, 2018). The weighted linear combination combines the inputs to each of the nodes. Then, the result is adjusted by a nonlinear function before being the output and input for the next layer. This helps in reducing the effect of extreme input values, hence rendering the outliers of the network to become more resilient. The weight is the coefficients that are attached to the predictors. The weight selection in the NN framework is through the use of the algorithm which minimises the cost function. The weighted values are controlled in preventing the values from becoming too large (Hyndman & Athanasopoulos, 2019). To keep the values within a manageable range, the activation function is used as it performs a transformation process on the input received. It is because once the values are multiplied by a weight and summed, they go beyond the original scale range. The values scale back to the next layer of neurons within a given range before passing those signals on.

This affects the sum of the weighted input value of the next layer which then affects the network's measurement of new weights and their distribution backward. Hence, the final output value(s) of the NN is affected. The activation function holds values within a suitable and useful range which then forwards the output to subsequent layers.

F. Model Evaluation

There were 38 observations in this data series of the unemployment rate in Malaysia by gender. Then the data were divided into two subsets with 75% of the data used for the estimation process from the year 1982 to 2009 while another 25% from the year 2010 to 2019 were used for the evaluation process. The followings are the two error measures used in this study which are root mean square error (RMSE) and mean absolute error (MAE).

$$\text{RMSE} = \sqrt{\frac{\sum_t^n e_t^2}{n}} \quad (2)$$

$$\text{MAE} = \frac{1}{n}\,|e_t\,| \quad (3)$$

where: $e_t = y_t - \hat{y}_t$, with y_t as the actual observation at the time t and $\hat{y}_t$ is the estimated value at the time t and n is the number of forecast errors produced by the model. The best model was identified after considering the model with the smallest error measure. Then, this best model was used in forecasting the unemployment rate of Malaysia by gender for 10 years ahead which is from the year 2020 to 2030.

IV. RESULTS AND DISCUSSION

The analysis began with a trend analysis of the unemployment rate by gender in Malaysia from the year 1982 to 2019 as shown in Figure 2. It was indicated that the unemployment rate for both genders in Malaysia decreased throughout the years from 1988 to 2019 with the unemployment rate for females being higher than the male population in most years. The unemployment rate for both genders increased from the year 1982 to 1986 and the rate slowly increased until it reached the highest point rate in the year 1988. Starting from the year 1988 to 1992, the unemployment rate for the male and female population decreased drastically. The lowest point ever reached for the male population was in the year 1996 while the female population was in the year 1997. The following years from 1996 to 2019 showed that the rate gradually became constant.

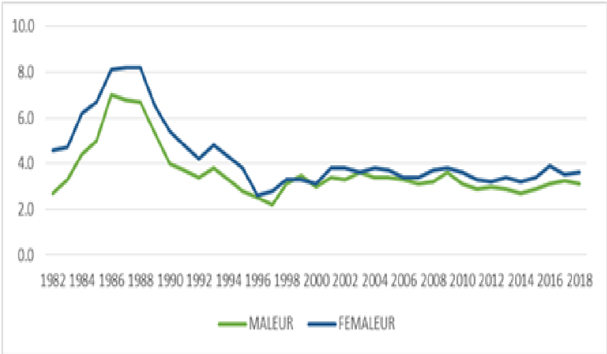

Figure 2. Malaysia Unemployment Rate for the Year 1982 to 2019 by Gender

In developing the NN model and forecasting the unemployment rate for 10 years ahead, the data from 1982 to 2009 were used for model estimation (training data) while the remaining years from 2010 to 2019 were used for model evaluation. After several experiments with different network architectures based on the rule-of-thumbs method, it is concluded that several NN models with one hidden layer and a maximum of six hidden neurons were used in this study in selecting the best NN architecture. The network structure with the smallest value of MAE and RMSE on the training dataset was chosen as the best model. There were five NN models with five different number of hidden nodes. The model comparison for male and female population among NN models with two, three, four, five, and six hidden nodes was observed as shown in Table 1 and Table 2, respectively. The best NN model obtained for both male and female population was NN with four hidden nodes as it had the smallest values of MAE and RMSE.

Figure 3 and Figure 4 show the NN architecture of the best NN model for the male and female population, respectively. The left-most nodes represent the network's input layer where each circle represents the input variables of the inflation rate, gross domestic product and population. Each arrow has a different weight which can be viewed as the effect of a node on the next layer node. The middle layer is the intermediate layer between the input and output layer which comprises one single layer that has four hidden nodes. The right-most node is the output layer which produces the result for inputs given with error of 0.105157 for the male population (Figure 3) and 0.05876 for the female population (Figure 4).

Figure 5 and Figure 6 present the plot of actual values for Malaysia's unemployment rate and fitted values generated by Model NN4 for both populations, respectively. The plots show that the gap between actual and fitted lines was rather close which explained that the model was able to generate an accurate forecast unemployment rate for both population with smaller error.

Table 1. Neural Network Models for Male Population

Model	Hidden layer	Hidden node	MAE	RMSE
NN2	1	2	0.0907	0.1193
NN3	1	3	0.086	0.1078
NN4	1	4	**0.0653**	**0.0867**
NN5	1	5	0.0825	0.1038
NN6	1	6	0.0805	0.1006

Table 2. Neural Network Models for Female Population

Model	Hidden layer	Hidden node	MAE	RMSE
NN2	1	2	0.0867	0.1136
NN3	1	3	0.0840	0.1082
NN4	1	4	**0.0485**	**0.0648**
NN5	1	5	0.0923	0.1272
NN6	1	6	0.0822	0.1031

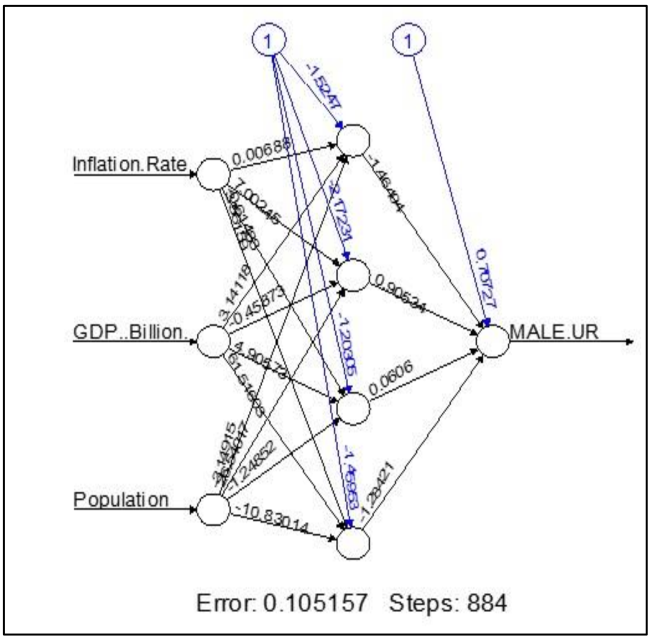

Figure 3. Neural Network Model Structure for Male Population

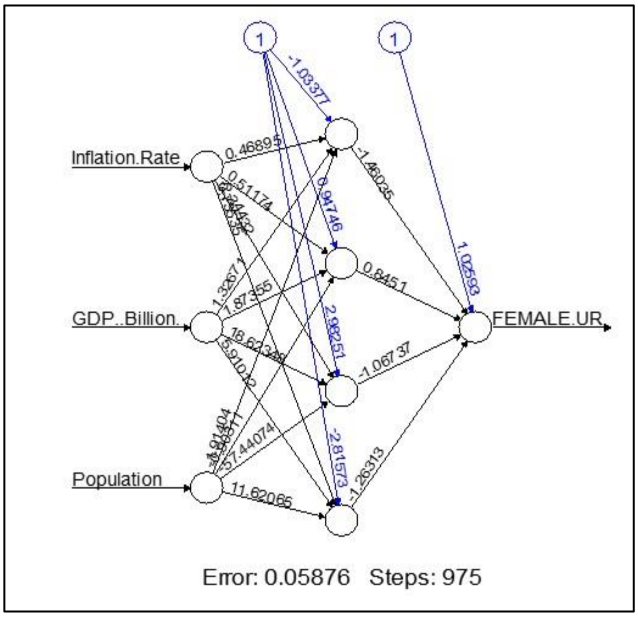

Figure 4. Neural Network Model Structure for Female Population

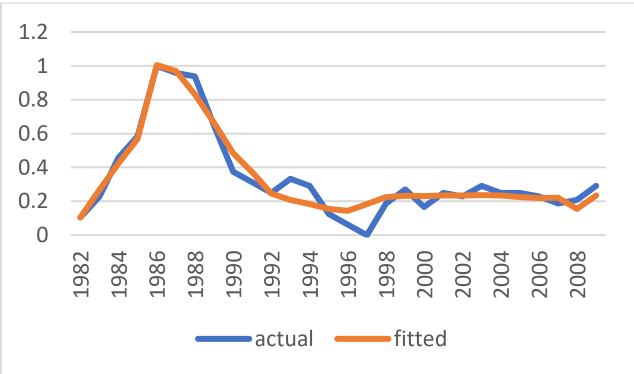

Figure 5. Actual and Fitted value of Malaysia Unemployment Rate for Male Population using NN4

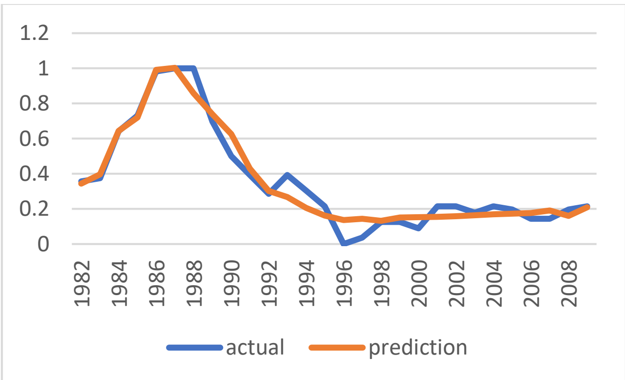

Figure 6. Actual and Fitted value of Malaysia Unemployment Rate for Female Population using NN4

In finding the best NN model for forecasting the unemployment rate for both male and female population, the performance of forecast accuracy of all NN models was evaluated based on testing data set from the year 2010 to 2019. The model with the smallest values of RMSE and MAE was used in forecasting Malaysia's unemployment rate. According to Tashman (2000), the best model in the in-sample evaluation may not necessarily produce the most accurate forecast in the out-sample evaluation. Although the best model was chosen beforehand based on the lowest value of MAE and RMSE on the training data-set, checking the performance of all models fitted on the testing data-set from the year 2010 to 2019 was still required.

The forecast accuracy of Malaysia unemployment rate of all possible NN models for male and female population is obtained and shown in Table 3. The results indicated that Model NN4 had the lowest values of RMSE and MAE for males while Model NN2 for females. Hence, the NN model with four hidden nodes and two hidden nodes became the best model to forecast Malaysia's unemployment rate for the male population and female population, respectively.

Table 3. Forecast Accuracy of Malaysia Unemployment Rate for the Year 2010 to 2019

Model	**Male**		**Female**	
	RMSE	**MAE**	**RMSE**	**MAE**
NN2	0.0442	0.0382	**0.0526**	**0.0448**
NN3	0.1415	0.1372	0.1224	0.1153
NN4	**0.0389**	**0.0316**	0.0697	0.0643
NN5	0.1260	0.1215	0.0822	0.0732
NN6	0.2553	0.2495	0.2133	0.2020

Table 4 shows the forecast value of unemployment rate for male and female population. For males, the trend of forecast rates showed a gradual constant throughout the years which was around 3.1. For females, the trend for forecast rates showed a decrement in the year 2020 with 3.5 compared to 3.7 in 2019; whereas starting from the year 2021 to 2030, the trend showed a gradual constant of around 3.4 throughout the years. The trend of these forecast values is illustrated in Figure 7 and Figure 8 for both population, respectively. Both figures clearly show that the trend for the future unemployment rate in Malaysia for both genders in the next ten years will gradually be constant throughout the year of 2020 to 2030.

Table 4. Forecast value of Malaysia Unemployment from the Year 2020 to 2030

Year	Male	Female
2020	3.121527	3.549293
2021	3.136991	3.428369
2022	3.140317	3.395571
2023	3.137163	3.402781
2024	3.133738	3.412613
2025	3.132422	3.416099
2026	3.132702	3.415908
2027	3.133369	3.415123
2028	3.133745	3.414767
2029	3.133775	3.414743
2030	3.133663	3.414802

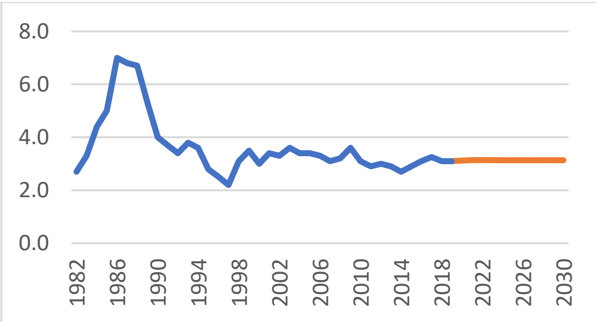

Figure 7. Trend of Forecast Malaysia Unemployment Rate for Male Population from the Year 2020 to 2030

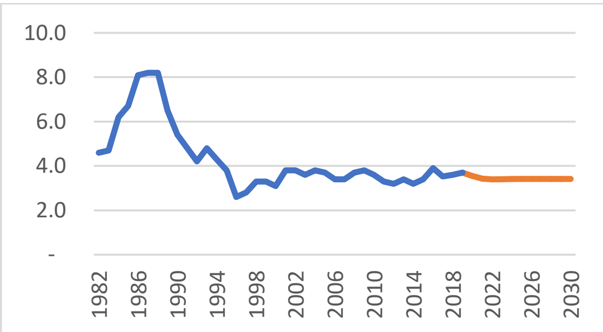

Figure 8. Trend of Forecast Malaysia Unemployment Rate for Female Population from the Year 2020 to 2030

V. CONCLUSION

Unemployment is a socio-economic problem faced by all countries in the world, affecting both the standard of living of the people and the socio-economic status of the nation. In most cases, it has become an important predictor and a fundamental tool for planning risk management by the government. For this reason, the unemployment rate is commonly recognised as the key labour market indicator which is included as one of the indicators for measuring progress towards achieving the SDGs under Goal 8. Hence, examining the trend and forecasting the future unemployment rate is essential. This study examined the trend of the unemployment rate in Malaysia by gender. From the year 1982 to 2019, the unemployment rate in Malaysia for gender females was mostly higher than the rate for gender males. Besides that, the gender gap in employment seemed to be narrower in 2030.

NN model was developed using the time series data of the unemployment rate in Malaysia for both genders by considering GDP, number of population and inflation rate as the input factors. Several NN models with different number of hidden nodes were developed and evaluated. Results showed that the best model for the male population was the NN model with four hidden nodes in one hidden layer while the NN model with two hidden nodes in one hidden layer was the best for the female population. Then, the 10-step ahead forecasts of the unemployment rate in Malaysia starting from the year 2020 to 2030 were generated for both male and female population. Results showed that the trend for the future unemployment rate in Malaysia for male and female population in the next ten years will gradually be constant throughout the year of 2020 to 2030. The gap rate between both males and females showed that the rate decreased from the year 2020 to 2022 and started to gradually become constant from the year 2021 to 2030.

However, the data coverage for this study was based on the historical data of the unemployment rate from 1982 to 2019 which was before the pandemic of Covid-19. The trend of the unemployment rate may be affected due to this unexpected pandemic; hence, future researchers may consider the data coverage until 2021 to consider the current situation of the unemployment rate in Malaysia. In addition, future researchers may also consider using other methods to contribute to the body of knowledge in forecasting Malaysia's unemployment rate since to date, there are only a few studies being conducted on forecasting Malaysia's unemployment rate. The development of the NN model in this study only used a few independent variables as inputs; therefore, further research can consider other variables to obtain more appropriate findings as the unemployment rate is affected by a lot of factors.

VI. ACKNOWLEDGEMENT

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