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Prediction of World Happiness Scenario Effective in the Period of COVID-19 Pandemic by Artificial Neuron Network (ANN), Support Vector Machine (SVM), and Regression Tree (RT)

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ABSTRACT

Objectives: To comparison, the effectiveness of prediction world happiness based on data of world happiness in the period of the COVIT-19 pandemic.

Methods: The prediction is used the qualitative analysis with further process of Artificial Neuron Network (ANN), Support Vector Machine (SVM), and Regression tree (RT) by MATLAB.

Results: The prediction of world happiness effective increasing of ladder weight that's the trend of happiness based on data of six valuable impact of happiness consist of GDP per capita, Social support, Healthy life expectancy, freedom to make life choices, Generosity, Corruption Perception, Residual error. The study found the significant ladder weight prediction increasingly used ANN, SVM, and regression tree analysis. The ANN # 3 model 6-20-1 is effective by the sign of the highest accuracy as 83.68%, among of diver error analysis i.e., SVM2 is found the significant testing RMSE0.5454, and the regression of Three2 model have significant testing of error RMSE 0.57815. The study found the prediction of World Happiness Effective Scenario on the period of COVIT-19 was found increasingly based on data of WHO from 2020 consist with Finland from 7.809 (7.748-7.870) score in 2017-19 with 7.889 (7.784-7.995) score in 2020.

Conclusions: This is an advantage of SVM compared to neural networks, which have multiple solutions associated with local minima. Also, SVM can be used with short-length data set. Therefore, SVM is simpler to use than ANN but is the first choice of option for the world happiness prediction is ANN. Because the error analysis was suitable with the prediction the effectiveness of the world happiness rate of ladder and error values less.

KEYWORDS: Artificial Neuron Network, Support Vector Machine, Regression tree, World Happiness, COVID-19.

INTRODUCTION

World happiness is the key of the Sustainable Development Solutions Network and reports use six factors to explain life evaluations. That explains important variables intended to illustrate lines of correlation factors in statistical. The world happiness was present in the numerical as a rate to measure the world scenarios which country are happy and that fulfills the world from sadness even the rate are the lowest that will stimulate all stockholders to recheck and gain as well as possible. It has impacts on the modes of people to demand happiness in terms of necessity and contribute to the society peached. Supplication of happiness in our society is called and in backward it's responded people cultivation especially in the period of the epidemic. Unknown the future has motivated slowness and unhappiness into several stakeholders in present society.

Regression studies reflect the relationships between a target or response variable and one or more explanatory variables. The case of a single explanatory variable, leading to simple regression, is easy to understand at least intuitively since the scatterplot tells the story. The reason for implementing this backpropagation artificial neural network is because this method can make predictions based on past data that has already taken place (Setti, Wanto, Syafiq, Andriano, & Sihotang, 2019; Afriliansyah et al, 2019; Febriadi, Zamzami, Yunefri, & Wanto, 2018). Backpropagation is a learning algorithm to reduce the level of error by adjusting its weight based on the difference in output and the desired target. Backpropagation is also a systematic method for multilayer training of Artificial Neural Networks (Nasution, Zamsuri, Lisnawita, & Wanto, 2018). The competence of developed SVM models has been proved by conducting a comparative study with artificial neural network-based models. Dan Assouline et al. (2017) estimated the rooftop solar PV potential for the urban areas in Switzerland using the combination of Support Vector Machine (SVM) and geographic information systems (GIS). Ji-Long, Chen et al. (2013) developed seven SVM models using different input attributes. All the SVM models give good performances and significantly outperform the empirical models. Modern statistical approaches to regression include k-nearest neighbors (Fix, & Hodges, 1951) kernel regression (Watson, 1964; Nadaraya, 1964) local polynomial regression (Stone, 1977; Cleveland, 1979) radial basis functions, neural networks, projection pursuit regression, adaptive splines, and others. However, the data is described in much more detail here. The credit goes to the source of Statistical Appendix for World Happiness Report 2020.

METHODS

The world happiness although is public data but it presents what's the world scenarios especially during the time faced by the pandemic. The study has the implementation approach to the context of social as well as the institutional attractive with comprising various stakeholders and their interactions. The study uses a qualitative base on nonlinearities of the domain are captured by the axis orthogonal partitions rather than by the models fitted within those partitions. The prediction is had effective for some time but it is a huge effect on varied people and their organizations. The research is to predict the measure of world happiness by using ANN, SVM, and RT that compared. The total input number is 157 data of the 2017-2019 ranking of happiness scores includes 153 countries/territories that have the happiness scores in the 2017-2019 period. It's appeared in regression analysis that uses data from outside the GWP survey, a WP5-year needs to have the necessary external information (GDP, healthy life expectancy, etc.). The regression analysis thus does not necessarily cover all of the countries/territories in the GWP. Nor does it necessarily cover all the countries/territories that are ranked by their happiness scores in this report. The underlying principle is that we always use the largest available sample. In a different kind of analysis/ranking, the largest available samples can be different. Regions some of the analysis includes dummy indicators for regions, namely Western Europe, Central and Eastern Europe, Commonwealth of Independent States, Southeast Asia, South Asia, East Asia, Latin America and Caribbean, North America and ANZ, Middle East and North Africa, and Sub-Saharan Africa. A later set of tables list individual countries by their region grouping. MATLAB R2010a computing software is used for developing the computer codes for ANN and empirical models. ANN models and regression tree the training data set are used, also to determine the empirical coefficients of the empirical models and for training the SVM, Further the models are validated using the testing dataset.

RESULTS AND DISCUSSION

The prediction of World Happiness before COVID-19

The statistics of GDP per capita (variable name GDP) in purchasing power parity (PPP) at constant 2011 international dollar prices are from the November 28, 2019 update of the World Development Indicators (WDI). The GDP figures for Taiwan, Syria, Palestine, Venezuela, and Djibouti, up to 2017, are from the Penn World

(1) GDP (GDP/C) per capita in 2019 is not yet available as of December 2019. We extend the GDP-per-capita time series from 2018 to 2019 using country-specific forecasts of real GDP growth in 2019 first from the OECD Economic Outlook No 106 (Edition November 2019) and then, if missing, forecasts from World Bank's Global Economic Prospects (Last Updated: 06/04/2019). The GDP growth forecasts are adjusted for population growth with the subtraction of 2017-18 population growth as the projected 2018-19 growth.

(2) Social support (SS) (or having someone to count on in times of trouble) is the national average of the binary responses (either 0 or 1) to the GWP question "If you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?"

(3) Healthy Life Expectancy (HLE). Healthy life expectancies at birth are based on the data extracted from the World Health Organization's (WHO) Global Health Observatory data repository. The data at the source are available for the years 2000, 2005, 2010, 2015, and 2016. To match this report's sample period (2005-2019), interpolation and extrapolation are used.

(4) Freedom to make life choices (FMLC) is the national average of responses to the GWP question "Are you satisfied or dissatisfied with your freedom to choose what you do with your life?"

(5) Generosity (GE) is the residual of regressing the national average of response to the GWP question "Have you donated money to a charity in the past month?" on GDP per capita.

6) Corruption Perception (CP): The measure is the national average of the survey responses to two questions in the GWP: "Is corruption widespread throughout the government or not" and "Is corruption widespread within businesses or not?" The overall perception is just the average of the two 0-or-1 responses. In case the perception of government corruption is missing, we use the perception of business corruption as the overall perception. The corruption perception at the national level is just the average response of the overall perception at the individual level.

Table 1

Code and definition of variables used in estimates

No	Code	Valuables	Description
1	GDP/C	GDP per Capita	The GDP growth forecasts are adjusted for population growth with the subtraction of 2017-18 population growth as the projected 2018-19 growth.
2	SS	Social Support	The national average of the binary responses (either 0 or 1) to the GWP question "if you were in trouble, do you have relatives or friends you can count on to help you, whenever you need them or not?"
3	HLE	Healthy Life Expectancy	Healthy life expectancies at birth are based on the data extracted from the World Health Organization's (WHO) Global Health Observatory data repository.

4	FMLC	Freedom to Make Life Choices	The national average of responses to the GWP question "Are you satisfied or dissatisfied with your freedom to choose what you do with your life?"
5	GE	Generosity	The residual of regressing national average of response to the GWP question "Have you donated money to a charity in the past month?" on GDP per capita.
6	CP	Corruption Perception	The measure is the national average of the survey responses to two questions in the GWP. "Is corruption widespread throughout the government or not" and "Is corruption widespread within businesses or not?"

The measurement of world happiness was rankings of country-based this year (2019) on the pooled results from Gallup World Poll surveys from 2015-2017 even it change and stability. There is a new top-ranking country as Finland, but the top ten positions are held by among a group of countries as in the last two years. Four different countries have hit on the top spot since 2015 was Switzerland, Denmark, Norway, and Finland. The part period from 2008-2010 was faced with the financial crisis especially 2007-2008 impacted to the ranking (Helliwell, Layard, & Sachs, 2018) (Table 1).

Table 2

The predictor of regressions to explain average happiness across countries in the past 2005-2017. (Pooled OLS) (KR, & Blessie, 2018)

Independent Variable	Dependent Variable			
	Cantril Ladder	Positive Affect	Negative Affect	Cantril Ladder
GDP/C	0.311	-0.003	0.011	0.316
	(0.064)***	(0.009)	(0.009)	(0.063)***
SS	2.447	0.26	-0.289	1.933
	(0.39)***	(0.049)***	(0.051)***	(0.395)***
HLE	0.032	0.0002	0.001	0.031
	(0.009)***	(0.001)	(0.001)	(0.009)***
FMLC	1.189	0.343	-0.071	0.451
	(0.302)***	(0.038)***	(0.042)*	(0.29)
GE	0.644	0.145	0.001	0.323
	(0.274)**	(0.03)***	(0.028)	(0.272)
CP	-0.542	0.03	0.098	-0.626
	(0.284)*	(0.027)	(0.025)***	(0.271)**
Positive affect				2.211
				(0.396)***
Negative affect				0.204
				(0.442)
Year fixed effects	Included	Included	Included	Included

Number of countries	157	157	157	157
Number of obs.	1394	1391	1393	1390
Adjusted R-squared	0.742	0.48	0.251	0.764

Notes: This is a pooled OLS regression for a tattered panel explaining annual countrywide common Cantril ladder responses from all to be had surveys from 2005 to 2017. See Technical Box 1 for distinct facts approximately every of the predictors. Coefficients are pronounced with strong widespread mistakes clustered via way of means of us of in parentheses. ***, **, and * indicate importance on the 1, 5, and 10 percentage ranges respectively.3.2 Prediction of World Happiness after COVID-19.

Table 2 is predication in World Happiness report 2017 the major difference base dataset from 2017. The resulting changes to the estimated equation are very slight "Implementation of neural networks in predicting the understanding level of students subject," (Sumijan, Windarto, Muhammad, & Budiharjo, 2016). It's four equations in Table 3 as first equation explain national average life evaluation in six dimensions consist of GDP, SS, HLE, FMLC, GE, and CP. The six variables explained almost three-quarters of the variation in countrywide annual Cantril Ladder rankings amongst countries. The usage of statistics from the years 2005 to 2017 predictive of model power (Rezaei, Shahbakhti, Bahri, Abdul Aziz, 2014) is little modified if the year constant consequences in the model are removed, falling from 74.2% to 73.5% in terms of the adapted R-squared.

World happiness prediction using ANN, SVM, and RT

The current study uses architectural 3 models, consist of ANN # 1 Model 6-10-1 (6 stands for input layers, 10 stands for hidden layer neurons, and 1 stand for the output layer), ANN # 2 Model 6-15-1 (6 stands for input layers, 15 stands for hidden layer neurons, and 1 stand for the output layer), ANN # 3 Model 6-20-1 (6 stands for input layers, 20 stands for hidden layer neurons, and 1 stand for the output layer). The parameters used are bipolar sigmoid activation function and linear function (tansig and purelin) (Nasution, Zamsuri, Lisnawita, & Wanto, 2018), gradient descent training function, epochs 1000, learning rate 0.01, and minimum error 0.001-0.01. In terms of 5 architectural models are using the MATLAB software (Dixit, Chaudhary, & Sahni, 2020; Iranpour, Erfani, & Ebrahimi, 2018). The results obtained the best architecture models with ANN # 3 Model 6-20-1. The testing present results of prediction as an effective increasing ladder of happiness found accuracy 83.68%.

The Backpropagation learning algorithm (BPLA) has become a famous learning algorithm among ANNs. Backpropagation ANNs have been widely and successfully applied in diverse applications, such as pattern recognition, location selection, and performance evaluations (Gallup, 2017; Taghavifar, KhalilaryaSh, Jafarmadar, 2014). BP ANN is the most extensively used ANN model (Fig. 1). The typical topology of BP-ANN involves three layers: input layer, where the data are introduced to the network; hidden layer, where the data are processed, and output layer, where the results of the given input are produced (Huang, & Wu, 2017). The backpropagation training method involves feedforward of the input training pattern,

calculation and backpropagation of error, and adjustment of the weights in synapses (Tarigan, Nadia, Diedan, & Suryana, 2017).

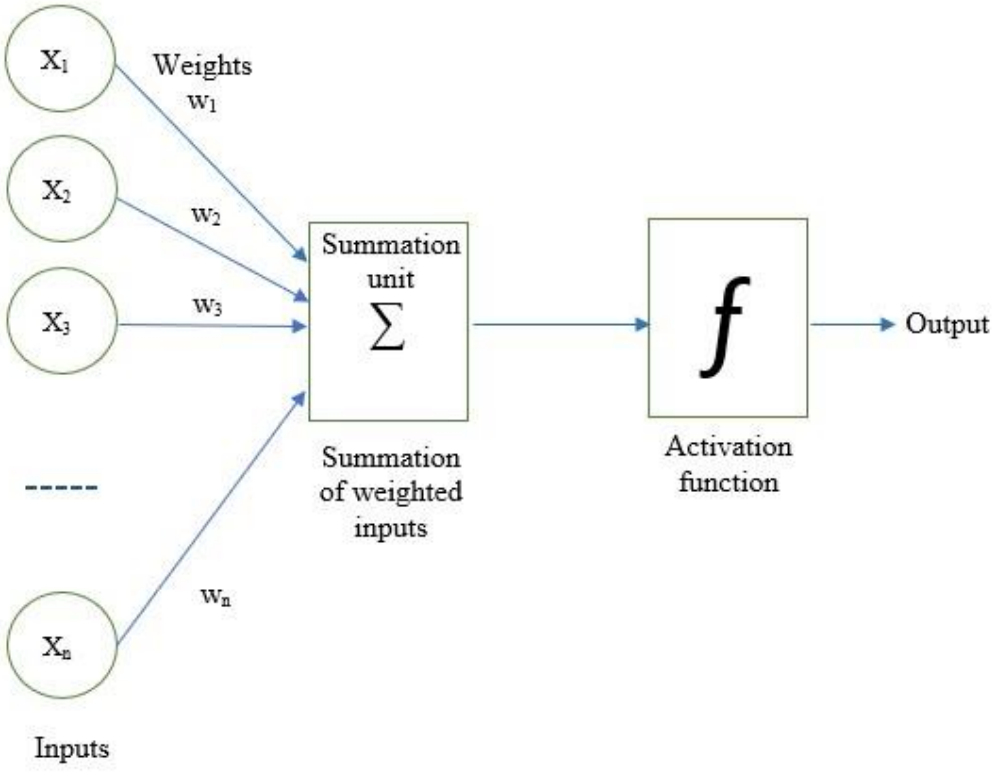
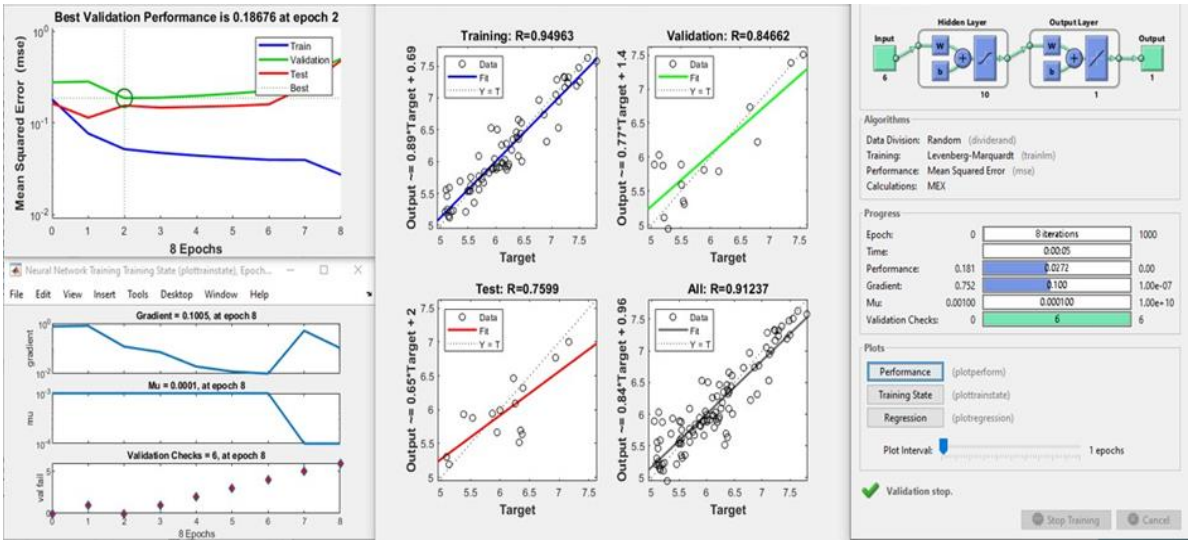


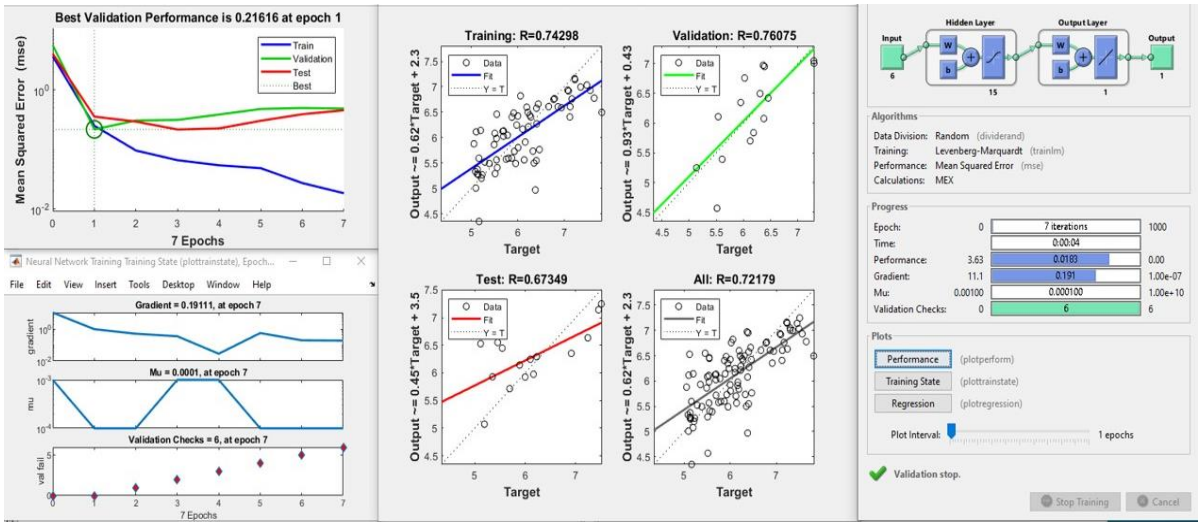
Fig. 1 A model sampling of BP-ANN

The comparison between R measuring's architecture 3 modes of ANN



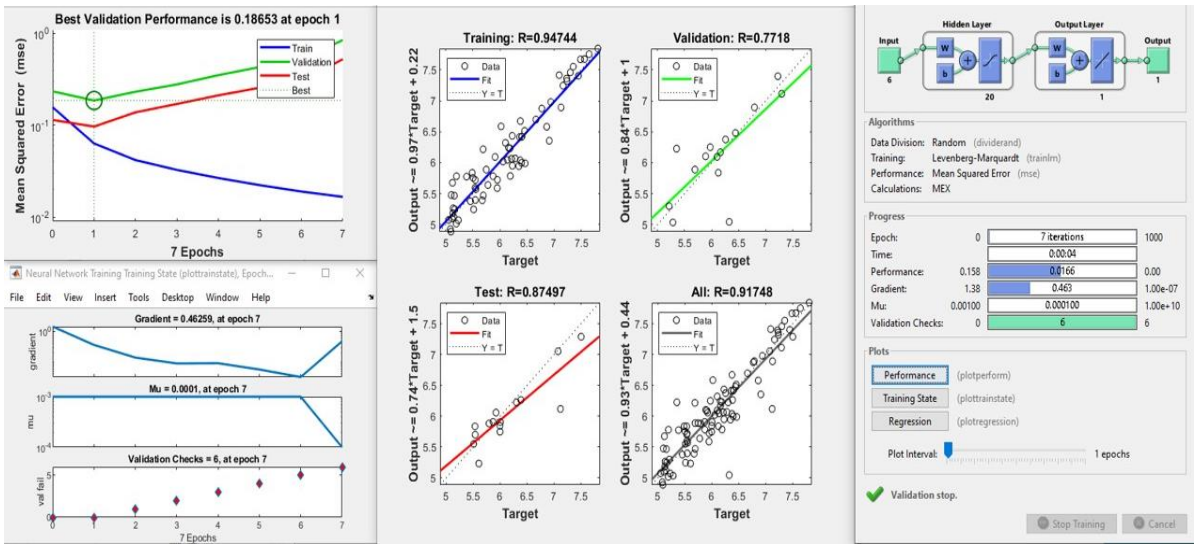
(a) (b) (C)

Fig.2 Architecture ANN # 1 a. epoch 8 b. R 0.91 c. Model 6-10-1



(a) (b) (C)

Fig.3 Architecture ANN # 2 a. epoch 7 b. R 0.72 c. Model 6-15-1



(a) (b) (C)

Fig.4 Architecture ANN # 2 a. epoch 7 b. R 0.92 c. Model 6-20-1

Table 3 Results of training and testing architecture 3 models

No	Architecture	Training					Testing		
		Time	Epoch	R	MSE	Accuracy	R	MSE	Accuracy
1	ANN # 1	0:00:01	8	0.91	0.027	91.24%	0.7	1.18E-24	69.43%
2	ANN # 2	0:00:04	7	0.72	1.83E-02	72.18%	0.43	0.026	43.33%
3	ANN # 3	0:00:04	7	0.92	1.66E-02	91.75%	0.84	0.002	83.68%

The current study uses architectural 3 models, consist of ANN # 1 Model 6-10-1 (6 stands for input layers, 10 stands for hidden layer neurons, and 1 stand for the output layer), ANN # 2 Model 6-15-1 (6 stands for input layers, 15 stands for hidden layer neurons, and 1 stand for the output layer), ANN # 3 Model 6-20-1 (6 stands for input layers, 20 stands for hidden layer neurons, and 1 stand for the output layer). The parameters used are bipolar sigmoid activation function and linear function (tansig and purelin) (Nasution, Zamsuri, Lisnawita, & Wanto, 2018), gradient descent training function, epochs 1000, learning rate 0.01, and minimum error 0.001-0.01. In terms of 5 architectural models are using the MATLAB software (Dixit, Chaudhary, & Sahni, 2020; Iranpour, Erfani, & Ebrahimi, 2018). The results obtained the best architecture models with ANN # 3 Model 6-20-1. The testing present results of prediction as an effective increasing ladder of happiness found accuracy 83.68%.

Fig. 5 is presented the comparison of accuracy (Lee, & Chen, 2020) between training and testing accuracy among of three models the most effective model is ANN#3 Model 6-20-1 had been training accuracy 91.75% and testing accuracy 83.68% another model was less effective seen instant ANN#1 Model 6-10-1 training accuracy 91.24% and testing accuracy 69.43%. The least effective is ANN#2 Model 6-15-1 training accuracy 72.18% and testing accuracy 43.33%.

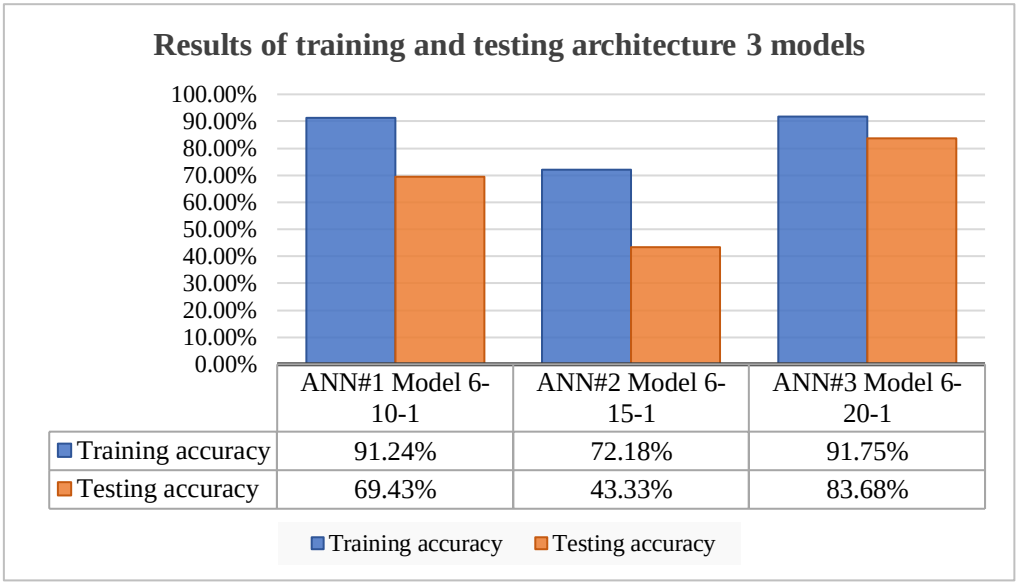


Fig. 5 Graph result of training and testing architecture 3 models

SVM analysis

The SVM prediction is typically used SVM forecast to be forward of world happiness data (Kumar, Kumar, Dutt, & Swarnkar, 2020). The examination of six model of SVM are result of testing as model SVM1 RMSE 0.439, SVM2 RMSE 0.545, SVM3 RMSE 0.648, SVM4 RMSE 0.569, SVM5 RMSE 0.737, SVM6 RMSE 0.611. The best model determines by the weight of RMSE is SVM2 with the weight enclosed as the most influential and effective of developed SVM models. The SVM2 models have performed better of the ladder world happiness as RMSE 0.545 (Table 4).

Table 4 SVM Six model analysis

Model no.	Optimizer options	Model type	Input attributes	Rank	Training				Testing			
					RMSE	R-Squared	MSE	MAE	RMSE	R-Squared	MSE	MAE
SVM1	Hyperparameter options disabled	Present: Medium Gaussian SVM Kernel function: Gaussian Kernel scale: 2.4 Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	1	0.4394	0.64	0.19307	0.35362	0.58885	0.01	0.34675	0.47971
SVM2	Hyperparameter options disabled	Present: Coarse Gaussian SVM Kernel function: Gaussian Kernel scale: 9.8 Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	2	0.4454	0.63	1.9837	0.34461	0.54542	0.15	0.29749	0.42619
SVM3	Hyperparameter options disabled	Present: Quadratic SVM Kernel function: Quadratic Kernel scale: Automatic Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	3	0.4487	0.62	0.20133	0.36398	0.64841	-0.2	0.42044	0.47615
SVM4	Hyperparameter options disabled	Present: Linear SVM Kernel function: Linear Kernel scale: Automatic Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	4	0.47499	0.57	0.22562	0.35679	0.56917	0.08	0.32395	0.45631
SVM5	Hyperparameter options disabled	Present: Cubic SVM Kernel function: Cubic Kernel scale: Automatic Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	5	0.56887	0.39	0.32361	0.405	0.73684	-0.55	0.54293	0.56635
SVM6	Hyperparameter options disabled	Present: Fine Gaussian SVM Kernel function: Gaussian Kernel scale: 0.6 Box constraint: Automatic Epsilon: Automatic Standardize data: true	GDP/C, SS, HLE, FMLC, G, CP	6	0.61977	0.27	0.38411	0.51623	0.61102	-0.06	0.37334	0.48515

Table 4 shows six models of architectures on SVMs that the column gives a comparison between training and testing features on errors analysis of four types as RMSE, R-Squared, MSE, and MAE. The best of the lowest training algorithm is Model SVM1 RMSE 0.439, R-Squared 0.64, MSE 0.354, and the same model SVM1 has fond the testing lowest error measurement was RMSE 0.589, R-Squared 0.01, MSE 0.348, and MAE 0.480. The model SVM1 algorithm is the height effective to predict world happiness.

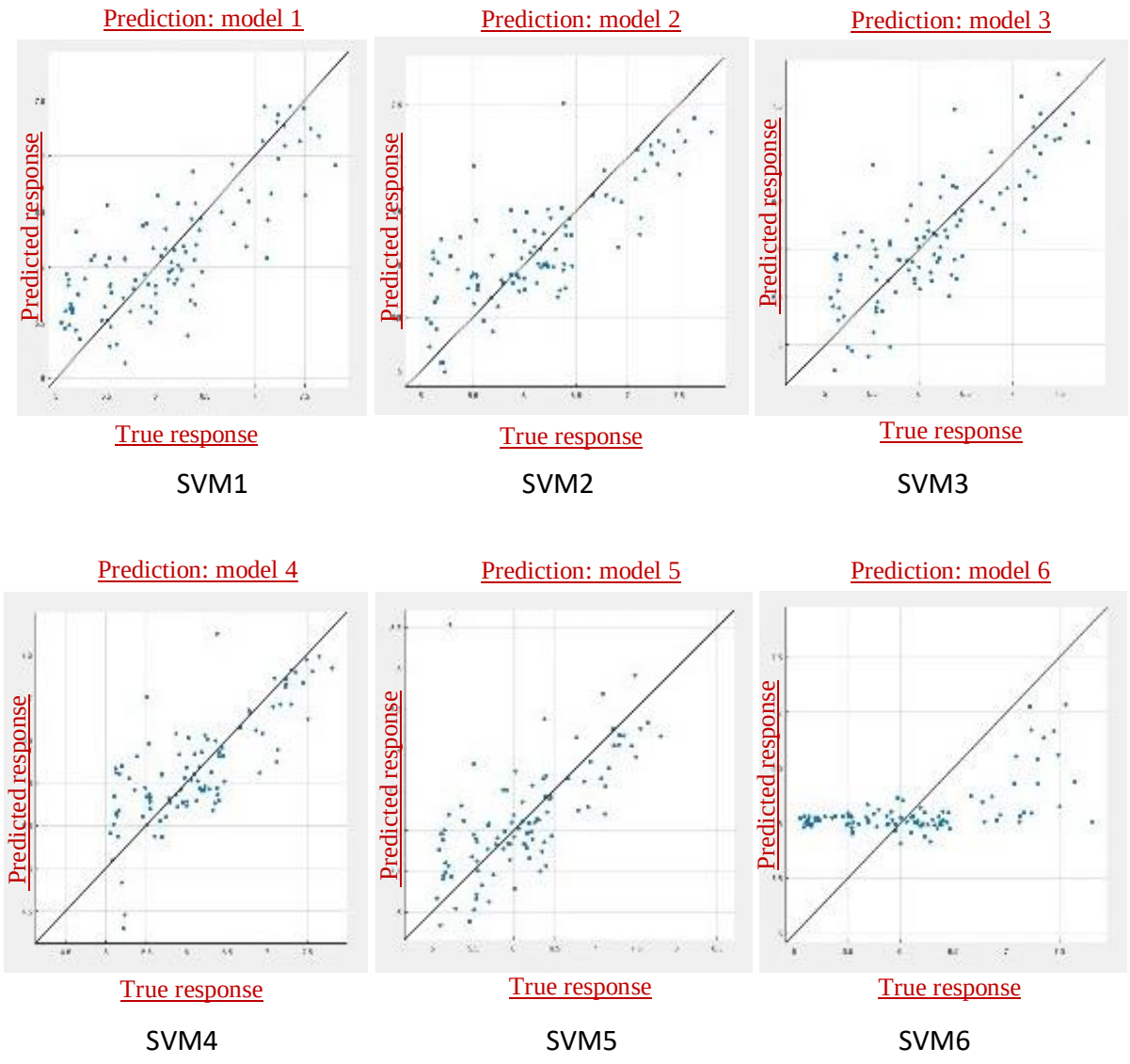
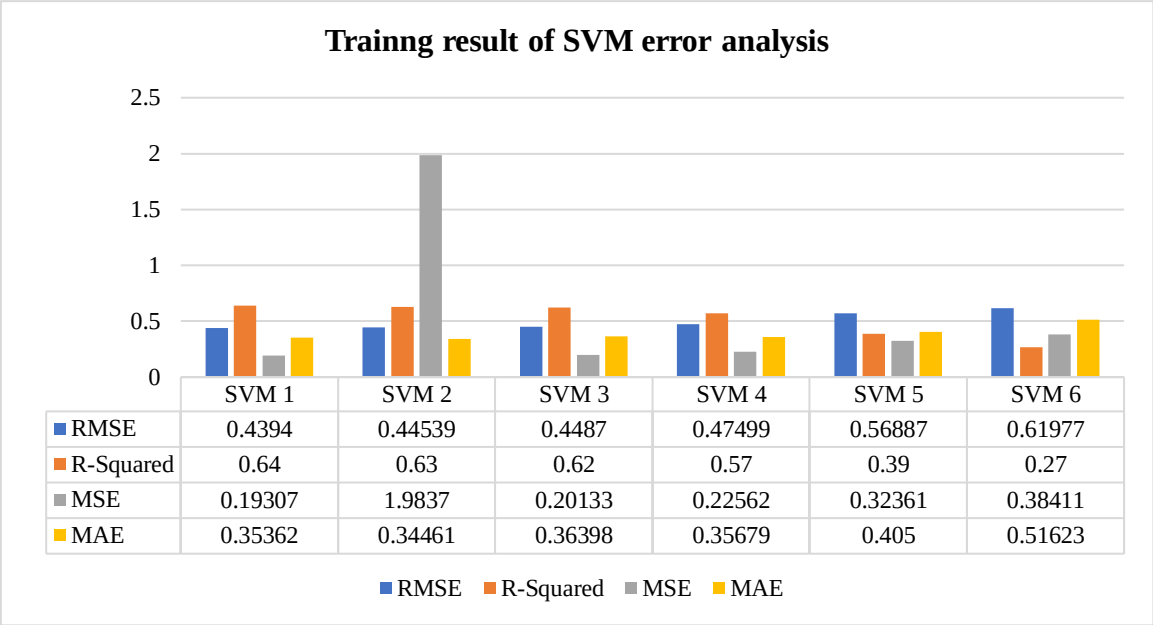


Fig. 6 Prediction used linear regression of world happiness in of different SVM model.

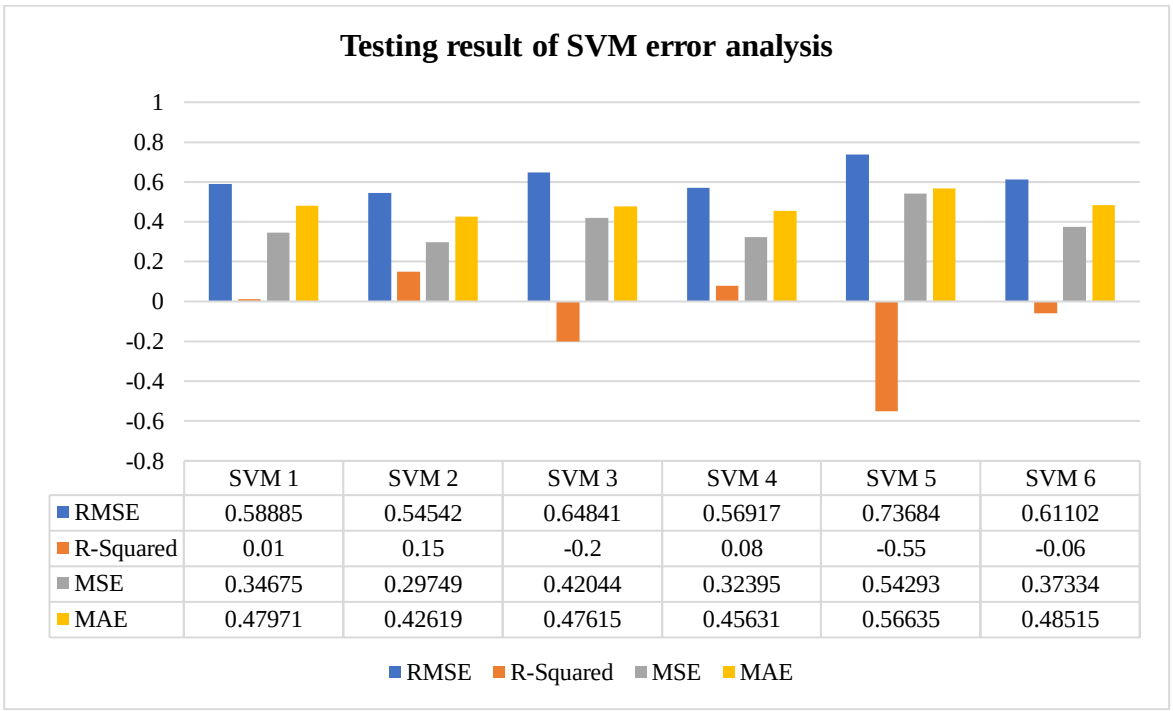
Linear regression has used SVM (Du Ni, Xiao, & Feng, 2018) to predict in Fig. 6 of the present study, which is showing the fragmentation of information in numerous measuring of world happiness approach measure the residuals square and then sum up the squares to modeling the relationship between y-axis is predicted response and x-axis is a true response. The multiple R-squares was SVM1: 0.64, SVM2: 0.63, SVM3: 0.62, SVM4:0.57, SVM5: 0.39, and SVM6: 0.27.



	SVM 1	SVM 2	SVM 3	SVM 4	SVM 5	SVM 6
RMSE	0.4394	0.44539	0.4487	0.47499	0.56887	0.61977
R-Squared	0.64	0.63	0.62	0.57	0.39	0.27
MSE	0.19307	1.9837	0.20133	0.22562	0.32361	0.38411
MAE	0.35362	0.34461	0.36398	0.35679	0.405	0.51623

Fig. 7 Training result of SVM error analysis

Fig. 7 showed the measurements of training result of the six model SVM error analysis (Kawintiranon, Buatong, & Vateekul, 2016) in in present study where the errors (RMSE) is found the model of SVM1: 0.439, SVM2: 0.445, SVM3: 0.449, SVM4: 0.475, SVM5: 0.569, and SVM6: 0.620. R-squared are measuring of different models seeing as SVM1: 0.64, SVM2: 0.63, SVM3: 0.62, SVM4: 0.57, SVM5: 0.39, and SVM6: 0.27. The measure of MSE are SVM1: 0.193, SVM2: 1.984, SVM3: 0.201, SVM4: 0.226, SVM5: 0.324, and SVM6: 0.384. At last the measure of MAE is SVM1: 0.354, SVM2: 0.345, SVM3: 0.364, SVM4: 0.357, SVM5: 0.405, and SVM6: 0.516.



	SVM 1	SVM 2	SVM 3	SVM 4	SVM 5	SVM 6
RMSE	0.58885	0.54542	0.64841	0.56917	0.73684	0.61102
R-Squared	0.01	0.15	-0.2	0.08	-0.55	-0.06
MSE	0.34675	0.29749	0.42044	0.32395	0.54293	0.37334
MAE	0.47971	0.42619	0.47615	0.45631	0.56635	0.48515

Fig. 8 Testing result of SVM error analysis

Fig. 8 has explored measurements (Lotsari, Verykios, Panagiotakopoulos, & Kalles, 2014) of testing result of the six model SVM error analysis (Ji-Long, Chen et al., 2013) in four types of errors consist of RMSE, is found the model of SVM1: 0.589, SVM2: 0.546, SVM3: 0.648, SVM4: 0.569, SVM5: 0.737, and SVM6: 0.611. R-squared are exhibited as SVM1: 0.01, SVM2: 0.15, SVM3: -0.2, SVM4: 0.08, SVM5: -0.55, and SVM6: -0.06. The measure of MSE are SVM1: 0.347, SVM2: 0.297, SVM3: 0.420, SVM4: 0.324, SVM5: 0.543, and SVM6: 0.373. And the measure of MAE is SVM1: 0.480, SVM2: 0.426, SVM3: 0.476, SVM4: 0.456, SVM5: 0.566, and SVM6: 0.485.

RT analysis

The architecture is the 'traning' by three models consist of Tree1 model, Tree2 model, and Tree3 model. The tree analysis results of testing is the Tree1 RMSE 0.6399 R -0.17 MSE 0.4095 and MAE 0.5107, for the Tree2 RMSE 0.57815 R 0.05 MSE 0.3342 and MAE 0.44942, the last is Tree3 RMSE 0.59231 R 0 MSE 0.35083 and MAE 0.4823. The best model is the Tree3 model that has a significant (Dixit, Chaudhary, & Sahni, 2020) of RMSE as the lowest, and enclosed 0 is 0.57815 (Table 5).

Table 5 Regression tree output

Model no.	Optimizer options	Model type	Input attributes	Rank	Training				Testing			
					RMSE	R-Squared	MSE	MAE	RMSE	R-Squared	MSE	MAE
Tree1	Hyperparameter options disabled	Present: Medium Tree Minimum leaf size: 12 Surrogate decision splits: Off	GDP/C, SS, HLE, FMLC, G, CP	1	0.51504	0.5	0.26526	0.40775	0.63998	-0.17	0.40958	0.51078
Tree2	Hyperparameter options disabled	Present: Fine Tree Minimum leaf size: 4 Surrogate decision splits: Off	GDP/C, SS, HLE, FMLC, G, CP	2	0.55643	0.41	0.30961	0.43752	0.57815	0.05	0.33426	0.44942
Tree3	Hyperparameter options disabled	Present: Coarse Tree Minimum leaf size: 12 Surrogate decision splits: Off	GDP/C, SS, HLE, FMLC, G, CP	3	0.63953	0.23	0.40899	0.53915	0.59231	0	0.35083	0.48236

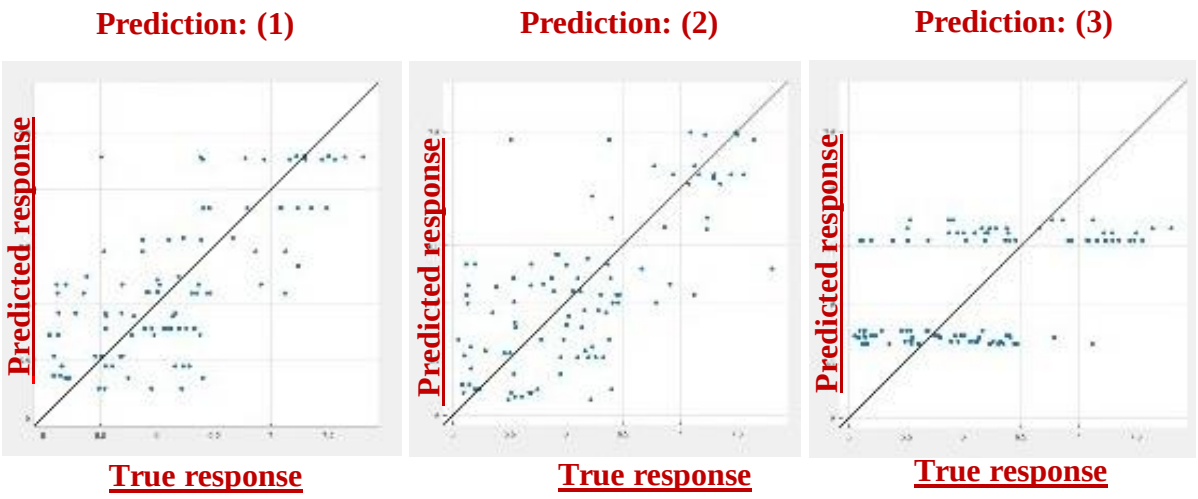
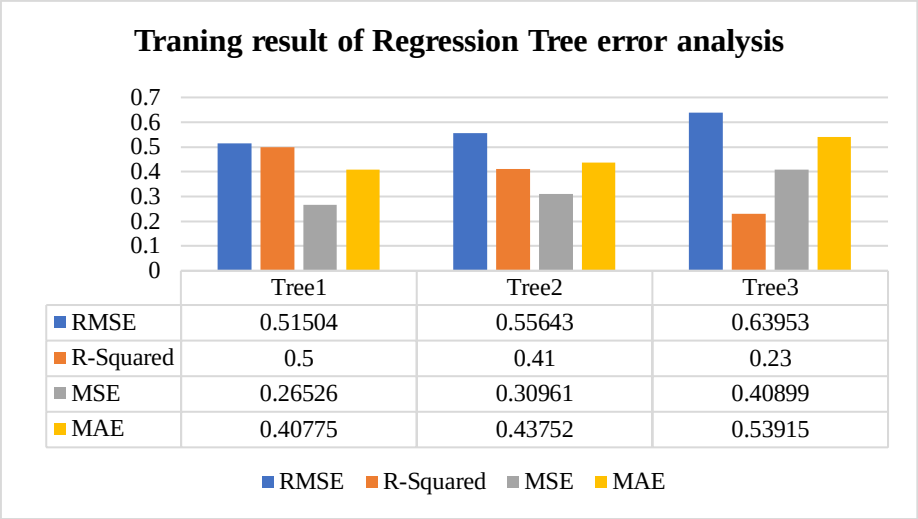


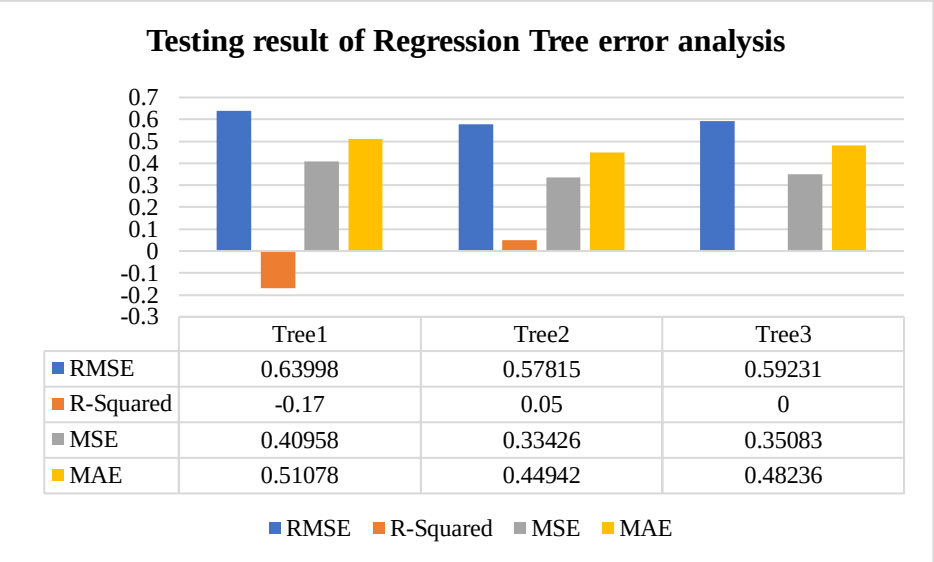
Fig. 6 Prediction used linear regression of world happiness in different RT models: (a) Tree 1, (2) Tree 2, and (3) Tree 3

In fig. 6 presented the prediction using linear regression of serval Regression Tree models. It predicts the value of the dependent variable of world happiness the y-axis is the predicted response and the independent variable of the x-axis is a true response.



	Tree1	Tree2	Tree3
RMSE	0.51504	0.55643	0.63953
R-Squared	0.5	0.41	0.23
MSE	0.26526	0.30961	0.40899
MAE	0.40775	0.43752	0.53915

Fig. 7 Graph training result of regression tree error analysis



	Tree1	Tree2	Tree3
RMSE	0.63998	0.57815	0.59231
R-Squared	-0.17	0.05	0
MSE	0.40958	0.33426	0.35083
MAE	0.51078	0.44942	0.48236

Fig. 8 Graph testing result of regression tree error analysis

Fig. 7 and 8 is presented error values of training and testing (Tofallis, 2020) results of Regression Tree. That compares between traing : testing values of error defferent model (Goff, Helliwell, & Mayraz, 2018; Nichols, & Reinhart, 2019) seem as RMSE Tree1 0.515:0.640, Tree2 0.556:0.578, and Tree3 0.640:0.592, R-squared Tree1 0.5:-0.17, Tree2 0.41:0.05, and Tree3 0.23:0, MSE Tree1 0.265:0.410, Tree2 0.310:0.334, and Tree3 0.409:0.351, MAE Tree1 0.410:0.511, Tree2 0.438:0.450, and Tree3 0.540:0.482

Conclusion

The comparison between the three methods are ANN, SVM, and regression tree was significant prediction method is ANN # 3 6-20-1 model by testing the accuracy 83.68%. SVM2 is found the significant testing as R 0.15 and RMSE0.5454. The regression of the Three2 model has significant testing of error RMSE 0.57815 that the lowest and enclosed O. The ANN models have accurate results than the empirical and SVM models. But ANN requires a large training time for a huge dataset and also the optimization step is very complex. The accuracy of ANN varies every time a new simulation is run. But SVM delivers a unique solution since the optimality problem is convex. This is an advantage of SVM compared to neural networks, which have multiple solutions associated with local minima. Also, SVM can be used with short-length data set. Therefore, SVM is simpler to use than ANN but is the first choice of option for the world happiness prediction is ANN. Because the error analysis was suitable with the prediction the effectiveness of the world happiness rate of ladder and error values less.

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Reference

1. Afriliansyah, T. et al. (2019). “Implementation of Bayesian Regulation Algorithm for Estimation of Production Index Level Micro and Small Industry.” Journal of Physics: Conference Series, 1255(1), 1–6.
2. Cleveland, W.S. (1979). Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association, 74, 829-836.
3. Dan Assouline, Nahid Mohajeri, & Jean-Louis Scartezzini (2017). Quantifying rooftop photovoltaic solar energy potential: a machine learning approach. Sol. Energy. 141, 278-296.
4. Dixit, S., Chaudhary, M., & Sahni, N. (2020). Network Learning Approaches to study World Happiness. Cornell University. arXiv preprint arXiv:2007.09181.
5. Du Ni, M. K., Xiao, Z., & Feng, X. (2018). Exploring Subjective Well-Being Factors with Support Vector Machine. International Journal of Engineering & Technology, 7(3.36), 164-166.
6. Febriadi, B. Zamzami, Z. Yunefri, Y. and Wanto, A. (2018). Bipolar function in backpropagation algorithm in predicting Indonesia’s coal exports by major destination countries. IOP Conference Series: Materials Science and Engineering, 420 (012087). 1–9.

7. Gallup. (2017). World Poll surveys. http://news.gallup.com/poll/216377/new-indexshows-least-accepting-countries-migrants.aspx.
8. Goff, L., Helliwell, J. F., & Mayraz, G. (2018). Inequality of Subjective Well-Being as a Comprehensive Measure of Inequality. Economic Inquiry, 56(4), 2177-2194.
9. Iranpour, S. M., Erfani, N., & Ebrahimi, M. I. (2018). Explanation and Prediction of Quality of Life and Happiness Based on the Time Span of Students. Iranian Journal of Psychiatric Nursing, 5(6), 8-15.
10. Ji-Long Chen, Guo-Sheng Li, & Sheng-Jun Wua (2013). Assessing the potential of support vector machine for estimating daily solar radiation using sunshine duration, Energy Convers Management, 75, 311-318.
11. Kawintiranon, K., Buatong, Y., & Vateekul, P. (2016). Online music emotion prediction on multiple sessions of EEG data using SVM. In 2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE). IEEE, 1-6.
12. KR, M. V., & Blessie, E. C. (2018). Efficient prediction of Student Performance Using hybrid SVM Classifier. International Journal of Computer Science & Engineering Technology (IJCSET). 9(03), 32-39.
13. Kumar, S. A., Kumar, H., Dutt, V., & Swarnkar, H. (2020). COVID-19 Pandemic analysis using SVM Classifier: Machine Learning in Health Domain. Global Journal on Application of Data Science and Internet of Things, 4(1).
14. Lee, C. C., & Chen, M. P. (2020). Happiness sentiments and the prediction of cross-border country exchange-traded fund returns. The North American Journal of Economics and Finance, 54, 101254.
15. Lotsari, E., Verykios, V., Panagiotakopoulos, C., & Kalles, D. (2014). A Learning Analytics Methodology for Student Profiling in Artificial Intelligence: Methods and Applications. 300-312.
16. Nadaraya, E.A. (1964). On estimating regression. Theory of Probability and its Applications, 9, 141-142.
17. Nasution, N., Zamsuri, A., Lisnawita, L., & Wanto, A. (2018). Polak-Ribiere updates analysis with binary and linear function in determining coffee exports in Indonesia. IOP Conference Series: Materials Science and Engineering, 420(12089), 1–9.
18. Rezaei J, Shahbakhti M, Bahri B, Abdul Aziz A. (2014). Performance prediction of HCCI engines with oxygenated fuels using artificial neural networks. Appl Energy, 138, 460–73.
19. Setti, S., Wanto, A., Syafiq, M., Andriano, A., & Sihotang B. K. (2019). Analysis of Backpropagation Algorithms in Predicting World Internet Users. Journal of Physics: Conference Series, 1255(1), 1–6.
20. Stone, C.J. (1977). Consistent nonparametric regression. The Annals of Statistics, 5, 595-645.
21. Sumijan, A. Windarto, P., Muhammad, A., & Budiharjo, (2016). Implementation of Neural Networks in Predicting the Understanding Level of Students Subject. International Journal of Software Engineering and Its Applications, 10(10), 189–204.
22. Tofallis, C. (2020). Which formula for national happiness? Socio-Economic Planning Sciences. 70, 100688.
23. Watson, G.S. (1964). Smooth Regression Analysis. The Indian Journal of Statistics, Series A, 26, 359-372.