ARTIFICIAL NEURAL NETWORK IN FORECASTING RICE YIELDS THROUGH CLIMATIC FACTORS

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ABSTRACT

There is a need to monitor the rice production capability of the country in order to maximize its agricultural economy. Establishing a mathematical model that will forecast rice yield will help mitigate the threat of famine and attain the goal of the country to be self-sufficient. Rice production needs specific climatic conditions to attain optimum yield. In the Philippines, studies showed that climate changes have become a major threat to the agricultural economy. To develop regional and national policies concerning food security, accurate forecasts of rice yield are critical. The ability to forecast crop yield in response to climate change such as drought and high temperatures has been addressed variably by governments, farmers, and markets. The challenge in rice yield forecasting is to determine rice crop yields before harvesting. This study will introduce a scalable and inexpensive method to forecast rice crop yields using data from various government agencies. Climatic data, particularly pressure, temperature, relative humidity, rainfall, wind, cloudness and sunshine from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) and rice yield from the Department of Agriculture (DA) all in Region III will be used in this study. The training data are the said climactic factors and rice yield from 2009 to 2017 while the test data will be from 2018. Using Artificial Neural Network (ANN) with Back-Propagation Algorithms, rice yield will be forecasted to develop a mathematical model. This study will also help determine through ANN which among the climactic factors significantly contributed to rice yield.

KEYWORDS: Artificial Neural Network, Forecasting, Rice Yield, Climatic factors, Back-Propagation Algorithm

I. INTRODUCTION

Rice is one of the country's top staple food and foremost crop, and planting such is also a source of income for others [1]. Rice plays an important role in the Philippine economy and development. Tools for both the farmers and those who plan and manage the country's economy should be available. An estimated 2.3 million Filipinos had been reported to experience hunger due to lack of food to eat during the first three months of 2018 [2]. This problem can be due to several factors: underemployment, higher food prices and shortage of food supply among others. Despite being an archipelago and vast lands for agricultural products, a number of Filipino household is still hungry.

Food security is not only a concern in the Philippines. It is mostly experienced worldwide. With increasing population, food security becomes compromised as more people consume one or two crops included in their diet [3]. In addition, the United Nations (UN) Organization has also attempted to address the insufficiency of food across the globe. The Food and Agriculture Organization (FAO) had reported that in 2015, 793 million people are malnourished. To reach the 2030 zero hunger goal of the organization, practical ways of reducing the number of people who are food insecure has been determined [4].

An Israeli agriculturist recognized the fertility of Philippine soils that can even feed the whole world [5]. The Philippines has vast lands for agriculture and yet, the government continues to import rice from nearby countries. The necessity of importing rice is motivated by the insufficient domestic production [6] and a way of the government to address food security and poverty alleviation. However, this act of the government will not be able to sustain the increasing number of people to be fed and future economic factors will also be at risk. Instead of rice importation as the first option, it should be the last option of the government. To make rice importation the last option for the government, a method or a technology should be developed in order to determine if such action or decision is needed.

Japan, for example, has attempted to apply IT such as sensing, communications and bio-technology in agriculture not only to revitalize their agriculture but also to help the farmers' trade products [7]. This report indicated that Japanese farmers use IT in several ways: for sales and management, for production management, for checking market prices, weather data, government farm policies, and for purchasing materials. Also, the application of IT in agriculture was beneficial among the farmers as it helped them gather data. It further improved farm management, speedy data adjustment, sales expansion and customer base. If these are the realities of the Japanese farmers in utilizing IT in their practice, then our very own farmers may also enjoy the same advantages and benefits that technology will bring.

Like the rest of Asia, the Philippine rice crop suffers either from too little water (drought) or too much of it (inundation). Limited land and water resources to produce its rice and corn requirement, high prices of agricultural inputs, rising population, and climatic factors, including adverse environmental factors that cause stresses on crops have all played roles in constraining the nation to reach its food self-sufficiency goals [6]. Most studies on constraints to high rice yield indicate water as the main factor for yield gaps and yield variability from experiment stations to farms. Adequate water supply is one of the most important factors in rice production. Through the years, huge sum of money has been invested in agriculture primarily to finance construction and development of irrigation systems. Efforts in irrigated agriculture, however, have been challenged by natural calamities and the inadequacy of funds for regular maintenance activities. This results to deterioration of infrastructure, which consequently impacts sustainable agricultural production.

The said scenarios along with other climatic and agronomic factors, contributes to the insufficiency of rice production. The fluctuations of temperature per year were identified as the main source of uncertainty in predicting crop yield while the increasing population threatens food security that pervades to be an imminent challenge for many governments [8]. However, in the Philippines much study shows that climate changes have become a major threat to the agricultural economy. Keeping this in mind, this study is embarked on the impacts of climatological factors specifically pressure, temperature, relative humidity, rainfall, wind, cloudness, and sunshine. These data are from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) while the rice yield data sets are from the Department of Agriculture (DA). Both PAGASA and DA gave the data sets which are all from Region III.

Statistical models based climatic factors and its effect in crop yields, or a combination of the two, are now widely used to investigate the effects of recent and future climate changes on crop yields. Various researches have been done exploring the connections between large-scale climatologically phenomena and crop yield. Artificial Neural Networks (ANN) has been demonstrated to be powerful tools for modeling and prediction, to increase their effectiveness and as well as other algorithm. Rice crop yield prediction in this study will be using parameters related to climate and agronomical factors.

It is deemed that there is a need to monitor the rice production capability of the country in order to maximize its agricultural economy [9]. Establishing a tool that will predict rice production will help mitigate the threat of famine and will help attain the goal of the country to be self-sufficient. Rice production needs specific climatic conditions to attain optimum yield in rapport with the economy [10]. A changing climate could have both beneficial and harmful effects on crops. Climate change over time has greatly affected the country's agricultural economy. To develop regional and national policies concerning food security, accurate predictions of crop yield are critical. The ability to predict crop yield in response to climate change such as drought and high temperatures has been addressed variably by governments, farmers, and markets [8]. A central challenge is rice yield estimation, which is to predict rice crop yields before harvesting. This study will introduce a scalable and inexpensive method to predict crop yields using publicly available data from government agencies.

A. Statement of the Problem

The study aimed to provide a validated set of artificial neural network models in forecasting rice yields through climatic factors.

Specifically, this study aimed to answer the following:

1. How to construct feed-forward neural network?
2. How to apply back propagation algorithm in adjusting the weights of neurons in an artificial neural network?
3. How to evaluate the accuracy of the developed rice yield forecasting models?

B. Scope and Limitations of the Study

The study is focused on providing a validated set of artificial neural network models in forecasting rice yields through climatic factors. First, the researchers described the locale, Region III, in terms of climatological parameters and rice yields for the past ten (10) years. The reports from PAGASA situated in Clark Air Base Zone on climatic factors particularly pressure, temperature, relative humidity, rainfall, wind, cloudiness and sunshine in Region 3 were considered in this study. The said reports detailed the climatic factors from 2008 to 2018. The rice yield reports from 2009 to 2018 came from the Regional Field Office III of the Department of Agriculture. Region III will be described in terms of the climatic factors and rice yield reports from 2009 to 2018. Using Albeit data preprocessing for data cleaning, the researchers conducted collecting the data, cleaning the data, analyzing the data, and publishing the results to the locale's representatives. A feed-forward neural network with single hidden layer was generated through Weka 3.8 to determine the initial weight for each of the climatic predictors which served as inputs. The sigmoid function is the output of the neural network towards determining the forecasted rice yield. The back propagation algorithm was used in adjusting the weights of neurons of the artificial neural network. In adjusting the weights, Microsoft Excel's Generalized Reduced Gradient (GRG) Nonlinear in Solver was used. In adjusting the weights, the researchers considered adjusting the weights based on the computed feed forward neural networks. In the first model, the weights 10 years ago were adjusted. The second model had an adjusted weight of the most recent year while the third model had an adjusted weight of all the weights under study except for the initial weight. Error rates of all the three (3) models were computed to evaluate the most accurate rice yield forecast. The study is limited to the data for Region III pertaining to the recently mentioned irrigated rice yield and climatic factors. The initial weight of the ANN network was determined through the use of Multilayer Perceptron of Weka 3.8. The ANN used in this study implemented a multilayer feed-forward neural network consisting of an input layer with seven (7) factors, one hidden layer, and an output layer. Then, only back-propagation algorithm was performed in adjusting the learning weights of the network. No other hidden layer was added.

II. METHODOLOGY

The data sets from DA and PAGASA were used to describe Region III through graphs. Changes in climatic factors over the past 10 years were noted as well as the irrigated rice yield variations were presented. The data sets were subjected to data cleaning tasks in preparation for computations and analysis. Using Weka 3.8, the feed-forward network was constructed. Running the data sets in Weka was necessary to determine the initial weight for computation the feed forward.

Using the inputs namely pressure, temperature, relative humidity, rainfall, wind, cloudness, and sunshine, and the threshold yielded in Weka, the activation rate of the sigmoid function for the hidden nodes (H_1 to H_n) were computed.

Considering that every linkage calculation [10] in ANN is similar, the sigmoid relationship between the input variables and the activation rate of the hidden nodes and the activation rate of output nodes can be assumed as H_1 to H_n. Therefore, for a particular H_1, the equation to find activation rate is $Log(H_1) = W_1(I_1H_1) * I_1 + W_2(I_2H_1) * I_2 + W_3(I_3H_1) * I_3 + W_4(I_4H_1) * I_4 + W_5(I_5H_1) * I_5 + W_6(I_6H_1) * I_6 + W_7(I_7H_1) * I_7 + threshold = f$. Assuming that f is the sigmoid output for H_1, δ, $\delta H_1 = 1/(1+e^{-f})$.

Using the activation rate of the hidden nodes and linkages to the output, the activation rate of the output node was computed using the same formula as stated and replacing the values as needed. For the back propagation, recalibration of weights is an extensive process. The only nodes where the error rate is known is the output node. Re-calibration of weights on the linkage between hidden node and output node is a function of the error rate on the output node. To find the error rate at a hidden node H_1, the researcher used $Error@H_1 = W_1(H_1O)*Error@O$ [10]. Using the errors rates for H_1 to H_n, the weights of linkage between hidden nodes and the input nodes were recalibrated in a similar manner. This calculation is done multiple times for each of the observation in the training set. Finally, using the final linkage weight score, the activation of the output node was computed.

The back propagation were used to adjust the weights in three different ways to arrive at three models using ANN. For the first model, ANN1, the weights in the linkages in 2009 or the oldest data sets were adjusted. In the second model, ANN2, the weights in the linkages in 2017 or the weights of the most recent data sets were adjusted. Finally in ANN3, the weights in the linkages were all adjusted except for the initial weights of the inputs. The the error rate computed as:

ErrorRate =ABS(OutputNode-IrrigatedRiceYield)/IrrigatedRiceYield *100.

III. RESULTS

The following section presents the results of analyzing the historical data on climatic factors and rice yield towards the development of various forecasting models using ANN.

A. Feed-Forward Neural Network

The cleaned data that summarized the climatic factors and rice yields from 2009 to 2018 were used as training data sets in Weka 3.8. Data set on rice yield for 2018 was used as validation or test data set. The training data set saved as .CSV file was run using the MultiLayerPerceptron in Weka 3.8.

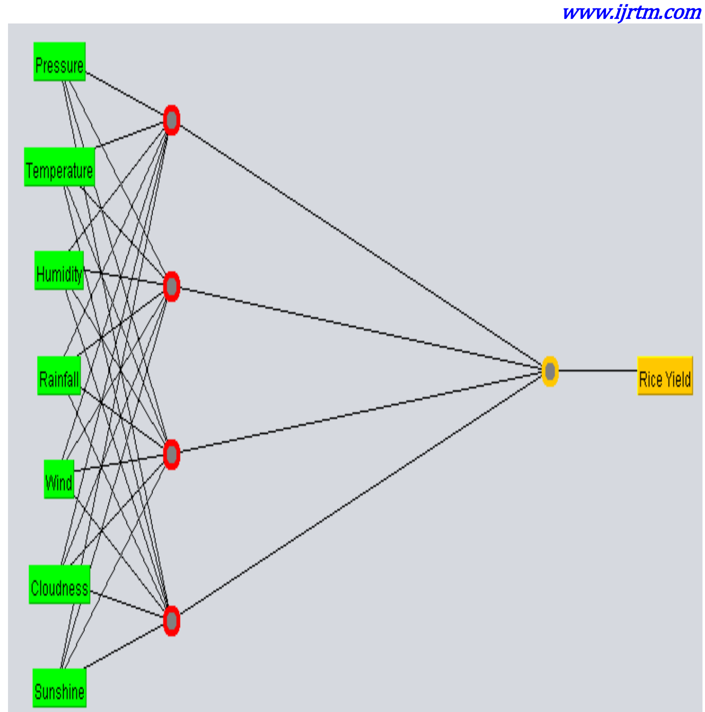

Figure 1. Neural Network Generated Using Weka

Figure 1 shows the neural network generated by Weka 3.8. In the network diagram, the seven (7) climatic factors were set as inputs. Each of the linkages have a corresponding weight value to get the four nodes in the single hidden layer. The hidden layer will also have weights and threshold for the computation of the rice yield forecasting output.

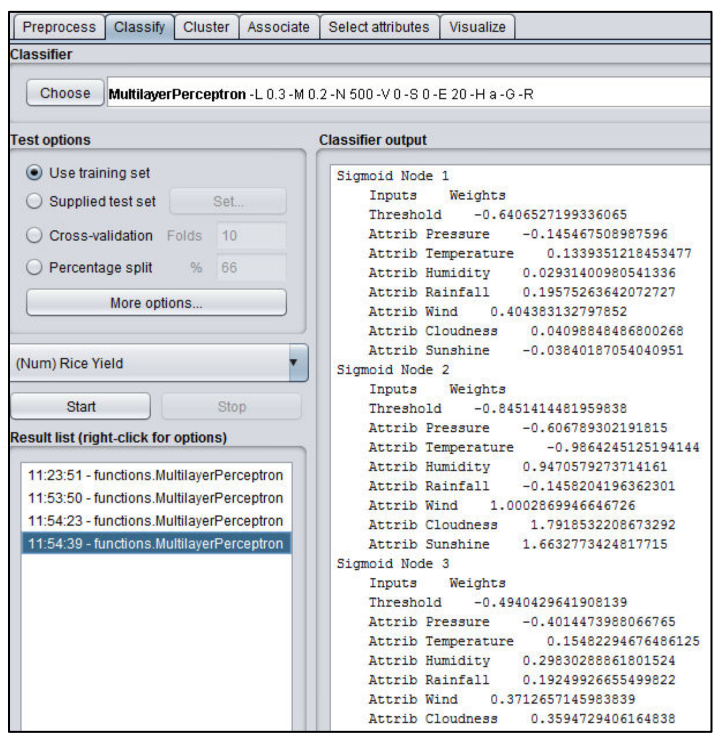

Figure 2. Neural Network Generated Using Weka

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As shown in Figure 2, Weka 3.8 provided sets of weights and threshold or bias values used in the computation of sigmoid function of the feed forward network.

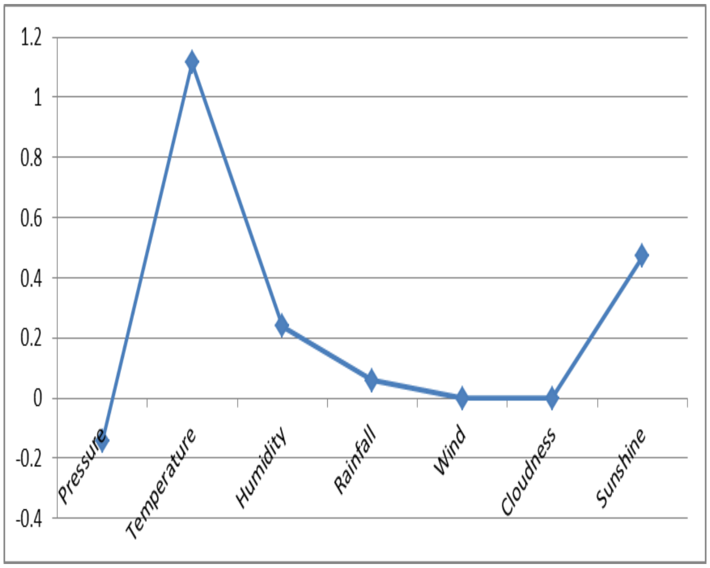

Figure 3. Initial Weights

Figure 3 depicts the initial weights assigned by Weka as plotted in a chart using MS Excel. From the initial weights, Weka assumed that the given training data set should allocate more weight to temperature and sunshine with respect to the rice yields.

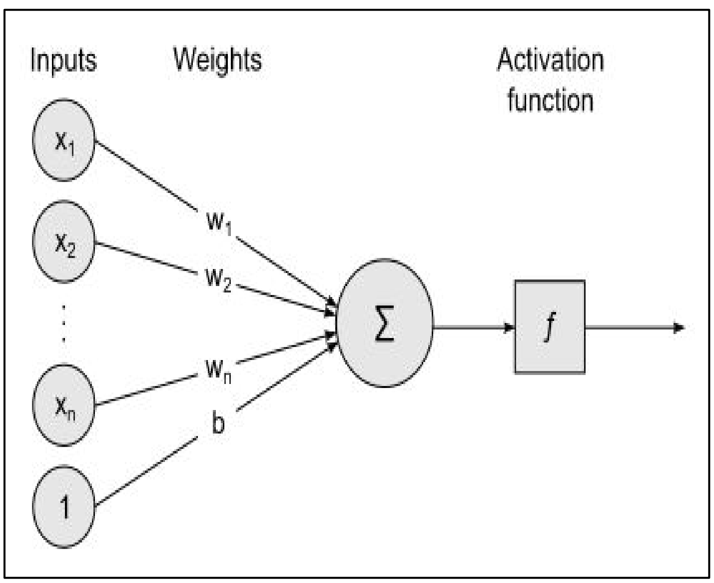

Figure 4. Feed Forward Network Representation of Computation

As depicted in figure 4, the each of the nodes in the feed forward network is computed as the summation of all the inputs multiplied by the weights and then add the value of the bias (b) also called the threshold. Each of the nodes will then produce an activation function (f).

	X0	X1	X6	Pressure	Temperat	Humidity	Sunshine	Net	b	Net Plus	Sigmoid
	Pressure	Temperat	Sunshine	W0	W1	W2	W6	SUM(W*X)	Threshold	Threshold	Node 1
2009	993.2666	30.88671	5.525063	-0.14547	1.12012	0.23853	0.471593	-75.19963917	-0.64065272	-75.84029189	1
2010	994.2178	32.12413	6.644578	-0.14547	1.114378	0.237895	0.471409	-80.68976671	-0.64065272	-81.33041943	1
2011	993.0204	30.82782	5.415125	-0.14547	1.114378	0.237895	0.471409	-77.9467936	-0.64065272	-78.58744632	1
2012	992.6829	31.35245	5.832253	-0.14547	1.114378	0.237895	0.471409	-76.03647374	-0.64065272	-76.67712646	1
2013	993.0842	31.44331	5.914892	-0.14547	1.114378	0.237895	0.471409	-77.89273608	-0.64065272	-78.5333888	1
2014	993.5303	31.22915	6.334321	-0.14547	1.114378	0.237895	0.471409	-80.66218651	-0.64065272	-81.30283923	1
2015	994.3741	31.45426	7.013904	-0.14547	1.114378	0.237895	0.471409	-77.6524074	-0.64065272	-78.29306012	1
2016	993.886	32.03604	6.331387	-0.14547	1.114378	0.237895	0.471409	-77.99274654	-0.64065272	-78.63339926	1
2017	993.4472	32.03367	6.191588	-0.14547	1.114378	0.237895	0.471409	-80.02353076	-0.64065272	-80.66418348	1
2018	993.1564	31.76683	6.285755	-0.14547	1.114378	0.237895	0.471409	-75.09207599	-0.64065272	-75.7327871	1

Figure 5. Feed Forward Network Computation Using Excel

As shown in Figure 5, to compute for the sigmoid activation of Node 1 (H_1) in the hidden layer of a particular year, Log(H_1) = $W_0 * X_0 + W_1 * X_1 + \ldots W_n * X_n + b = f$. Assuming that f is the sigmoid output for node 1 (H_1), δ, $\delta H_1 = 1/(1+e^{-f})$. The process is repeated for all the inputs and weights for all the years under study.

B. Back-Propagation

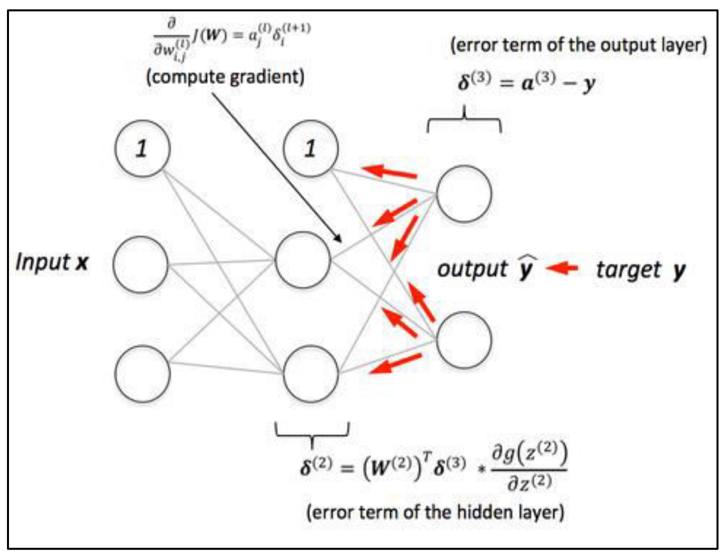

Figure 6. Feed Forward Network Representation of Computation

As shown in Figure 6, back-propagation [19] is a mathematical way of propagating the total loss due to error back into the neural network and to know how much is the error of the linkage of each the node and subsequently updating the weights in order to minimize the error by giving the nodes with higher error rates with lower weights and vice versa.

In using the back propagation, the researcher used three (3) ways to adjust the weights and therefore arriving at models called ANN1, ANN2 and ANN3. For ANN1, the weights in the linkages in 2009 or the oldest data sets were adjusted. In the second model, ANN2, the weights in the linkages in 2017 or the weights of the most recent data sets were adjusted. Then in ANN3, the weights in the linkages were all adjusted except for the initial weights of the inputs.

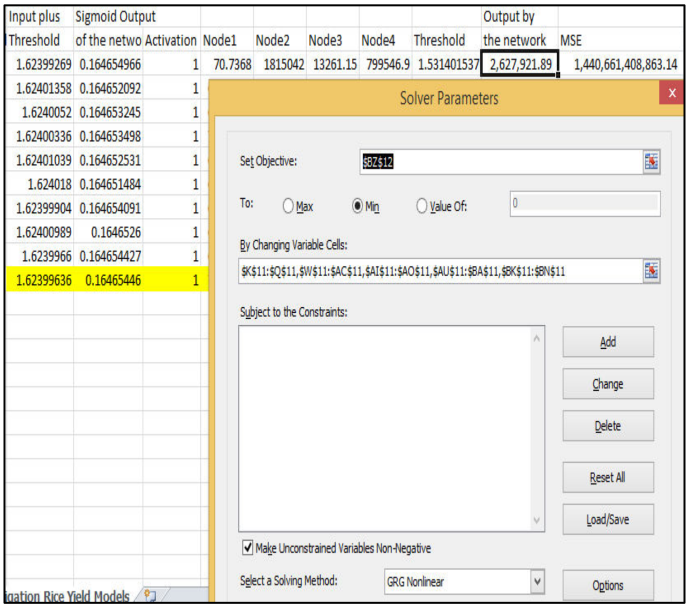

Figure 7. Feed Forward Network Representation of Computation

As shown in figure 7, in adjusting the weights in all of the models, the Solver feature of MS Excel was used. The Min value in the GRG Nonlinear of MS Excel solver was used to compute for the back propagation which started from the computed output of the network determined through forward-feed.

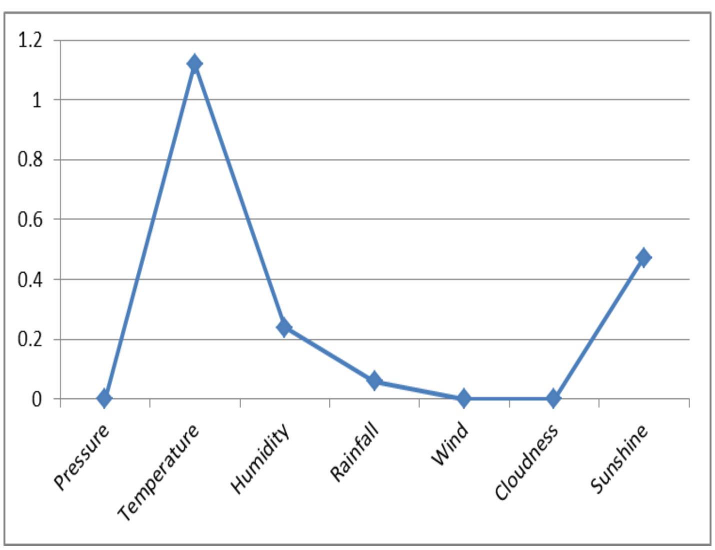

Figure 8. ANN1 Adjusted Weights

As shown in Figure 8, the researcher plotted the adjusted weights in MS Excel. The chart shows that when the residual losses due to errors are adjusted, this model gives the most weight to temperature and sunshine. This implicates that when the oldest data is considered in the adjustment of weights, rice yield is more dependent in temperature among all the climatic factors. Next predictor considered important to rice yield using ANN1 is sunshine. This findings implicates the importance of temperature and sunshine in rice yield when the oldest data and its weight are considered.

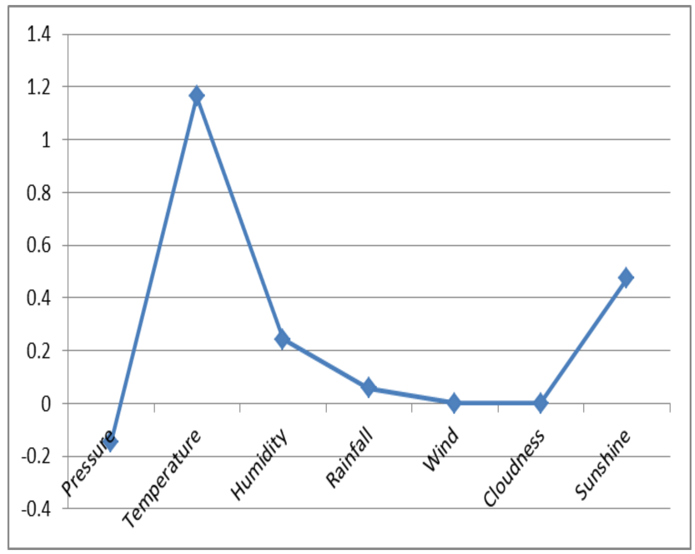

Figure 9. ANN2 Adjusted Weights

Figure 9 indicates the adjusted weights of ANN2 when plotted in MS Excel chart. In ANN2, the residual losses due to errors were adjusted using weights that affect the most recent data. Like ANN 1, this model gives the most weight to temperature and sunshine. This implicates that when the most recent data is considered in the adjustment of weights, rice yield is more dependent in temperature among all the climatic factors. Next predictor considered important to rice yield using ANN2 is sunshine. This findings implicates the importance of temperature and sunshine in rice yield when the most recent data and its weight are considered.

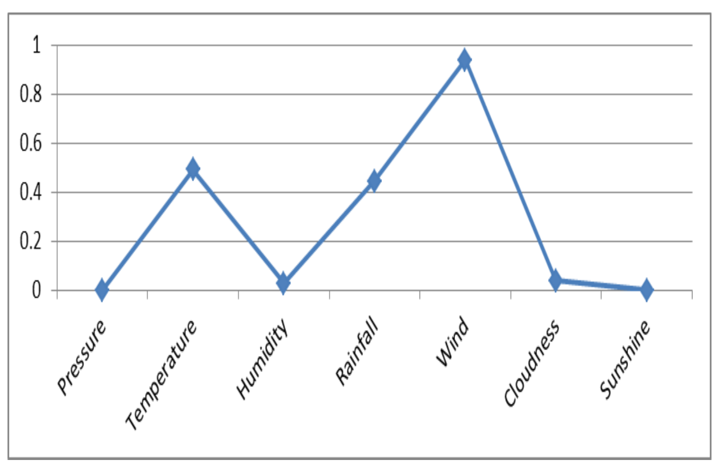

Figure 10. ANN3 Adjusted Weights

Figure 10 indicates the adjusted weights of ANN3 as plotted in an MS Excel chart. In ANN3, the residual losses due to errors were adjusted using weights that affect all the factors except from the oldest to the most recent data. However, in this model, the initial weights of the predictors were not adjusted. Thus, the back-propagation was considered incomplete in this model. This model gives the most weight to wind. This implicates that when all weights of the data is considered in the adjustment of weights, but the initial weights were not included in the adjustment, rice yield is more dependent towards wind among all the climatic factors. This findings implicates that rice yield will be dependent on wind when back-propagation is not completed in ANN.

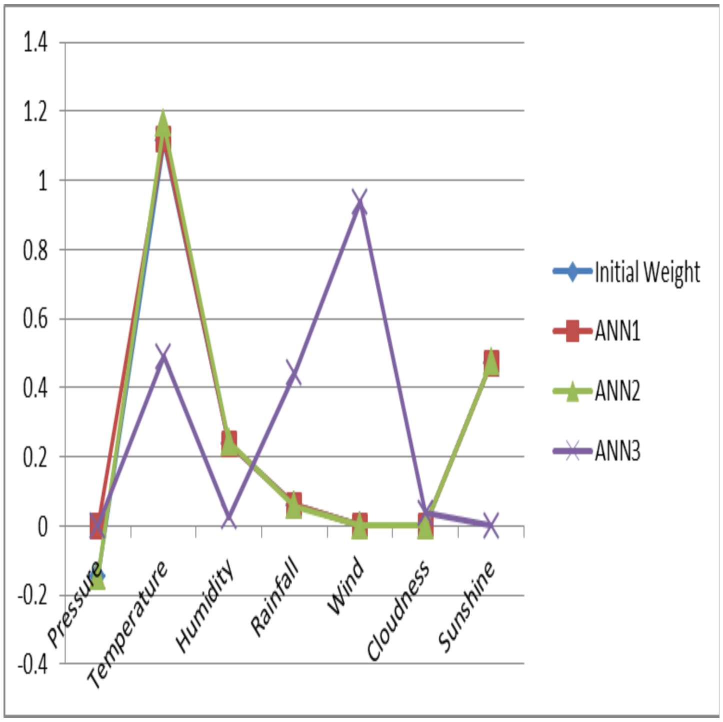

Figure 11. ANN3 Adjusted Weights

When the initial weights and all the adjusted weights of ANN1, ANN2 and ANN3 models are plotted in a single chart, the difference between ANN2 and the initial weight is almost similar. However, the complexity of ANN makes such minute difference to be significant. There is still a need to use back-propagation to adjust the weights of ANN models to arrive at reasonable forecasts with small error rates.

C. Evaluation of Accuracy

Table 1 shows the error rates of all the ANN models developed in this study. Error rate were computed using the formula:

ABS(Forecasted_Rice_Yield - Actual_Rice_Yield) / Actual_Rice_Yield * 100.

It is percentage of error of the absolute value of the forecasted rice yield against the actual rice yield.

ANN2 has the lowest error rate which is 90% among all the yearly forecasts. This shows that ANN2 or adjusting the weights of all the predictors using the most recent year will result into the most accurate model. It can be as high as 100% accuracy and only as low as 76.78%.

On the other hand, ANN1 may have as high as 100% accuracy only once but the rest of its accuracy is as low as 4.87%. ANN3 also has an accuracy as high as 100% at one time but as low as 58.16%.

TABLE 1. EVALUATION SUMMARY OF ANN MODELS

Year	ANN1	ANN2	ANN3	Lowest
2009	0.00	3.56	0.00	ANN1,ANN3
2010	93.86	3.05	26.57	ANN2
2011	93.00	10.08	16.62	ANN2
2012	94.32	10.66	32.33	ANN2
2013	94.61	15.08	35.68	ANN2
2014	95.13	23.22	41.84	ANN2
2015	94.55	14.03	34.88	ANN2
2016	94.64	15.59	36.06	ANN2
2017	95.01	0.00	40.45	ANN2
2018	95.01	21.47	40.52	ANN2

IV. CONCLUSIONS

In the feed-forward network diagram created through Weka 3.8, the seven (7) climatic factors were set as inputs while the rice yield was set as output. Each of the linkages had a corresponding weight value to get the four nodes in the single hidden layer. The hidden layer will also have weights and threshold for the computation of the rice yield forecasting output. Weka assumed that the training data set should allocate more weight to temperature and sunshine with respect to the rice yields. The sigmoid activation of the nodes were computed and the process is repeated for all the inputs and weights for all the years under study.

Back-propagation was used in propagating the total loss due to error back into the forward-feed neural network. The researcher used three (3) ways to adjust the weights and developed the models called ANN1, ANN2 and ANN3. For ANN1, the weights in the linkages in 2009 or the oldest data sets were adjusted. In the second model, ANN2, the weights in the linkages in 2017 or the weights of the most recent data sets were adjusted. Then in ANN3, the weights in the linkages were all adjusted except for the initial weights of the inputs. ANN1 stressed the importance of temperature and sunshine in rice yield when the oldest data and its weight are considered.In ANN2, wherein the most recent data is considered in the adjustment of weights, rice yield is more dependent in temperature among all the climatic factors.In ANN3, the initial weights of the predictors were not adjusted. Thus, the back-propagation was considered incomplete. This model implicates that rice yield will be dependent on wind when back-propagation is not completed in ANN. There is a need to use back-propagation to adjust the weights of ANN models to arrive at reasonable forecasts with small error rates.

ANN2 has the lowest error rate which is 90% of all the yearly forecasts. This implicates that ANN2 or adjusting the weights of all the predictors using the most recent year will result into the most accurate model.

Forecasting rice yield in an especially tropical country like the Philippines is quite a challenge. The incessant changes in climate has shown that climatic factors are not the only elements needed to be considered in order to produce a more reliable forecasting ability. However, through ANN, determining which factor affects the rice yield may produce technologies to help lessen the effect of climatic factors on the growth of rice before harvesting season arrives.

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