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An Artificial Neural Network for Predicting Crop Yields in Nepal

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Abstract

This paper examines the application of artificial neural networks (ANNs) for predicting crop yields for an agricultural region in Nepal. The neural network algorithm has become an effective data mining tool and the outcome produced by this algorithm is considered to be less error prone than other computer science techniques. The backpropagation algorithm which iteratively finds a suitable weight value is considered for computing the error derivative. Agricultural data was collected from thirteen years from paddy field cultivation in the Siraha district, an eastern region in Nepal, and used for this investigation of neural networks. Additionally, climatic parameters including rainfall, maximum temperature and minimum temperature along with the fertilizer use were also used as input values. The experiment shows that the trained neural network produced a minimum error which indicated that the test model is capable of predicting crops yield in Nepal.

***Keywords*:** artificial neural network, back propagation model, agriculture, Nepal

Introduction

Agriculture is one of the important industrial sectors in Nepal and the country's economy is highly dependent on it for rural sustainability. Agriculture contributes around 34% in the gross domestic product (GDP) and provides employments to about 76% of households in fiscal year 2013. Nepal is divided into mountains, plain (Terai) and hill areas with approximately 3.1 million hectares used for agricultural purposes (Sapkota, 2013). Although agriculture is a major sector in Nepal, there are many factors that are barriers to maintaining high productivity including climate change, insufficient irrigation, traditional farming practices, low literacy rates and poverty.

The aim of this paper is to identify a model that can accurately predict crop yields in Nepal from climate and agricultural data. Although, some studies revealed statistical information about the agriculture in Nepal, few studies have investigated crop prediction based on the historic climatic and production data. ANNs have been used for various purposes including classification, clustering, vector quantization, pattern association, function approximation, forecasting, control applications and optimization (Mehrotra, Mohan and Ranka, 1996). Using ANN predictions have been used for financial industry and climate prediction. In this paper an ANN is used to predict crop yields based on the data provided from the Siraha district in Nepal.

The following section will provide details of the agriculture systems and various influential factors on agriculture in Nepal to set the scene of the research. This will be followed by descriptions of AI techniques; a review of related studies; and the details of the development of the ANN to analyse data from agriculture sectors. Finally, the paper will provide the data analysis and discussion of the findings and its application for Nepalese agriculture.

Agriculture in Nepal:

The different agricultural regions in Nepal include both mountains, plains and hills landscapes. Hills regions are separated into high hills, mid hills and low hills. The mountains situated above 3000 meters in the north, the hills situated between 900 to 3000 meters in the middle, and the plains (Terai) situated below 300 meters in the south of Nepal. Each of these regions has a distinct climatic and geographical setting (Belbase & Grabowski, 1985). Based on the monsoon climate, there are three seasons: pre-monsoon which falls on February to May, monsoon is June to September and winter is October to January. Approximately 80% of rainfall occurs during monsoon periods. There is less rain in eastern Terai and western regions, moderate rain in far western region and heavy rain in the mid-western region creating flood, landslide and inundation (Malla, 2008). The variable temperature and rainfall directly affect the production of crops.

Researchers have been investigating various factors that influence agricultural production in Nepal. The major factors identified were climate change, poverty, lack of education and nominal use of technologies in agriculture. Devkota and Upadyaya (2013) identified that poverty and agricultural production are negatively correlated. The study shows that an increase in the agricultural production reduces poverty in Nepal. Likewise, Dhakal, Grabowski and Belbase (1987) found that the low levels of education, lack of communication facilities and poor roads limit the extent to which farmers can attain technical efficiency. Pokharel and Pant (2009) investigated the trends of organic agriculture in Nepal and identified the impact of excessive use of pesticides, fertilizers and other agro-chemicals to meet growing demands for food and its negative consequences on the quality of products. Other studies by Bhandari and Ghimire (2013) on modern farm technologies and their impacts on fertility transition found that the use of modern farm technologies, such as tractors to substitute the labour intensive work, reduce births in farm households. Brown (1997) found that socio-economic factors including land tenure, culture and poverty directly impact on nutrient inputs which lead to soil fertility degradation. Raut, Sitaula, Aune, and Bajracharya (2011) explained the evolution of the agricultural intensification in the mid-hill region in Nepal by analysing various components including external drivers, trends in fertilizer use, landholding, cropping patterns, irrigation and labour used.

Belbase & Grabowski (1995) and Khanal (2009) stressed the potential impact of climate change on agriculture in Nepal. The climatic zones are shifting rapidly due to climate change which is causing the reduction of biodiversity in several regions. Average temperature in Nepal has increased by 1.8^0C during last 32 years (Belbase & Grabowski, 1995). Although increase in temperature appears to be advantageous for mountains and hills region, it causes more damage in the Terai regions. With the increase in temperature, cropping patterns may change; for example regions once famous for vegetable may not be suitable for growing them in future but may be suitable for other crops instead (Joshi, Maharjan, & Piya, 2011).

Siraha district is situated in Terai region surrounded by Saptari, Dhanusha, Udayapur district and Madhubani of India on the East, West, North and South respectively. The district main natural resources are agriculture area, forest and water resources. Approximately 74% of the total land area of the district is used for agriculture, 21% of the land area is covered by forest and remaining part is occupied by pastures and other purposes. About 81% of the total population is dependent on agriculture. Various crops are cultivated in this district including paddy, maize and wheat. The paddy crop covers approximately 73 thousand ha. In the district there are many rivers, streams and ponds making the district much water resourceful. The main rivers and streams situated in this district are, Kamala, Ghrmi, Balan, Mainabatti, Khutti, Gagan, Sarre, Sahaja, Bataha, Jiba and Bhedawa. However, irrigations are also dependent on rainwater, tube, canal, wells and ponds. Figure 1 shows the monthly aggregate precipitation and average temperature at 2m in Siraha district from 1980 to 2009 (Disaster Risk Management Plan Siraha District, 2011).

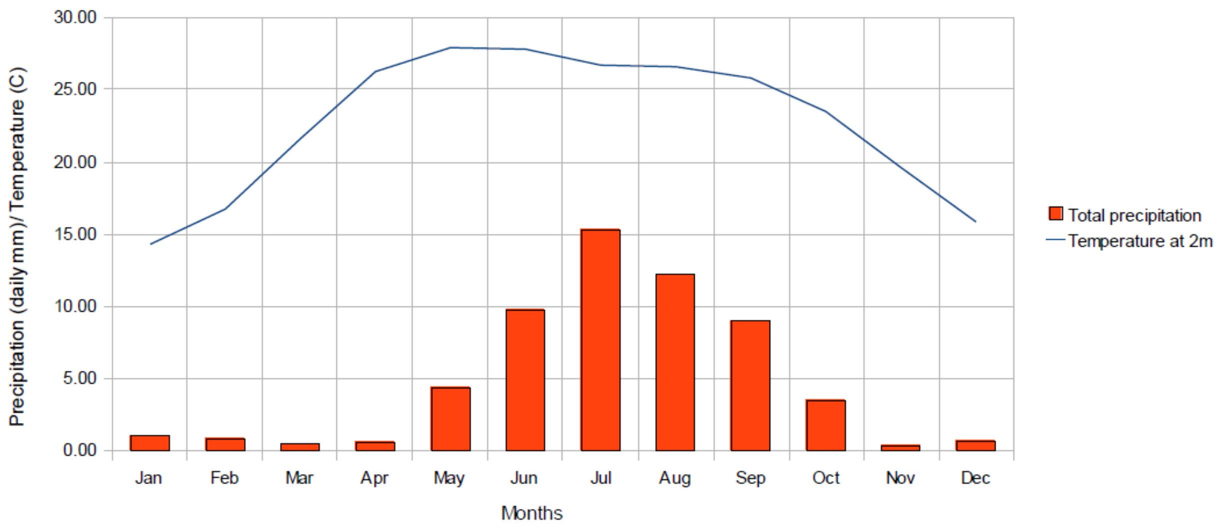

Figure 1: Monthly aggregates precipitation and temperature at 2m in Siraha, Lahan from 1980 to 2009 (Source: Disaster Risk Management Plan Siraha District, 2011).

Artificial Neural Network

In a human brain, neurons gets signals through the end of branches of the neuron cell called dendrites and produce an output signal called an axon. An ANN, which is also called a multilayer perceptron, works as information processed by the human brain (Hinton, 1992). A number of units representing neurons are interconnected to form an ANN (Gershenson, 2003 and Yagnanarayana, 2006). The synapses, which are tips of an axon, are represented by a modifiable weight. Each unit receives an input which integrated with the weight, a floating point number, and transfers other units. Each input unit multiplies with its associated weight on the connection and all weighted inputs are added to get a quantity called the total input. The output produced by the network are highly influenced by the associated weights and the input-output function of individual units (Yagnanarayana, 2006).

In order to perform a specific task using a neural network, the connection of the units with other units has to be determined (Yegnanarayana, 2006 and Hassoun, 1995). The influence of one unit upon others is determine by their interconnections. Generally ANN contains three layers for each unit. An input layer is connected to a hidden layer and the hidden layer is connected to an output layer. The input unit represents a vector of data provided to the network. The hidden layer perform tasks on the basis of input and weight. The output depends on the activity of the hidden layers associated with their respective weights (Hassoun, 1995).

The process begins with the training of the network. In the training phase, values in the input unit are provided with the expected output. Subsequently the error will be calculated. The error is defined as the square of the difference between the actual and the desired output (Rojas, 1996). The weight of each connection is changed to improve the accuracy of the desired output. The process will be iterated for many data sets of each kind of result until the network classified the output correctly.

The backpropagation algorithm is a method of computing the error derivative (EW) in ANN. The backpropagation algorithm computes each EW by computing the rate at which the error changes as the activity level of a unit is changed (Hinton, 1992). Basically, the errors are back-propagated from the output units towards the input unit during training phase. This algorithm is important as the hidden units do not have target values and these units should be trained based on errors from the previous layers. The weight value continuously get update as the errors are back-propagated. Training phase will continue until the errors in the weights are minimized (Rojas, 1996 and Hassoun, 1995). The process involves in the backpropagation algorithms is shown in the following steps:

Step 1: Provide the input data sets and desired outcomes
Step 2: Compute the error between the actual and desired outcomes
Step 3: Amendment of the weights associated with inputs and functions
Step 4: Compare the error and the tolerance ratio
Step 5: If error is still higher than the tolerance, begin from the step 1 again otherwise stop

Related Studies

The analysis of agricultural production is largely through the use of traditional statistical analysis; however, recent trends have seen various artificial intelligent techniques investigated with some promise. A wide range of AI techniques have been applied to model agricultural systems including regression analysis (Rub and Kruse 2010), knowledge based models (Sharma and Mehta 2012), genetic algorithms (Noguchi and Terao, 1997), agent-based systems (Berger, 2001), swarm intelligence (Xinsheng et al., 2009).

An earlier study by Kumar et al. (2002) introduced an artificial neural network for estimating daily grass reference crop evapotranspiration and compared the performance of the algorithm with the conventional method called Penman-Monteith equation. The equation requires an input value of temperature, gust, humidity and solar radiation. Likewise, Sastny, Konecny and Trenz (2011) used the multi-layer neural network for predicting the crop yield. The study also compared the accuracy of the well-known regression model designed with the result of the neural network. The study was focused on the data generated for the brown onion. More recently, Liu, Yang and Li (2013) investigated crop yield using the artificial neural network in response to soil parameter. The study was based on a back propagation neural network in which the authors have investigated data from Shunyi, Beijing in 2000. The authors claimed that the neural network was an effective tool in predicting the crop yield.

While there has been a number of studies that have reported on how ANNs may be effectively used for the prediction of crops yield in different environments, none have been applied in terms of Nepalese agricultural systems. This paper investigates whether the algorithm can be effectively utilized in the context of Nepal where the climate, soil and other treatments, including fertilizer and sowing, of farming are completely different from other countries. This study attempts to use some of the influencing factors to predict crops yield at Siraha district in Nepal.

Experimental Setup

Using the backpropagation algorithm in the artificial neural network, the experiment was conducted on data provided for Siraha district in Statistical Information on Nepalese Agriculture (2009, 2010, 2011, 2012 and 2013), Government of Nepal, Disaster Risk Management Plan Siraha District, 2011 and OpenNepal (2014). In this study, two hidden layers with four neurons in each hidden layer were employed. A number of hidden layers, number of neurons, are determined by conducting the trial and error method iteratively. This method ensured that the chosen structure for the network is adequate for this study.

Input Layer	Covariates	1	MonsoonRainfall
		2	MonsoonMaxTemp
		3	MonsoonMinTemp
		4	Urea
		5	DAP
		6	Potash
	Number of Units[a]		6
	Rescaling Method for Covariates		Adjusted Normalized
Hidden Layer(s)	Number of Hidden Layers		2
	Number of Units in Hidden Layer 1[a]		4
	Number of Units in Hidden Layer 2[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	PaddyYield
	Number of Units		1
	Rescaling Method for Scale Dependents		Adjusted Normalized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Figure 2: Network information indicating the input, output, hidden layers and neurons

The variables selection is an important and complex task which was done expecting the chosen variables will cohere with the predicted value. In this study, the neural network was trained with climatic and fertilizers use data. The climatic factors include rainfall, maximum temperature and minimum temperature and fertilizers such as Urea, DAP and Potash are used as inputs. Data from monsoon climatic factors, June to September, were chosen. For yearly data, rainfall is a cumulative value of a total of four months rainfall measured in millimetre. The maximum and minimum temperature are averaged Celsius measured from June to September.

Figure 2 shows the network information that contains six covariates, excluding a bias unit, which are used as input units. Two hidden layers with 4 neurons in each layer are used in the network. The adjusted normalized method is used for rescaling method for covariates. The method normalized values to fit between -1 and 1 by using the formula, $[2*(x-\min) / (\max-\min)] -1$. PaddyYield is a variable used as an output of this network. Automatic architecture selection was applied to select the activation function for both the input and output layer. Sum of Square error is used in the output layer as an error function which the network tries to minimize during training.

Result and Discussion:

This section presents the outcome produced by the neural network from the climatic and agricultural data. Figure 3 depicts information about the neural network configuration. Data collected over thirteen years are used in the network in which automatic architecture selection has chosen 61.5% of the total available data for training purpose and 38.5% of data for testing purpose. Prediction are made based on the past and current information.

		N	Percent
Sample	Training	8	61.5%
	Testing	5	38.5%
Valid		13	100.0%
Excluded		0	
Total		13	

Figure 3: Neural network configuration

Figure 4 depicts four layers of information that include an input, two hidden and one output layer. The input layer consists of seven units including a bias unit. Each hidden layer possesses with four neurons and one bias unit. The second hidden unit transfers five inputs to generate a final outcome, PaddyYield. Automatic architecture selection identified that the hyperbolic tangent and identity activation functions are suitable for the input unit and output unit respectively for this network. The figure also shows the interaction between various nodes in the network. The connection between nodes are indicated either by a grey or blue line. The grey line indicates that the synaptic weight is high which implies the strength of communication between nodes are strong. The blue lines indicates a weak strength of communication between nodes.

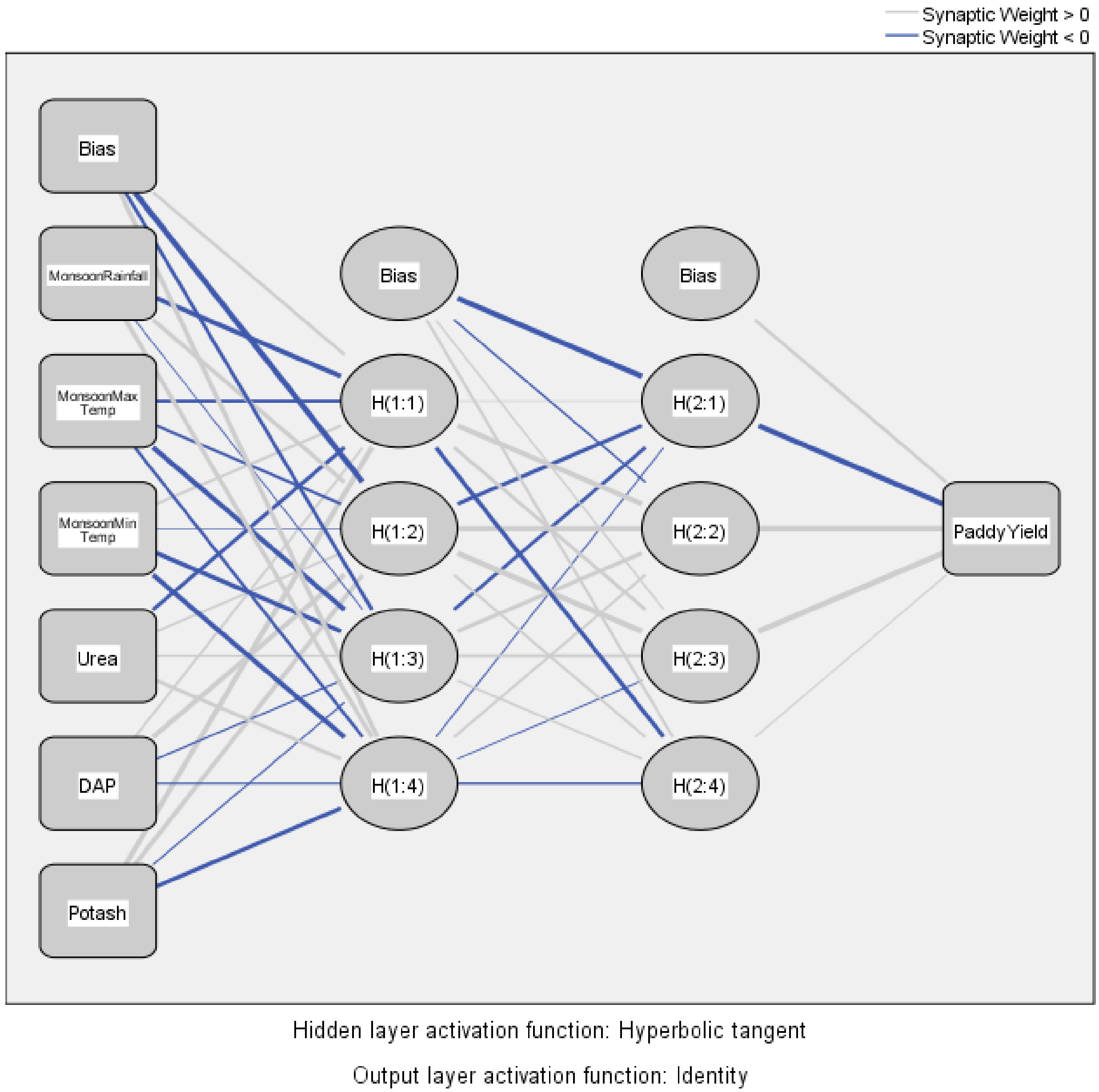

Figure 4: Neural network with the input, hidden and output layer

Table 1 shows weight values used in the network in the input and hidden layers. The positive and negative value are represented by a grey and blue line respectively in Figure 4. A higher positive value indicates the stronger bond; for example, the first node in the first hidden layer has highly strong bond with Potash that the other input units. Contrary, MonsoonRain variable has weakest bond with the first node in the hidden layer.

Table 1: Weight values that are generated by the neural network for the input and hidden layers

Predictor		Hidden Layer 1			
		H(1:1)	H(1:2)	H(1:3)	H(1:4)
Input Layer	(Bias)	.257	-.706	-.314	.425
	MonsoonRainfall	-.427	.401	-.077	.419
	MonsoonMaxTemp	-.263	-.214	-.453	-.252
	MonsoonMinTemp	.207	-.017	-.416	-.440
	Urea	-.352	.197	.166	.349
	DAP	.197	.468	-.135	-.118
	Potash	.584	.423	-.101	-.383
		Hidden Layer 2			
Hidden Layer 1	(Bias)	H(2:1)	H(2:2)	H(2:3)	H(2:4)
	H(1:1)	-.613	-.161	.141	.214
	H(1:2)	.065	.549	.304	-.394
	H(1:3)	-.365	.657	.690	.203
	H(1:4)	-.303	.379	.227	.190
		-.089	.203	-.086	-.180
	(Bias)	**Output Layer (PaddyYield)**			
Hidden Layer 2	H(2:1)	.295			
	H(2:2)	-.584			
	H(2:3)	.889			
	H(2:4)	.723			

The network model was also tested on the available set of data to validate its outcome with the actual output. Figure 5 shows the comparison between the expected and neural net outcome. The expected outcome is represented by the x-axis and the predicted values are represented by the y-axis. The total yield in kilogram per hectare. Although some points are scattered, most points are lined up in the diagonal starting from the origin to the top right corner which indicates the expected and predicted value are not largely vary. The correlation between the expected output and neuralnet output is 0.74631 which also shows that there is a strong positive correlation between these two factors.

Table 2 shows the sum of square error and relative error in the training and testing phase. The network tries to minimize the sum of square error during the training phase. This error is displayed when the output layer has scale-dependent variables. The model returned the sum of squares error 0.164 and 1.471 in the training and testing phase respectively. The relative error is 0.47 and 0.302 in the training and testing phase respectively. The sum of square error with other error values, in this model relative error, are used to compute for the rescaled values of the dependent variables, PaddyYield. The process completed in less than one seconds. The neural network output shows that the model is suitable to predict crops yield in Nepal. The following points evidence the accuracy of the model:

- The neural network prediction process stopped when the error did not decrease.
- The relative error in the testing and training phase is moderate which indicates that the model is not overtrained and that the error in future cases scored by the network will not be far from the error reported in this table.

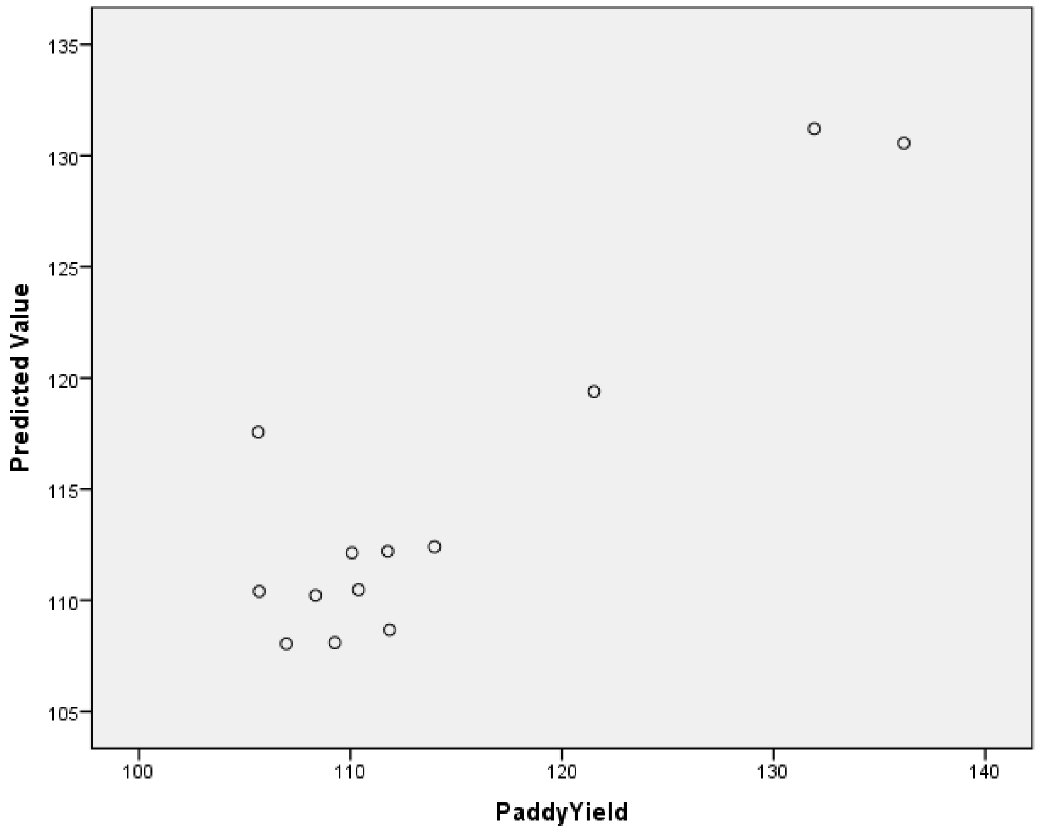

Figure 5: Comparison between the expected and neural net output

Table 2: Sum of Squares and Relative Errors in the training and testing phase

Training	Sum of Squares Error	.164
	Relative Error	.047
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.05
Testing	Sum of Squares Error	1.471
	Relative Error	.302

Dependent Variable: PaddyYield

Error computation are based on the testing samples

Conclusion:

In this paper, the performance of an artificial neural network is examined to predict crop yields in Nepal. In the training phase, the neural network model provided moderate error which shows the accuracy of this model. Also, the comparison between the expected and neural net outcome shows the similar result which further evidence the accuracy of the prediction values using this neural network model. The predicted outcome can be utilized for enhancing the paddy yield in Siraha district and also in other regions where the topography and vegetation are similar to Siraha district.

Future work includes the investigation of other neural network architectures including feedforward, acyclic and modular neural network and comparison of their performances. Also, the suitable input parameters, appropriate number of hidden layers and number of neurons can be selected to enhance the accuracy of prediction by using the search algorithms such as the genetic algorithm.

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