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Neural Network Modeling of Height Diameter Relationships for Himalayan Pine through Back Propagation Approach

M. Iqbal Jeelani, Afshan Tabassum, Khalid Ul Islam Rather and Mansha Gul
Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Srinagar, J&K, India

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SUMMARY

Neural network models offer a number of advantages as they have an ability to tactically detect complex non linear relationships between dendrometric variables of tree, which are very helpful in tree height modeling. In this study, artificial neural network (ANN) models and nine conventional height diameter equations were employed to validate the height diameter relationship in Chir Pine plantations. Height diameter measurements of 1500 Chir Pine trees in150 sample plots from three forest divisions of Jammu province of UT of J&K, India were used. For the purpose of developing and validating models, the data was randomly partitioned into training (80%) and testing (20%) sets. All the fitted height diameter models resulted in significant coefficients, which indicated that these models were able to capture the underlying height diameter relationships. Out of the nine traditional height diameter models, M7 height diameter model had the highest fitting precision, with lower values for Akaike Information criteria (AIC),Bayesian information criteria (BIC). However, under cross validation artificial neural networks (ANN) outperformed conventional models in every aspect as they resulted in lower values of prediction error rates (PER) and other selection criteria, where neural network model with 10 numbers of neurons came out be superior in comparison to other fitted models.

Keywords: Model; Height; Diameter; Validation; Prediction error rate; Chir Pine.

1. INTRODUCTION

Tree height is one of the most significant variable in forest management, the measurement of which forms the basis for identifying forest's vertical structure, assessing site quality and biomass (Watt *et al.*, 2015; Burkhart *et al.*, 2016). Tree height is typically difficult to measure directly and takes a lot of time. However, because of the significant correlation that exists between tree height and diameter at breast height (dbh), the height diameter models can predict height using dbh as a predictor (Sharma *et al.,* 2016). This method fits mathematical functions with various forms and number of parameters using measurements of tree height and dbh, accordingly best fitted model is selected using common statistical indices.Such modeling approach is generally known as traditional modeling, and its main theme is to establish the mathematical equations and get the tree prediction by solving them (Koirala *et al.,* 2017).Several models in this regard are available literature (e.g. Curtis, 1967; Moor *et al.*, 1996; Zhang; 1997; Fang and Bailey, 1998; and Zhang, 2004; Tremesgen and Gadow, 2004; Sharma and Portan, 2007; Haung *et al.,* 2000; Trincado *et al.*, 2007; Sharma Newton and Amponsah, 2007; Wagle, 2007, Jeelani *et al.,* 2015, Hassanzad *et al.,* 2016; Jeelani *et al.,* 2018; Harsh *et al.,* 2022). However all these models are liable to produce large extrapolation errors which results in imprecise tree height predictions, thereby affecting forest management policy and planning works.

The most frequent problem while fitting such models is that the height variable's value is proportional with the error variation (Parresol, 1993) which is inconsistent with the least squares model's starting assumptions that errors are randomly distributed with a constant variance and a zero mean. This may be because the real data, which must be provided in these modelling methodologies, may be noisy in nature and likely to have variability or non-normal distribution.

Corresponding author: M Iqbal Jeelani
E-mail address: jeelani.miqbal@gmail.com

Hence, a strategy is needed which can overcome such short-comings and artificial neural network (ANN) models can be used as best alternatives under such circumstances, as they don't rely on any statistical assumption and have become most favourable choice of data scientists due to their capability in automating the detection of hidden data pattern and modelling (Diamantopoulou *et al.,* 2018). ANN modelling is a component of artificial intelligence that draws inspiration from human brains. A neural network is made up of various connected information processing units which are similar to human nervous system. Conventional make of an ANN model is made up of three layers such as input layer, hidden layer, and output layer. An ANN model's input layer takes in raw input data, processes it, and then, after applying weights, sends the processed results to the hidden layer. The output layer receives information from the hidden layer where it under goes a number of repetitions until it hits a particular threshold level. The essence of ANN model is based on the activation function, which decides whether a neuron is to be activated or not. Due to their ability to automate the detection of hidden data patterns, ANN models are currently preferred choice among researchers (Reis *et al.,* 2018). An ANN model has been claimed as a reliable tool for prediction and validation of dendrometric relationships because of their ability to map nonlinearity in complex situations (Sheela and Deepa, 2013; Ozcelik *et al.,* 2013; Vieira *et al.,* 2018 ; Mushar *et al.,* 2020). However, there aren't many studies that use artificial neural networks to investigate height diameter relationships with varying number of neurons.

Chir pine (*Pinusroxburghii*) forest, which makes about 6.3% of the India's total forest area, is situated in a subtropical area at an altitude ranging from 1000 m to 2000 m (Anonymous, 2021a). Chir pine forest makes a significant economic contribution to local and national development, hence models for individual trees or stands at the species or stand-level must be established for its scientific management. A lot of work for modelling Chir pine has been done for assessment andevaluation of tree height and other tree attributes,butthe information on height diameter relationship in terms of ANN is stilllimited in this species. Therefore, this study is aimed to develop conventional height diameter models using basicnonlinear growth equations and artificial neuralnetworks (ANN) models with different number of neurons to describe the height diameter relationship in *Pinusroxburghii* ofJammu province, UT of J&K, India.

2. MATERIALS AND METHODS

2.1 Area of study area and description of data

Pinusroxburghii (Sarg.) also known as chir pine is one of the most important conifer and dominates in lower Himalaya and provides various goods as well as services to the people of the Himalayan catchment (Kumar *et al.,*2020). Chir pine covers 869,000 ha and spreads in Jammu and Kashmir, Haryana, Himachal Pradesh, Uttar Pradesh, Sikkim, West Bengal, and Arunachal Pradesh states ranging from 450 to 2300 m above sea level (masl; Kumar *et al.,* 2020). Chir pine is a principal species of Himalayan subtropical forests and reported to be 3rd (3.97%) highest contributors in growing stock after sal andteak forests (Anonymous, 2021b).It covers 1,92552 ha in Jammu and Kashmir, 1,82543 ha of which are in the province of Jammu, and typically grows up to 30 m tall, 2.5 m wide, with a cylindrical clean bole of around 12 m (Anonymous, 2021a) .

The study was conducted in the Jammu, Nowshera, and Batote forest divisions of UT J&K in India (Fig. 1). The mean minimum and maximum temperature for study sites under winter, summer and monsoon season is 1°C, 21°C and 18°C, 41°C and 14°C, 32°C, respectively. 150 permanent 0.75-hectare (0.25 per forest division) sample locations with 500trees per forest division were used. To accomplish the objectives of the study, height diameter data of 1500 trees from three forests divisions of Jammu province was utilized. The summary statistics of the overall data is given in Table 1.

Table 1. Summary statistics of training and testing data sets

	Training (n=1200)		Testing (n=300)	
	Diameter (cm)	Height (m)	Diameter (cm)	Height (m)
Mean	37.32	25.95	38.16	25.39
Median	36.19	24.42	37.41	25.82
Kurtosis	3.81	3.05	4.37	3.09
Skewness	0.21	0.41	0.37	0.42

2.2 Model development and evaluation

In this study nine commonly used height diameter models which are most preferred models in forest

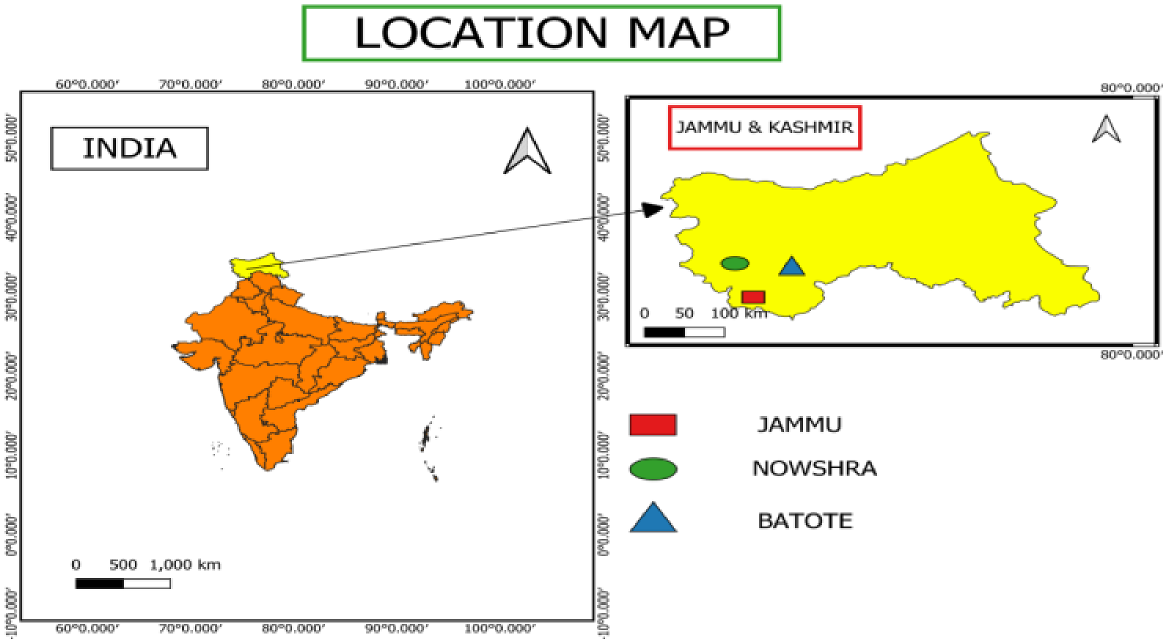


Fig. 1. Location map of the study area

management work were used with the following functional form:

$$H_i = 1.3 + F(D_i, b) + \varepsilon_i$$

Where, H_i is the tree height, D_i is the diameter at breast height and ε_i is random error.A constant value 1.3 is added to avoid the prediction of height shorter than 1.3 m when D_i approaches zero, as the 1.3 meters is the standard height of tree at with diameter of tree is measured commonly known as diameter at breast height (Khanna. and Chaturbedi, 1994). A depiction of the models used in the present study are given in Table 2.

Where, d represents the vector of tree diameters in centimetres and h represents the vector of tree heights in metres. The variables a and b are called parameters. bh is the height used to determine the diameter of a tree (so called breast height).

2.3 Neural network Models

The library (neuralnet) of R studio, an integrated development environment of the well-known R software for statistical analysis and data visualisation, developed in 1995 by Ross Ihaka and Robert Gentleman (R Development Core Team 2019), was used in this study to create an artificial neural network (ANN) model. By using the formula $i = \sqrt{j+m} + R$, the number of neurons in the hidden layer were used to identify the

Table 2. Models used in the current study

Model Code	Model Equation	Reference
M1	$h = bh + \frac{d^2}{(a+bd)^2}$	Manfred.N1(1992)
M2	$h = bh + a\left(\frac{d}{1+d}\right)^b$	Curtis(1967)
M3	$h = bh + ae^{-bd^{-1}}$	Michailoff(1992)
M4	$h = bh + a\left(1-e^{-bd}\right)$	Meyer(1940)
M5	$h = bh + ad^b$	Zeide(1993)
M6	$h = bh + \frac{d^2}{(a+e^b d)^2}$	Manfred.N2(1992)
M7	$h = bh + \frac{d^2}{(e^a+bd)^2}$	Manfred. N3(1992)
M8	$h = bh + \frac{d^2}{(e^a+e^b d)^2}$	Manfred.N4(1992)
M9	$h = bh + \frac{ad}{b+d}$	Michaelis-Menten(1913)

type and complexity of the fitted ANN model. Where $i$is the number of neurons in the hidden layer, m is the number of neurons in the input layer, and j is the number of neurons in the output layer, R is any value between 1 and 10.(Shi and Zhang, 2012). Thus, in this study, the numbers of neurons in the hidden layer were chosen within the range of 1 to 10 to search for the best ANN model in terms of accuracy.

2.4 Model performance criteria

The relevance of the assumption of normality of fitted model errors was assessed using the Shapiro-Wilk test. For perdition performance of fitted of models, cross validation method of 80:20 approach were used. In this method the data was randomly partitioned into training and testing sets, where 80% of data was used for training and the remaining 20% for testing. Performance of models were tested by means of various libraries like caret and tidy verse of R studio. The adequacy of the fitted height diameter andneural network models with varying number of neurons were tested using different selection criteria like adjusted R^2_{adj}, AIC, etc. Some of the metrics used are given below:

$$R^2 adj = 1-(1-R^2)\times\left(\frac{n-1}{n\times k-1}\right)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \Big/ n}$$

$$MAE = \frac{\sum_{i=1}^{n}|\, y_i-\hat{y}_i \,|}{n}$$

$$AIC = n\times\ln(RMSE)+2k$$

Where y_i is the actual observation, $\hat{y}_i$ is the predicted value and $\overline{y}$ is themean of observed value and k is number of parameters, RMSE is Root mean square error, AIC is Akaike information criterion and MAE is Mean Absolute error. Since the normal practice, in model comparison is to choose the model which produces the lowest test sample RMSE. As RMSE and the MAE are measured in the same scale, dividing the RMSE by the average value of the predicted outcome variable gives usthe prediction error rate, which should be as small as possible (Jeelani *et al .,* 2022).

3. RESULTS

Table no 3 provides an overall summary of the coefficients along with selection criteria's of various height and diameter models. It is evident from the results that each height diameter model was equally well fitted to the tree height diameter data. All the model coefficients were statistically significant, showing that fitted models accurately reflect the relationships between height and diameter. Nearly all of the models explained at least 60% of the total variation in tree heights. These tables also illustrated how well height diameter models performed using different selection criteria, including RMSE, MAE, BIAS, RSE, AIC, BIC, MAE, RMSE, R^2 and Adj.R^2. Prior to validation M7 (Manfred N3) and M8 (Manfred.N4) height diameter models resulted in lower values for AIC, BIC, MAE, RMSE and higher values for R^2 and Adj.R^2, as well as a non-significant Shapiro Wilk test for normality of errors. From these results it is evident that these two

Table 3. Parameter estimates and selection criteria of height diameter models

MODELS	a	B	AIC	BIC	MAE	RMSE	R^2	Ad. R^2	Shapiro wilk Test
M1	5.02*	0.05*	571.75	578.54	3.53	5.46	0.77	0.72	0.90^{ns}
M2	134.66**	56.23*	670.28	678.09	4.78	6.70	0.86	0.83	0.89^{ns}
M3	132.81**	54.94*	526.01	532.26	3.24	5.05	0.79	0.76	0.90^{ns}
M4	-29.02*	0.01**	658.19	666.00	3.63	6.30	0.75	0.72	0.99^{ns}
M5	5.57*	-2.94*	657.51	665.33	3.57	6.28	0.75	0.73	0.80^{ns}
M6	0.16**	1.42*	669.61	677.43	4.73	6.68	0.66	0.63	0.10
M7	1.61*	0.09*	438.34	443.55	2.48	4.19	0.88	0.85	0.90^{ns}
M8	1.54*	-2.94**	512.59	518.60	2.98	5.03	0.86	0.84	0.91^{ns}
M9	-87.45*	-158.80*	664.02	671.84	3.72	6.49	0.69	0.66	0.91^{ns}

*: Significant at 5% level of significance

**: Significant at 1% level of significance models performed better lamong nine conventional height diameter models initially.

In Table 4 goodness of fit results for the training and testing datasets are presented. The performance criteria (AIC, BIC, MAE, RMSE, R^2 and Adj.R^2) are given in Table 4 for both training as well as testing sets. Models with the lowest RMSE, MAE, BIC and AIC values and the Adj.R^2 closest to unity are known to perform best. Under testing set R^2 and Adj.R^2 ranged from 0.61 (model 5) to 0.98 (ANN10)and 0.60 (model 5) to 0.97 (ANN10).As far as RMSE are concerned they varied from RMSE from 5.37 (model 7) to 2.35 (ANN10). Similarly AIC and BIC values ranged from 69.94 (ANN10) up to 147.20 (model 5) and 78.27(ANN10) up to 152.51(model5). A MAE value of 1.66 to 4.12 in case of ANN10 and model 5. It was also found that the AIC and BIC values ranged from 80.51 to 69.94 and 82.40 to 78.27 among ANN1 and ANN10, while as Adj.R2 values varied from 0.85 to 0.97 among ANN1 and ANN10. Almost all the fitted ANN models accounted for at least 85% of the total variation in tree heights which is significantly higher in comparison to the traditional height diameter models.

With the aid of the libraries like ggpubr and ggplot2 in R Studio, the evaluation of ANN models with varying range of neurons in relation to training and testing data sets are graphically presented inFig. No. 2 along with key performance metrics including a plot of Prediction error rates (PER) across training and testing data sets with respect to the number of neurons ranging from 1 to 10 (Fig. No. 3). Apart from this neural network plot of all the ANN models on testing data set created by utilizing library (neuralnet) of R studio is presented in Fig.No.4 revealed that the PER of the ANN models decreases as the number of neurons increases, hence improving the adequacy of ANN models. From the above results it is very much evident that ANN models performed better and ANN model with 10 number of neurons in hidden layer outperformed others.

4. DISCUSSION

The link between tree height and diameter, which is used to compute volume, yield, and site index, is an essential component of forest structure. It can also be used to explain how several tree species relate to one another in a particular environment. As a result, forest managers may develop straight forward and precise

Table 4. Performance of models under training and testing data sets

Training Data							Testing data					
MODEL	**AIC**	**BIC**	**MAE**	**RMSE**	**R^2**	**Ad.R^2**	**AIC**	**BIC**	**MAE**	**RMSE**	**R^2**	**Ad.R^2**
M1	452.633	458.16	4.32	6.78	0.74	0.73	105.01	107.48	3.24	4.31	0.76	0.76
M2	515.06	521.31	5.32	7.85	0.65	0.64	119.56	122.39	2.51	4.41	0.62	0.62
M3	458.03	464.09	3.30	5.79	0.70	0.69	107.47	110.00	2.31	4.20	0.69	0.67
M4	473.86	479.61	4.90	7.22	0.67	0.67	119.51	122.35	3.43	4.80	0.70	0.69
M5	602.85	610.03	7.03	9.63	0.60	0.60	147.20	152.51	4.12	5.33	0.61	0.60
M6	447.20	452.52	5.26	7.18	0.76	0.76	96.61	98.88	2.98	3.97	0.76	0.75
M7	592.32	599.51	6.12	9.03	0.64	0.63	123.79	126.62	4.10	5.37	0.64	0.63
M8	394.88	399.67	4.08	6.02	0.79	0.79	91.92	94.10	2.64	3.69	0.81	0.80
M9	590.44	597.62	5.91	8.92	0.65	0.65	120.76	123.60	3.73	4.96	0.64	0.63
ANN(1)	118.25	121.08	5.86	9.29	0.83	0.83	80.51	82.40	2.49	5.31	0.86	0.85
ANN(2)	111.47	115.23	5.79	9.10	0.85	0.83	80.11	82.05	2.39	5.01	0.87	0.86
ANN(3)	108.69	113.38	5.54	8.80	0.86	0.84	79.72	81.70	2.30	4.59	0.87	0.87
ANN(4)	103.92	109.53	5.41	8.65	0.87	0.85	79.32	81.36	2.21	4.06	0.90	0.87
ANN(5)	99.14	103.68	5.39	8.31	0.90	0.85	78.92	81.01	2.12	3.88	0.91	0.90
ANN(6)	93.37	101.83	5.15	8.06	0.91	0.86	78.22	80.66	2.03	3.48	0.92	0.91
ANN(7)	89.59	96.98	5.01	7.82	0.93	0.87	78.03	80.32	1.93	3.09	0.93	0.93
ANN(8)	86.81	94.13	4.86	7.57	0.93	0.87	77.63	79.97	1.84	2.78	0.96	0.95
ANN(9)	80.04	90.28	4.72	7.33	0.94	0.88	75.43	79.62	1.75	2.52	0.96	0.95
ANN(10)	75.26	87.43	4.28	6.85	0.96	0.89	69.94	78.27	1.66	2.35	0.98	0.97

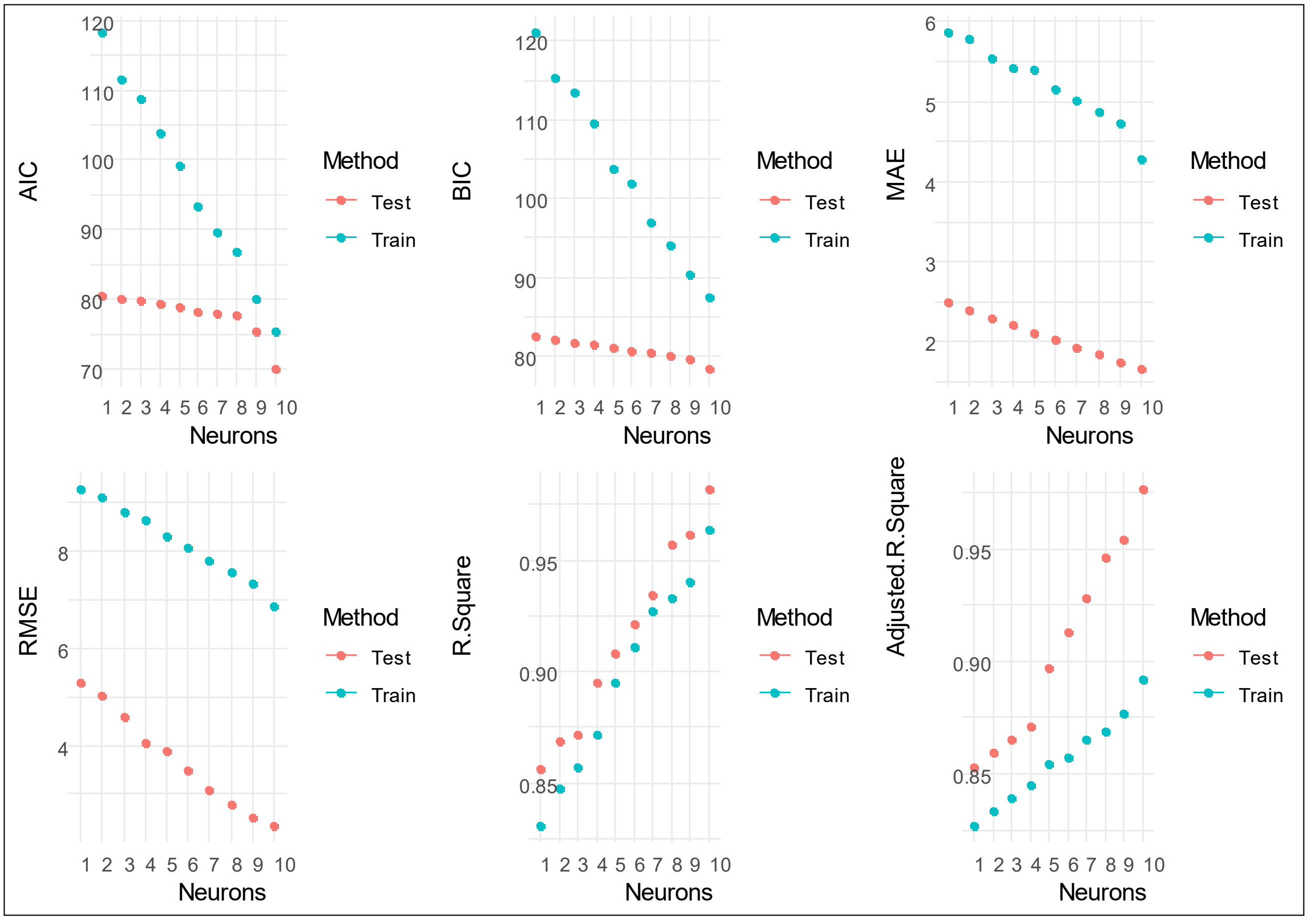


Fig. 2. Performance criterion across number of neurons

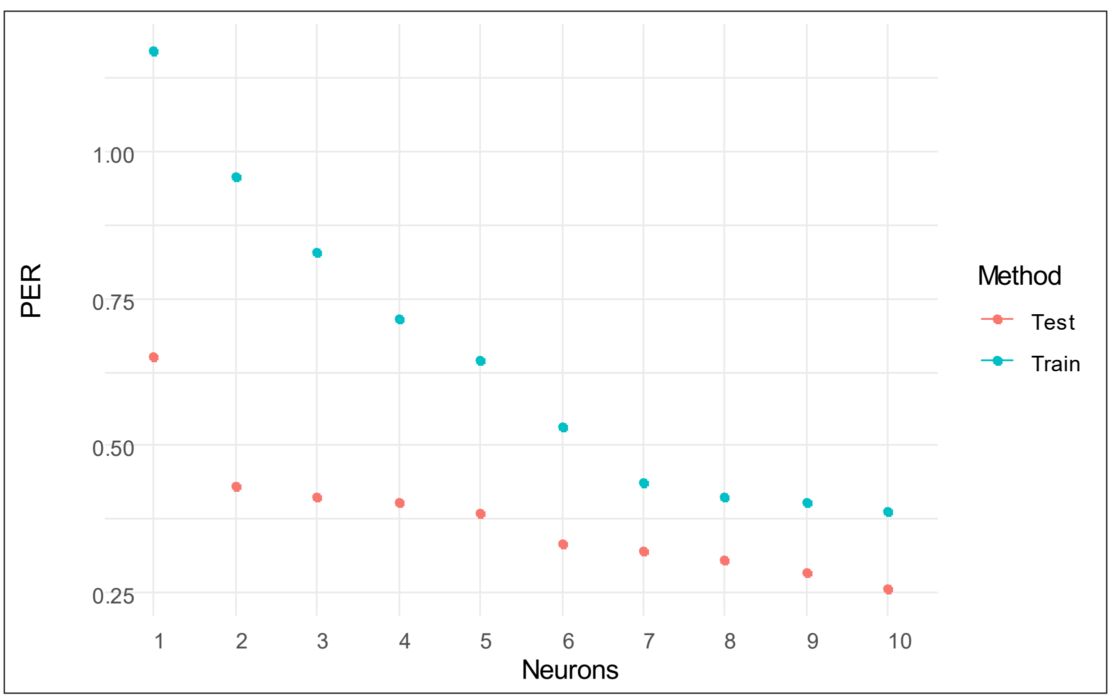
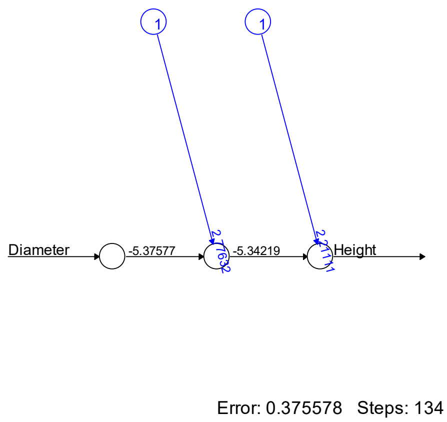
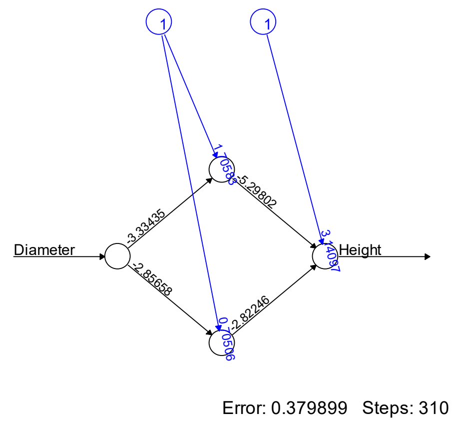


Fig. 3. Prediction error rates across training and testing data along with number of neurons



PER= 0.651



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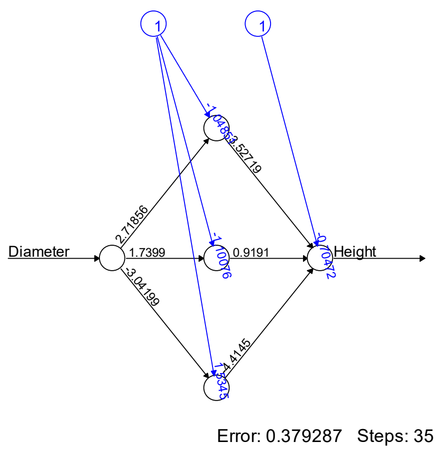
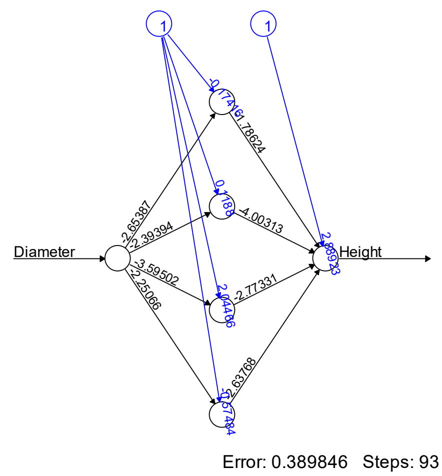
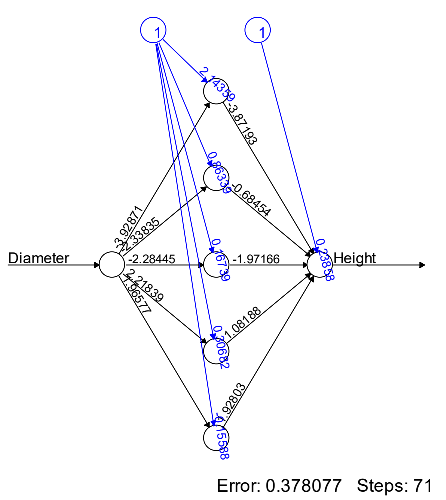


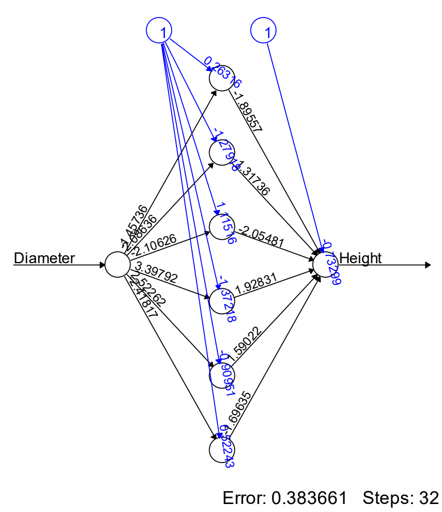
PER= 0.411



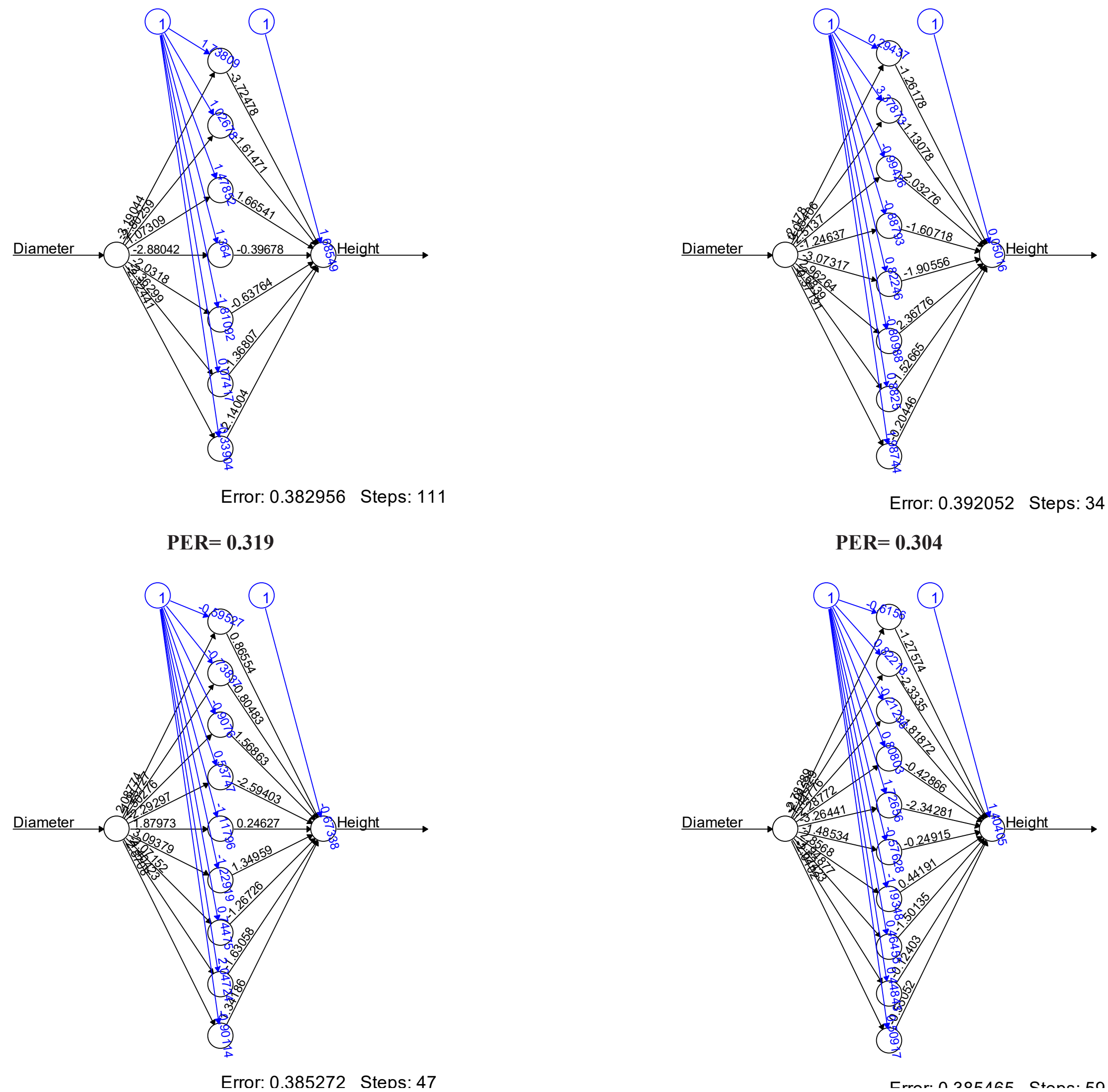
PER= 0.402



PER= 0.384



PER= 0.334



PER= 0.319 **PER= 0.304**

PER= 0.285 **PER= 0.256**

Fig. 4. Neural network plot of testing data indicating the PER and number of neurons

height and diameter models to accurately anticipate the height of trees in forests. We developed a modelling technique based on combinatorics mathematics that could provide various neural network height diameter models. By comparing the fitting and prediction accuracy of these models, we chose the best ANN model. In order to generate the ideal height diameter model for Chir Pine plantations in Jammu Province of India, the neural network back propagation method was used. The pine tree species is one of the most significant plantation tree species in India and is acknowledged as a focal point for research on woody plants and the perfect source of materials for bioenergy studies. This study examines the performance of a single hidden layered neural network approach in terms of fitting, which may be informative and helpful to other researchers. Single-layer neural network height diameter models and nine conventional height diameter models were compared. The neural network models appeared substantially superior to the traditional height diameter models in predicting tree height (Table 4, Fig. 4). Our findings are in accordance with those of Ozcelik *et al* ., (2013), who predicted tree height for unevenly aged beech forests in northwest Spain and Crimean juniper in southwest Turkey. They contrasted neural network models with nonlinear regression models.In this study, nine height diameter models together with ANN model with neurons varying from 1 to 10 were examined and evaluated. Height diameter models were fitted to data collected during the primary stage about the height and diameter variables of 1500 Chir Pine trees. Nearly all of the parameters across the models were found to be significant in the initial research, indicating that they are effectively capturing the height diameter relationship. The second stage used multiple selection criteria, including AIC, BIC, MAE, RMSE, R^2 and Adj.R^2, to examine the fitted height diameter models' predictive power. On the selection criteria, it can be concluded that M7 (Manfred N3) and M8 (Manfred.N4) height diameter model performed better than all other models in the corresponding forest divisions. Cross validation was used to examine the prediction abilities of the fitted height diameter models and ANN models utilizing using 80 percent of the data for calibration and the remaining 20 percent for validation. Prediction error rates were the primary metrics used to evaluate models which indicated that the ANN models performed better than other conventional height diameter models, because they produced lower PER values.

With different numbers of neurons in the hidden layer, our modelling system presents a technique for choosing the optimal neural network configuration. When classical regression models and neural network models share the same input factor, such as diameter at breast height (DBH) in our example, a model comparison would make sense. DBH was the only element taken into account for both modelling methodologies in this study because it is a major factor influencing tree height.In our upcoming research, in addition to DBH, the impacts of other variables on the growth of the tree can be taken into account, and models can be developed to be more intricate and detailed. Incorporating a large number of variables, however, does not ensure that the models created using any modelling approach will be very accurate. Because neural network models are capable of efficiently optimising the model through the combinatorial optimization process, this approach can be thought of as more appropriate than other modelling approaches, such as conventional least square regression modelling approaches.

5. CONCLUSION

Based on combinatorics mathematics, we suggested a modelling approach that can produce many neural network models with best fitting precision. The number of neurons in the hidden layer was taken into consideration while determining the structure of the neural network. In order to characterise the height diameter relationships of *Pinusroxburghii* in forest stands of Jammu province, India, this study used nine conventional height diameter equations functions and ANN models. We demonstrated that the ANN models outperformed all conventional height diameter models using performance criteria statistics. Our findings imply that in order to offer more precise estimations of tree height, ANN based height diameter models must be developed. The Himalayan Pine may be measured at the individual tree and stand levels using the ANN models, which offer a novel method for doing so, as these models appeared biologically more realistic than previous methods. The neural network modelling approach that has been suggested might be appropriate for other forest modelling research of comparable or other types, such as modelling of tree crowns, modelling of height and diameter increments, and so forth.

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