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Studying on Crop Response Model for Grapes under Climate Change Scenario: Statistical Study Approach

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Grapes vine originally a temperate fruit crop and it's also grown successfully under tropical conditions. Grape is one of the economically important fruit crops grown in India. As Theni district is the leading producer of grape in Tamil Nadu, followed by Coimbatore and Dindigul, this study is centred on the Theni-Kambum block area. In this region, Muskat Humbug is a well-liked cultivar that yields more than other varieties. In this study, this cultivar was employed. In this study, an artificial neural network (ANN), multiple linear regression (MLR), and elastic net (ELNET) regression methods were used to construct a yield prediction model (ANN) using twelve years secondary data. Additionally, we evaluate our model over a two-year period using field-level data from GRS and neighbouring farms. Finding the best-fit model for predicting grape yield and PDI using meteorological parameters in the Theni district is the goal of this communication. The model is chosen according to many performance indicators including RMSE, MAPE, MAE, and R^2. Among the three techniques developed in the study, the Artificial Neural Network is found to be best for prediction of grape yield based on weather and disease incidence for the available data in the studied region.

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Keywords: Grapevine; fruit crops; artificial neural network; weather; disease.

1. INTRODUCTION

Grapes are produced on every continent, in temperate, subtropical, and tropical climates, and in a variety of agro-ecological settings ranging from mountains to plains to sea beaches. Grapes are produced in a range of temperatures and soils in India, with more than 80% of the land area lying within the tropical climatic region. India holds the distinction of having the greatest grape yield in the world. Grape suffers significant crop losses due to downy mildew, powdery mildew, and anthracnose. [1]. Plant disease prediction has evolved as a well-established component of epidemiology that is quickly being integrated into disease management. The mathematics of disease progression has advanced to the point of being a powerful and acknowledged component in epidemic management and prediction [2]. S. Sannakki et al. [3] forecast the weather using a modified k-NN technique and a Feed Forward Neural Network, and then use characteristics such as humidity and temperature to forecast disease outbreaks in grapes. Plant disease models have traditionally employed Leaf Wetness Duration (LWD) and temperature to forecast infection and colonisation, and subsequently determine the risks of an epidemic. These models have been used with observed climate data to monitor advantageous times, indicating control methods or strategies [4]. Precipitation (availability of water) and air temperature are the primary meteorological elements that influence grape and wine quality and utilised an ensemble of CMIP6 model data to assess all possible changes in water availability in the area around Sevastopol by the middle and end of the twenty-first century for two shared Socio-economic Pathway scenarios (SSP2-4.5 and SSP5-8.5) [5]. A new technique for evaluating regional climate scenarios based on the statistical region model STAR has been developed. The approach improves applicability and reliability in viticultural elements and focuses on evaluating adaption measurements rather than predictions [6]. Multiple regression approach was used to develop an agro-climate grape yield (ACGY) model using climatic parameters and the developed model had been statistically tested for its predictive ability. Sensitivity analysis was carried out for the developed ACGY model using the parametric sensitivity method [7].

Previously, Estefan Gonzalez Fernandez et al. [8] have developed the yield prediction for grape in the Northwest Spain Ribeiro Designation of Origin vineyards, by means of aerobiological, meteorological and flower production analysis. Nicolas Verdugo-Vásquez [9] have obtained models for predicting and validating the phonological scales of table grapes. The meteorological, seasonal and climatic models and data sets used to answer the viticulturist needs; from short-term and mid-term forecast by Ignasi Porras [10]. André Barriguinha [11] have reviewed yield estimation, forecast for grape. S.J. Kadbhane et al. [12] have ACGY model was developed using multi-regression analysis using less number of data. M. Bindi et al. [13] have analysed the future climate scenario on yield and yield variability of grapevine. G.V. Lyashenko [14] has discussed the modelling of grapevine yield under climate change scenario. Fernando Palacios [15] have derived the yield prediction for grape for different varieties using machine learning.

According to the literature survey, there are many yield-estimating models that can be used to estimate the yield of for grapes under climatic scenario. So far, no models have been reported for the estimation exactly of grape yield in Indian terrain. There were several models in grape yield prediction using various factors but there was low accuracy in those models. This study intends to develop a prediction model with high accuracy using yield as a dependent variable with climatic variables and percent disease incidence as independent variable and PDI as dependent variable with climatic variables as independent variable.

2. MATERIALS AND METHODOLOGY

2.1 Study of Data Collection

Availability of data on the south part of Tamil Nadu's climate, including maximum temperature (Tmax), minimum temperature (Tmin), rainfall (mm), relative humidity (RH1), relative humidity (RH2), and rainfall (RF) for 12 years (2010-2021) collected from sample region. Monthly weather data for twelve years (2010-2021) and yield prediction were used to create the model. The expected yield for grapes from various years was compared to the monthly mean values of each of the weather factors separately. As a result, it was possible to determine which month was the most crucial for each weather condition and utilise the corresponding data to create a model for predicting grape yields. Two years of

Table 1.

Year	MAXT	MINT	RH	RF	PDI	Yield
2010	31.85	22.11	70.56	77.38	10.32	25.27
2011	30.64	21.63	63.88	93.72	11.38	24.38
2012	31.29	21.69	68.62	48.08	10.41	24.79
2013	31.98	22.48	76.04	96.27	10.47	25.00
2014	31.94	22.14	68.18	47.01	10.86	23.53
2015	31.29	21.69	68.61	96.52	9.58	22.19
2016	32.35	22.68	76.67	2.61	12.14	26.75
2017	31.89	22.35	75.82	84.83	10.63	24.49
2018	31.36	21.48	77.04	89.75	10.79	22.15
2019	31.69	22.66	72.15	90.00	11.52	22.58
2020	30.24	22.21	74.19	83.42	10.74	27.44
2021	30.93	21.52	70.64	129.08	12.45	20.12

independent data (2021–2022) on the weather, disease incidence, and yield were used to validate the model. The statistical mean value is summarized in the above Table 1.

In statistical analysis, the above climatic factors and PDI are positively correlated for grape yield. Using correlation matrices of predictor variables (see Fig. 1), this variable only multi-collinearity. The correlation is given in above matrix. In this concept, we can choose correlated variable will predict more precise model for grape.

2.2 Methodology

2.2.1 Multiple linear regression

Multiple regressions are a statistical method for predicting the outcome of a response variable by integrating a number of explanatory factors. The linear relationship between explanatory (independent) and response (dependent) variables is attempted to be represented using multiple linear regression. Multiple regressions are simply an extension of ordinary least-squares (OLS) regression since it includes more than one explanatory variable.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + e \qquad (1)$$

where, for *i*=*n* observations:
Y_i=dependent variable
X_i=explanatory variables
β_0=y-intercept (constant term)
β_p =slope coefficients for each explanatory variable
e =the model's error term (also known as the residuals)

2.2.2 Elastic net regression

ELNET regression stands for elastic net regression, which is a mixture of penalties from LASSO and ridge regression [16] that improves statistical model regularisation. During the regularisation procedure, the L1 component of the penalty generates a sparse model. The penalty's quadratic component (L2), on the other hand, makes the L1 portion more stable on the path to regularisation, removes the quantity limit of variables to be picked, and promotes the grouping effect. As a result, it reduces the impact of certain aspects but not completely eradicating them [17].

$$\hat{\beta}(Enet) = \left(1 + \frac{\lambda_2}{n}\right)\{arg\ min_\beta \|y - X\beta\|^2 + \lambda 1\beta + \lambda 2\beta 2 \qquad (2)$$

where, λ_1 and λ_2 are LASSO and ridge regression penalities.

The lambda values with the lowest average mean squared error were chosen using cross-validation with leave-one-out . The overall strength of the penalty is controlled by tuning parameter. Analysis of the data was performed using the R package 'glmnet' [18-19].

2.2.3 Artificial neural network

A neural network is a massively parallel network of linked basic processors (neurons), each of which accepts a set of inputs from other neurons and computes an output, which is transmitted to the output nodes. A neural network may therefore be represented in terms of individual neurons, network connectivity, weights associated with neuron interconnections, and neuron activation function. The neuron gets a set of n inputs from its neighbours, x_i, I = 1,2,...,n, as well as a bias of one. Each input is connected with a weight (w_i).The weighted sum of the inputs determines the state or activity of a neuron and is given by

$$a = \sum_{i=1}^{n+1} w_i x_i = W^T X \quad (3)$$

Where, $X = \{x_1 x_2 \ldots x_n \; 1\}^T$. The output of the neuron is commonly described by a sigmoid function as

$$f(a) = \frac{1}{1+e^{-a}} \quad (4)$$

2.3 Model Performance Metrices

The performance of the statistical models was evaluated using coefficient of determination (R^2), Root mean squared error (RMSE), mean absolute percentage error (MAPE), and Mean absolute error (MAE) by following formulas:

$$R^2 = 1 - \frac{\sum_{j=1}^{n}(Y_j - \hat{Y}_j)^2}{\sum_{j=1}^{n}(Y_j - \bar{Y}_j)^2} \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{n}(Y_j - \hat{Y}_j)^2}{n}} \quad (6)$$

$$\text{MAPE} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{Y_j - \hat{Y}_j}{Y_j}\right| *100 \quad (7)$$

$$\text{MAE} = \frac{\sum_{j=1}^{n}|Y_j - \hat{Y}_j|}{n} \quad (8)$$

where, Y_j – Actual yield, $\hat{Y}_j$ – Model yield respectively, n-number of years.

2.4 Correlation

Correlation coefficients are used to quantify the strength of a linear association between two variables, x and y. A linear correlation coefficient greater than zero indicates a positive relationship. A number less than zero indicate a negative relationship. Finally, a value of 0 denotes that the variables x and y are unrelated.

$$\text{Correlation} = \rho = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (9)$$

In this study, the dependent variable is nut yield and the independent variables are plant height, stem girth, Female flowers in inflorescence, husk Thickness, copra content, minimum Temperature, rainfall, and relative humidity. Correlation is carried out between nut yield and all other factors to find the factors which are all highly responsible for multi collinearity between predictor variables.

3. ANALYTICAL RESULT FOR THREE DIFFERENT TECHNIQUES

The intercept and coefficients of multiple linear regression models are shown in the Table 2. The fitted models in the table revealed that the variables relative humidity and minimum temperature had positive impact on grape yield and the variables such as, rainfall, PDI and maximum Temperature were negatively impact on grapes yield .The Actual and predicted yield by multiple linear regression are shown in the Table 3. The Intercept and coefficients of PDI models are shown in the Table 4. The fitted models in the table revealed that the variables minimum temperature and relative humidity are showing positive impact on PDI and the other variables like maximum temperature and rainfall showing slight negative impact on PDI. The Actual and predicted yield by PDI are shown in the Table 5. The Intercept and coefficients of elastic net regression models are shown in the Table 6. Observed and Predicted value of ELNET model is shown in the Table 7. Intercept and coefficients of elastic net regression with PDI are shown in the Table 8. Observed and predicted value of ELNET model with PDI are shown in the Table 9. Predicted yield by ANN are shown in the Table 10. Observed and predicted value of ANN model for the years (2010-2021) are shown in the Table 11.

3.1 Artificial Neural Network

A mathematical model that attempts to imitate the structure and capabilities of biological neural networks is known as an Artificial Neural Network. Every artificial neural network starts with an artificial neuron, which is a simple mathematical model (function). A model contains three basic sets of rules: multiplication, summation, and activation. The inputs are weighted at the entry of the artificial neuron, which implies that each input value is multiplied by an individual weight. The sum function in the centre region of the artificial neuron adds all weighted inputs and bias. At the exit of an artificial neuron, the total of previously weighted inputs and bias passes through an activation function, also known as a transfer function.

Table 2. Intercept and coefficients of multiple linear regression models

Independent variables	Reg. coefficients (b)	Standard Error (SE(b))	T Test	p-value
Intercept	41.75484	29.00337	1.439655	0.200027
Maximum Temperature	-2.314**	0.877	-2.637	0.037755
Minimum Temperature	2.843*	1.235	2.303	0.059968
Relative Humidity	0.071	0.112	0.632	0.536572
Rainfall	-0.044**	0.015	-2.958	0.024579
PDI	-0.786	0.506	-1.552	0.169898

Table 3. Actual and predicted yield by multiple linear regression

Year	Actual yield	Predicted yield
2010	25.27	23.78114
2011	24.38	23.16853
2012	24.79	24.93047
2013	25.00	23.95473
2014	23.53	24.39819
2015	22.19	23.4507
2016	26.75	26.50789
2017	24.49	24.14511
2018	22.15	22.63229
2019	22.58	24.3132
2020	27.44	27.41715
2021	20.12	20.26463

Table 4. Intercept and coefficients of PDI models

Independent variables	Reg. coefficients (b)	Standard Error (SE(b))	T Test	p-value
Intercept	10.40915	21.34918	0.487567	0.640755
Maximum Temperature	-0.216	0.650	-0.332	0.745509
Minimum Temperature	0.306	0.914	0.335	0.750315
Relative Humidity	0.013	0.084	0.153	0.877668
Rainfall	-0.002	0.011	-0.157	0.875496

Table 5. Actual and predicted yield by PDI

Year	Actual yield	Predicted yield
2010	10.32	10.83898
2011	11.38	10.8317
2012	10.41	10.86152
2013	10.47	10.95588
2014	10.86	10.85827
2015	9.58	10.76451
2016	12.14	11.13124
2017	10.63	10.95449
2018	10.79	10.80761
2019	11.52	11.03571
2020	10.74	11.24892
2021	12.45	10.7523

Table 6. Intercept and coefficients of elastic net regression models

(Intercept)	7.595969
Maximum Temperature	0
Minimum Temperature	0
Relative humidity	0.114039
Rainfall	-0.0018
PDI	0.84348

Table 7. Observed and Predicted Value of ELNET model

Year	Observed value	Predicted value
2010	25.27	24.20834
2011	24.38	24.31131
2012	24.79	24.11563
2013	25.00	24.92588
2014	23.53	24.44693
2015	22.19	23.32742
2016	26.75	26.57449
2017	24.49	25.05627
2018	22.15	25.32153
2019	22.58	25.37917
2020	27.44	24.96572
2021	20.12	25.92124

Table 8. Intercept and coefficients of elastic net regression with PDI

(Intercept)	0.18477306
Maximum Temperature	-2.27533478
Minimum Temperature	4.12084136
Relative humidity	-0.10271152
RF	-0.01797528

Table 9. Observed and predicted value of ELNET model with PDI

Year	Observed value	Predicted value
2010	10.32	10.21824
2011	11.38	11.35727
2012	10.41	10.44909
2013	10.47	10.52533
2014	10.86	10.9253
2015	9.58	9.579368
2016	12.14	12.10541
2017	10.63	10.40887
2018	10.79	7.799166
2019	11.52	12.44111
2020	10.74	13.77059
2021	12.45	8.911966

The processing element is split into two parts. The weighted inputs are simply aggregated in the first portion; the transfer function, sometimes referred to as the activation function, or second part, is essentially a non - linear filter. The output values of an artificial neuron are constrained or compressed by the activation function to a region between two asymptotes. The sigmoidal function is the most often used function.

3.2 Comparitive Result

The yield and PDI developed models were compared using different performance metrics. Based on the comparison, ANN model for both yield and PDI developed models was performing far better than other models with high R-squared and low RMSE, MAE and MAPE values which are followed by ELNET and MLR. Manisha S. Sirsa et al. [20] predicted grapevine yield using climatic conditions, phenological dates, fertilizer information, soil analysis and maturation index data with the accuracy measure with low RMSE of 1459.4 (kg/ha) and low relative root mean squared error of 24.2% respectively. Estefanía Gonzalez Fernandez et al. [21] predicted grapevine yield using multiple regression model and applied Spearman rank correlation to identify influential variables based on reproductive variables and the influence of meteorological

Table 10. Predicted yield by ANN

Parameter estimates			
Predictor		**Predicted**	
		Hidden Layer 1	**Output Layer**
		H(1:1)	**Yield**
Input Layer	(Bias)	-0.117	
	MAXT	-0.921	
	MINT	0.370	
	RH	1.581	
	RF	-2.112	
	PDI	0.497	
Hidden Layer 1	(Bias)		0.351
	H(1:1)		0.706

Table 11. Observed and predicted value of ANN model for the years (2010-2021)

Year	Observed value	Predicted value
2010	10.32	10.41
2011	11.38	11.38
2012	10.41	10.33
2013	10.47	10.52
2014	10.86	11.20
2015	9.58	10.74
2016	12.14	12.14
2017	10.63	10.43
2018	10.79	10.44
2019	11.52	11.50
2020	10.74	10.99
2021	12.45	12.45

Table 12. Comparison of yield model

	R-squared	RMSE	MAPE	MAE
MLR	0.88	0.821824	2.41272	0.545572
ELNET	0.819305	3.405615	13.37552	2.962498
ANN	**0.983076**	**1.032531**	**4.378608**	**0.988**

Table 13. Comparison of PDI model

	R-squared	RMSE	MAPE	MAE
MLR	0.574	0.834425	5.15888	0.606602
ELNET	0.879	1.261784	18.88606	2.14034
ANN	**0.987**	**0.009016**	**1.525314**	**0.164**

conditions. Santos, J. A et al. [22] developed statistical grapevine yield model using climate parameters as predictors. These atmospheric factors control grapevine yield in the region, with the model explaining 50.4% of the total variance in the yield time series in recent decades.

4. RESULTS AND DISCUSSION

In this study a simple but accurate model based on secondary data expressed as temperature, relative humidity and rainfall to predict the yield of grapes grown under environmental conditions is proposed. This model obtained good prediction accuracy and had results similar to those observed in studies conducted on grapevine cultivars in different areas [23-25]. This is the very first time a large number of samples were used in a particular region (Theni district) and compared three different efficient techniques for yield prediction for grape using secondary data.

Fig. 1 explains that the variables were selected based on the correlation coefficient between yield and other variables. Like that, we had selected Minimum Temperature, Relative humidity and Rainfall as weather parameters for the same aspects. From Fig. 2, yield as a function of years, it is evident that the yield was peak at 2019-2020 thereafter it was decreased and reached lowest yield (20.12 t/ha) in 2020-2021. During 2020-2021 the disease incidence was increasing trend and having a value of (12.45%). In Fig. 3, the percentage disease incidence is increases as increasing the relative humidity and rain fall.

The number of principal components retained for this study is 4 which explain 90 percent of the variation in the data. The retained components are then used as an input layer to train Artificial Neural Network. The number of hidden layers selected is 1 and the optimum number of neurons in the hidden layer is 2. The network flow is represented in Figs. 4 and 5 and the connection weights are displayed. The ANN R coding can be found in Appendix.

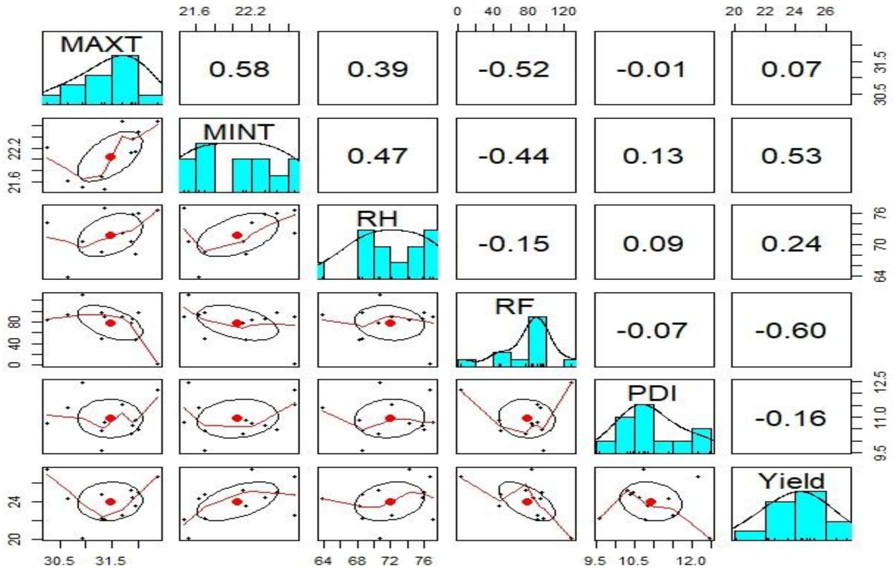

Fig. 1. Correlogram showing correlation between yield and climatic factors

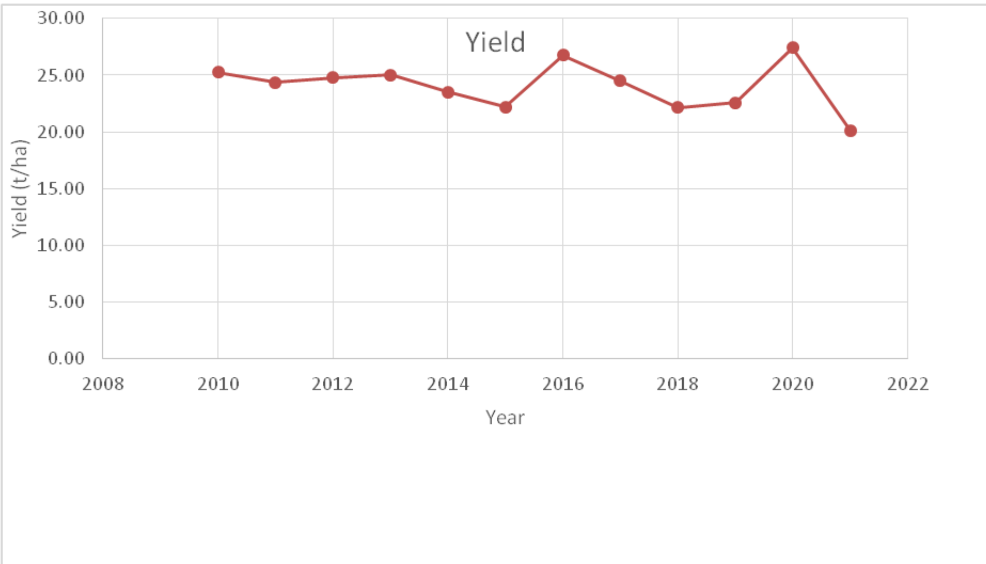

Fig. 2. Comparison of observed and predicted yield as a function of years for various values of climatic factors. The line represent the predicted yield and dot repreent the observed yield for Theni and surrounding villages

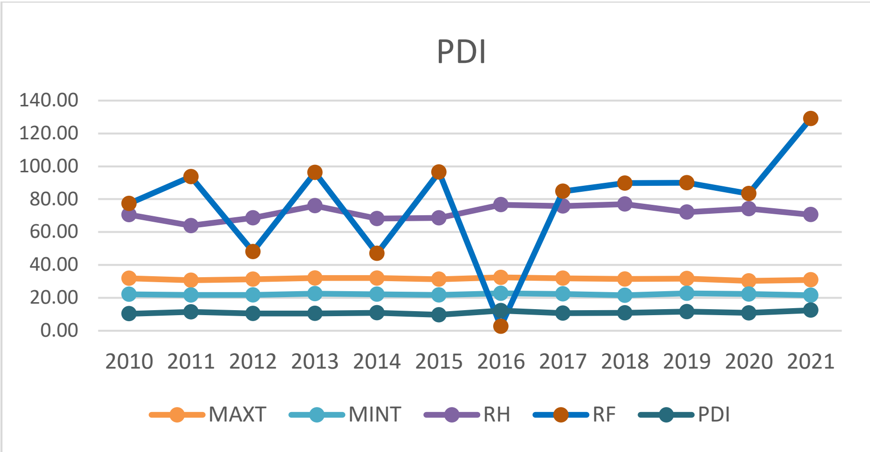

Fig. 3. Comparison of observed and predicted PDI as a function of years for various values of climatic factors. The line represent the predicted PDI and dot represent the observed PDI for Theni and surrounding villages

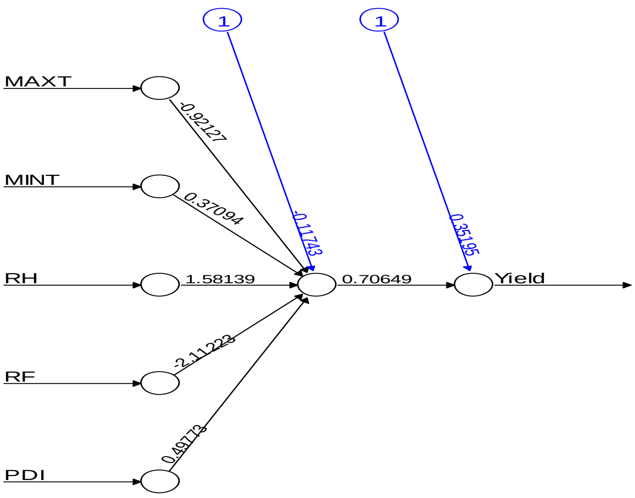

Fig. 4. Graphical representation of ANN

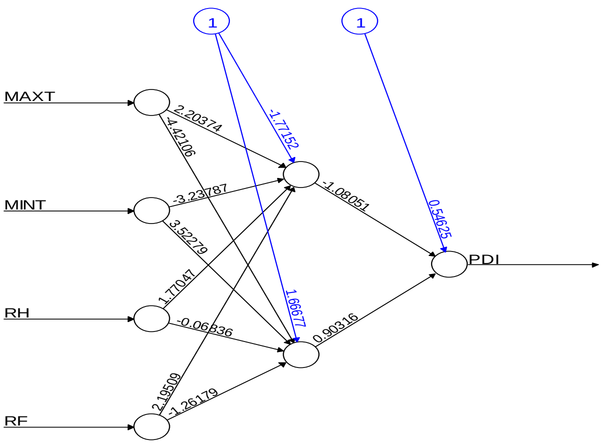

Fig. 5. Graphical representation of ANN model with PDI

5. CONCLUSION

From the study, three different statistical techniques were used and the techniques were compared by using different error measures. It is concluded that the ANN was found to be the best technique to predict the grape yield. This analytical result helps for the better understanding of the yield prediction for grape. Through numerical experiments we have been able to get further insight into thresholds for disease extinction that can contribute to crucial knowledge of disease control. Based on all the review cited, our model (ANN) predicted the grape yield with climatic factors and percent disease incidence with high accuracy of 98.3% and low RMSE value is summarised in Tables 12-13. By this, we can establish that ANN model is best for predicting grape yield in the studied region.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

ANN programme using R Code:

```
> set.seed(132)
> data<-data.frame(data)
> train_id<-data[1:7,]
> test_id<-data[8:9,]
> max = apply(data , 2 , max)
> min = apply(data, 2 , min)
> scaled = as.data.frame(scale(data, center = min, scale = max - min))
> trainNN = scaled[1:7,]
> testNN = scaled[8:12,]
> library(neuralnet)
> n<-neuralnet(Yield~.,data = trainNN,hidden=1,linear.output = TRUE)
> n$result.matrix
>plot(n)
> predict_testNN1 = compute(n, testNN[,-1])
> predict_testNN1
> predict_testNN = (predict_testNN1$net.result * (max(data$Yield) - min(data$Yield))) +
min(data$Yield)
> predict_testNN
> library(Metrics)
> mae(actual,predicted)
> mape(actual,predicted)
> rmse(actual, predicted)
```


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