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Assessment of bruchids density through bioacoustic detection and artificial neural network (ANN) in bulk stored chickpea and green gram

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A B S T R A C T

Acoustical detection of insects feeding and crawling sounds was used to automatically monitor internal and external grain feeding bruchids in order to assess the growth and density of food legume bruchids (*Callosobruchus chinensis* and *Callosobruchus maculatus*) in bulk stored chickpea and green gram. Bruchids hidden inside the grain kernels were detected acoustically through amplification and filtering of their mobility and feeding sounds. The multivariate technique of artificial neural network (ANN) was applied to assess and predict the bruchids' density in bulk stored legumes. Five levels of bruchids density (0, 5, 10 15 and 20 bruchids per 500 g) were monitored under without insulation and with insulated condition on the basis of formant parameter obtained by analysis of the acoustic sensor data. The K fold validation method with back propagation multilayer perceptron methodology was used for the prediction of bruchids densities. The maximum and minimum values of accuracy (R^2) of 0.99, 0.98 and 0.90, 0.89 could be achieved for both bruchids in stored green gram and chickpea under insulation and without insulation for the training and validation dataset, respectively. Least RMSE (0.82 and 0.89) was obtained for *C. maculatus* in sound insulated stored green gram for training and validation dataset, respectively. The accuracy of prediction and validation of experimental data with low RMSE and high R^2 values for both the food legumes indicated that the ANN modeling performed well in predicting bruchids density. Hence it can be concluded that, best prediction was obtained for the *C. maculatus* for green gram under insulated condition. The results further corroborated that bioacoustic detection technique with ANN provided a reliable and accurate monitoring technique for bruchids. The developed technique can be adopted in large bulk storage grain systems for the selected legumes for predicting and assessing the growth of bruchids thereby leading to safer storage.

1. Introduction

Chickpea and green gram are the important food legumes of India (IPGA, 2019). However, post-harvest losses are prominent in both the food legumes due to improper storage structures and storage management practices. One of the major consequences due to this is insect infestation especially of bruchids. The bruchids (*Callosobruchus chinensis, Callosobruchus maculatus* and *Callosobruchus analis*) are the primary insects which cause major post-harvest losses in stored cereals and food legumes (Banga et al., 2020). Thus, it is imperative to monitor the invasion caused by bruchids by adopting appropriate insect detection method, preferably at an early stage of insect's growth cycle, so as to take preventive measures at the right time. Insects incubation period is 3–6 days and larval development period is 12–20 days (Chavan et al.,

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1997). Larvae stage of insects are only responsible for feeding the legumes and the adult stage of insect survives for 10–12 days without any feeding (Fleurat-Lessard et al., 2006). Many sensor and non-sensor based detection methods such as probes, pheromones, visual lures, machine vision, X-ray imaging electrical conductance and acoustic etc. are being taken into consideration for the detection of infestation in food grains (Hagstrum and Flinn, 1993; Fleurat-Lessard et al., 2006; Banga et al., 2018). Among these methods, some methods like machine vision, X-ray imaging etc. are not very successful in detecting the early stage and internal infestation. Acoustical detection provides a fast and cost effective detection (Banga et al., 2019) even for internal or at the early stage of infestation.

Acoustical detection method uses insect feeding sounds to automatically monitor both internal and external grain feeding insects. Insects hidden inside the kernels of grain can be detected acoustically by amplification and filtering of their motility and feeding sounds (Fleurat-Lessard et al., 2006: Neethirajan et al., 2007: Njoroge et al., 2017, 2018, 2019). Feeding activity of *C. maculatus* in cowpea seeds was successfully monitored by using bioacoustic detection method with spectral responses of 16.4–26.5 kHz (Bittner et al., 2018). Banga et al. (2019) investigated bioacoustic detection of Callosobruchus species in bulk stored chickpea and green gram and reported that insect mobility sound formant parameter, a concentration of acoustic energy around a particular frequency in the sound spectrum, was the principal component in the detection of insect absence/presence in the bulk stored food legumes.

Recognition of pattern of sound activity of insects and data analysis is needed for interpreting the sound signals of bruchids for the identification purpose. Artificial neural networks (ANN) with multilayer perceptron (MLP), a feed forward neural network, is a multivariate statistical analysis useful for non-linear data driven self-adaptive approach in contrast to the traditional model based methods (Panagou and Kodogiannis, 2009). Perceptron is a simple neural network, which comprises of single or several neurons in a single layer (Vanneschi and Castelli, 2018). It determines and acquires the information of correlated patterns among input data sets and corresponding target values. Several researchers have analysed the signal patterns acquired by electronic nose and acoustic method by applying the statistical tools like the discriminant factorial analysis, principal component analysis, soft independent modelling class analogy and artificial neural network (ANN) (Banga et al., 2019; Srivastava et al., 2018, 2019a). A probabilistic artificial neural network and E-nose based classification of *Rhyzopertha dominica* infestation in stored rice grains via 18 metal oxide E-nose were conducted by Srivastava et al., 2019 and they found the applicability of E-nose with high accuracy of ANN in securing the data analysis time without loss of information.

Nonetheless, limited research has been conducted on the precise detection of infestation in stored food legumes, especially for detection of *C. chinensis* and *C. maculatus* in chickpea and green gram. Further, for deployment of such system in the field, robust models are required to predict the infestation level on the basis of insect acoustic activity. This research work aims to develop an artificial neural network (ANN) model to predict the insect density on the basis of insect sound formant.

2. Materials and Methods

2.1. Sample preparation

Chickpea (variety JF-6) sourced from the Indian Council of Agricultural Research-Central Institute of Agricultural Engineering (ICAR-CIAE) farm in the season which was harvested during March 2018 and green gram (variety ML-337) procured from the local market of Bhopal were used for the experimentation. Bruchids were cultured over green gram in controlled condition (25 °C, 75–85% RH) at ICAR-CIAE, Bhopal. Food legumes were stored at environment temperature of 24 °C and 51.70% relative humidity, monitored by using digital humidity and temperature (DHT 22) sensor module. The recommended storage temperature for food legumes is 20–40 °C (Mara et al., 2007). Five hundred gram samples of each of the food legumes considered in this investigation were stored for 15 days at 5 levels of bruchids (*C. chinensis* and *C. maculatus*) density (0, 5, 10, 15 and 20 per 500 g). Samples of zero days at zero levels were considered as controlled samples.

2.2. Development of acoustic sensor network system and storage bin

A Sensor network system consisted of two acoustic sensors (CZN-15E Omnidirectional Electret Condenser Microphone) was developed with signal processing, on laboratory scale for insect sound detection in a galvanized iron storage bin of 500 g capacity (80 × 110 mm). Sound Spectra of insect was screened by using open access Praat software (Boersma and Weenink, 1991). Source of power to the system was supplied through a 9 voltage battery, which reduced the noise level in the insect sound spectrum. Acoustic sensors were inserted into the bin through the hole made in the cap of the bin. A view of the experimental set up under ambient and insulated conditions is shown in Fig. 1 (a) and (b).

2.3. Monitoring of insect sound

Monitoring of insect sound spectrum with insulation and without insulation conditions at five levels (0, 5, 10, 15 and 20) of insect density for both the food legumes and both the species were measured. Sound of insects was monitored at 5 min interval, on each day. Peak formants of insect sound were extracted by using Praat Software. Two hundred and fifty observations for each insect species (*C. chinesnsis* and *C. maculatus*) and each food legumes (chickpea and green gram) in 500 g sample were randomly selected for the development of the model. Insect density was determined by using ISO 6639 of rapid method of determining hidden insect infestation (ISO 6639-3:1986).

2.4. Modelling of insect density using captured insect sound formants

Multilayer Perceptron (MLP) was applied for developing the artificial neural network (ANN) of captured insect sound formants with the insect density. Selection of optimum values of number of hidden layers, number of nodes, type of activation functions, learning rate and number of models were obtained by trial and error, to get the best prediction of insect density according to statistical parameters. Model development by ANN consisted of following steps:

2.4.1. Selection of variables

Variables were selected as dependent (insect sound formant) and independent (insect density) for the model development.

2.4.2. Formatting of training and validation dataset

The dataset was divided into training (166) and validation (84) sets for determining the corresponding relations. Training set used a large number of data to learn the pattern present in the input data set. The training set was the part, which estimated the model parameters. Validation of dataset used a part of dataset to estimate the model parameters and used the other part to evaluate the

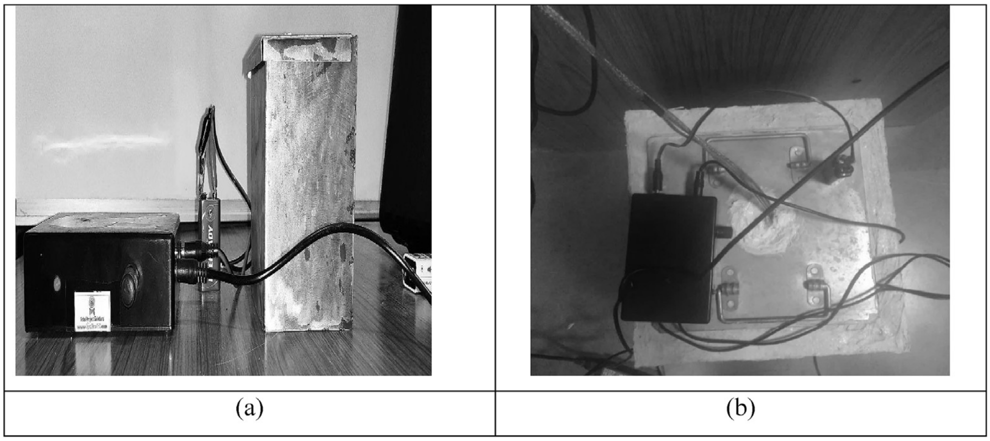

Fig. 1. (a) Ambient environment view of experiment set up, (b) Insulated environment view.

predictive ability of the model. Performance of the trained network set was made by using the validation data set. K fold validation method was used (Tufail et al., 2008), which divided the original data set into 3 subsets. All the sub sets were used to validate the model fit on rest of the data. The model, which confirmed to the best validation test statistics, was chosen as the final model.

2.4.3. Development of neural network architecture

I. Hidden Layer Structure: Architecture of neural network included the one hidden layer with input (X variable) and output layer (Y variable). In ANN architecture, node takes the input data and performs simple operations by applying activation function on the data. Each node was linked with each other with weighted link value. Hidden layer provided the generalization of the network. One hidden layer with nodes is useful for the approximation of the continuous function (Jha, 2007). Selection of optimum number of hidden nodes was followed by using the geometric pyramid rule given by Masters (1993). Hidden nodes are the non-linear functions of the original inputs. One output node was used. The number of links with hidden layer nodes exhibits the intricacy of the ANN, because they increase the number of connections in ANN (Tufail et al., 2008). The functions applied at the nodes of the hidden layers are called activation functions. Activation functions are mathematical formulae, which provide the output of a determining node. Non-linear function, hyperbolic tangent (TanH) was applied (Equation-1) for establishing the relationship between insect density and insect sound formant (Srivastava et al., 2019). It is a commonly used sigmoid function as it differentiates continuously, a desirable characteristic for network learning. Activation function affects the efficiency of ANN, because it is the only way to simulate the phenomenon between the input and output parameters (Gholipoor and Nadali, 2019).

$$f(x) = \frac{2}{(1+e^{-2x})} - 1 \qquad \text{Eq. (A.1)}$$

II. Boosting: It involved the process of developing a large additive neural network model by following a sequence of smaller models, which are scaled by learning rate. Ten number of models were applied for boosting. The learning rate must be $0 < r \leq 1$ (Vanneschi and Castelli, 2018). Learning rate of 0.1 was applied to reduce the over fitting of data. Learning rate also depended on the number of models applied (Ferentinos, 2018; Safa et al., 2018).

III. Fitting: It provides the functions for variable transformation and model fitting. Transform covariates was applied, as it transformed all the continuous variables to near normality. Transformation of variables to normality reduced the effect of outliers. Penalty method was used to mitigate the over fitting of data (Tufail et al., 2008). The penalty was $\lambda p(\beta i)$, where λ was the penalty parameter and $p(\beta i)$ was a function of parameter estimates. Different methods of penalty are available, but in this research work, squared method was applied, as it involved the fitting of all X variables for development of model.

Number of tours (10) was also applied as it specified the number of times to restart the fitting process of the model. Iteration of the process used different random stating values for the estimation of parameters. Model used the best validation statistics for developing the final model. Prediction of insect density was done in the JMP PRO 10 software (SAS Institute, 2005).

2.5. Statistical analysis of ANN

To evaluate the performance of different ANN configurations, three statistical parameters such as coefficient of determination (R^2), root mean sum-squared error (RMSE) and mean absolute deviation (MAD) were used (Safa et al., 2018). The parameters were calculated by using the following equations:

$$MAD = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i) \qquad \text{Eq. (A.2)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \qquad \text{Eq. (A.3)}$$

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2 \sum_{i=1}^{n}(P_i - \overline{P})^2}} \qquad \text{Eq. (A.4)}$$

Where, n = number of data, O_i is the observed values, P_i is the predicted values, and the bar is the mean of variables.

3. Results and discussion

3.1. Artificial neural network for assessing density of *C. chinensis* and *C. maculatus* with formant in bulk stored chickpea with and without insulated condition

Multi-layer perceptron artificial neural network (MLP-ANN) of *C. chinensis* and *C. maculatus* in bulk stored chickpea was developed by using K fold validation method.

Formant values of *C. chinensis* and *C. maculatus* at 05 density levels (0, 5, 10, 15 and 20) in bulk stored chickpea with and without insulated condition were fed to develop the ANN as formant (X variable) and density (Y variable). Prediction of insects densities were evaluated by applying ANN. Different values of formant were obtained at different insect density values. Sometimes formant values was increased and sometimes decreased such as at 5 insect density levels formant value was 1978 and in the next observation it was 1430 at same insect density level and prediction values of insect density by ANN on that formant values were 8 and 5, respectively. It was observed that formant values of insects were increased with the increasing value of insect density (Fig. 2). Predicted values of insect density were also increased in the similar way of experimental values with respect to formant values.

Statistical fitness measures of model developed for linking the *C. chinensis* and *C. maculatus* density with its sound pattern (formant) by ANN for training and validation set are given in Table 1. Statistical indices represented the accuracy of model to predict the insect density on the basis of insect sound formant. According to the results obtained for training and validation sets, validation set represented the model's predictive power for future observations. The R^2 statistic indices of validation set signified that the model was predicting well on data not used to train the model. The MAD represented the average distance between each data point and the mean, which provided the idea about the variability present in the dataset. Sum frequency represented the distribution of data between training and validation dataset.

ANN with tangent-sigmoid transfer achieved R^2 of 0.90 and 0.95 for the training and validation (0.89 and 0.94) dataset for *C. chinensis* under without and with insulated condition. The lower value of R^2 of validation dataset as compared to training dataset signified that the model was predicting well on data not used to train the model for both the insects. Model developed for *C. maculatus* density estimation in stored chickpea with and without insulated condition obtained the same R^2 of 0.95 and 0.94 for the training and validation dataset, respectively.

Statistical indices, RMSE which indicated the accuracy of ANN model were 2.23 and 1.69 for training and 2.29 and 1.60 for validation dataset for without and with insulated condition, respectively for *C. chinensis*. RMSE values of model developed for *C. maculatus* was 1.58, 1.55 and 1.73, 1.72 for the training and validation dataset under without and with insulation, respectively.

MAD in the training dataset for *C. chinensis* were 1.56 and 1.12 and 1.57 and 1.10 for the validation dataset under without and with insulation, respectively. MAD for *C. maculatus* were 1.18 and 0.97 for the training dataset and 1.27 and 1.07 for the validation dataset.

3.2. Artificial neural network for assessing density of C. chinensis and C. maculatus with formant in bulk stored green gram with and without insulated condition

In the similar way of chickpea stored experiments, formant values of *C. chinensis* and *C. maculatus* at 05 density levels (0, 5, 10, 15 and 20) in bulk stored green gram with and without insulation were acquired to develop an ANN. As in the previous cases of chickpea, similar trend of increasing and decreasing of formant values was observed at different insect density levels (Fig. 3). Prediction of insect densities was also evaluated by applying ANN.

Statistical fitness measures of model developed for linking the *C. chinensis* and *C. maculatus* density with its sound pattern (formant) in bulk stored green gram with and without insulation by ANN for training and validation set are given in Table 2.

R^2 of ANN model of *C. chinensis* achieved by applying tangent-sigmoid transfer was 0.94, 0.98 and 0.91, 0.98 for the training and validation dataset under without and with insulation, respectively. RMSE of ANN model of *C. chinensis* for training and validation model were 1.75, 0.96 and 2.08, 0.97 which indicated that a good model was built for the prediction of insect density on the basis of insect sound formant with low error values. MAD in the training and validation dataset were 1.23, 0.68 and 1.40, 0.64 for ANN model of *C. chinensis* for bulk stored green gram without and with insulation.

Coefficient of determination (R^2) for the modeling of *C. maculatus* density in bulk stored green gram without and with insulation alongwith formant was 0.97, 0.99 and 0.97, 0.98 for training and validation dataset. Low error values (RMSE) of the model were 1.20, 0.82 and 1.31, 0.89 obtained for *C. maculatus* for the without and with insulation in the training and validation data set, respectively. Variability representing indices MAD were 0.81, 0.56 and 0.92, 0.60 for ANN model of *C. maculatus* under without and with insulation, respectively.

3.3. Prediction profiler for the estimation of insect density

To understand the impact of X variable (formant) on Y variable (density) plots of prediction profiler were developed for *C. chinensis* and *C. maculatus* for chickpea and green gram under without and with insulated condition. The horizontal dotted line in the charts of prediction profiler shows the current predicted value of each Y variable for the current values of the X variables. Charts of prediction profiler of *C. chinensis* and *C. maculatus* density with formant in bulk stored chickpea and green gram without and with insulation for the estimation of insect density with formants are shown in Fig. 4. Sensitivity indicator (triangle shape) as shown in charts represented the sensitivity of insect detection at given sound formant and density value. These charts show the profile estimation for the prediction of insect density on the given insect sound formant. Desirability function was also applied in all the cases, which indicated the optimization of parameters to get the most desirable parameter. Different values of desirability were achieved for the different cases. Optimization of insect density with formant is shown in charts. Similar plots have also been considered in the prediction of *S. granarius* infestation in stored wheat (Mishra et al., 2018).

3.4. Plots of actual density and residual density versus predicted density

Plots of actual density versus predicted density for training and validation dataset of *C. chinensis* and *C. maculatus* in bulk stored chickpea and green gram with insulation and without insulation are shown in Fig. 5. As an additional assessment of model fit, plot of actual density versus predicted density gives the more additional assessment to the model. In all the plots of training and validation dataset values of all data resembles near by the diagonal line, which indicates that similar values were obtained for the prediction of insect density. These charts shows that model was accurate for predicting the insect density as there's a strong correlation between the predicted and actual values of insect density. In all the plots except validation plot of *C. chinensis* in green gram for with insulation condition, more values were clustered towards the negative values.

Accuracy of the developed model has been evaluated by plotting the predicted density values against the residual density values (Fig. 6). Positive values for the residual density on y-axis indicate lower prediction and negative values indicate higher prediction from the actual value. Zero point on y-axis indicates the correct prediction of insect density. In the below given plots at insect density value of 5 for *C. chinensis* in chickpea without insulated condition of training dataset, more values are distributed towards

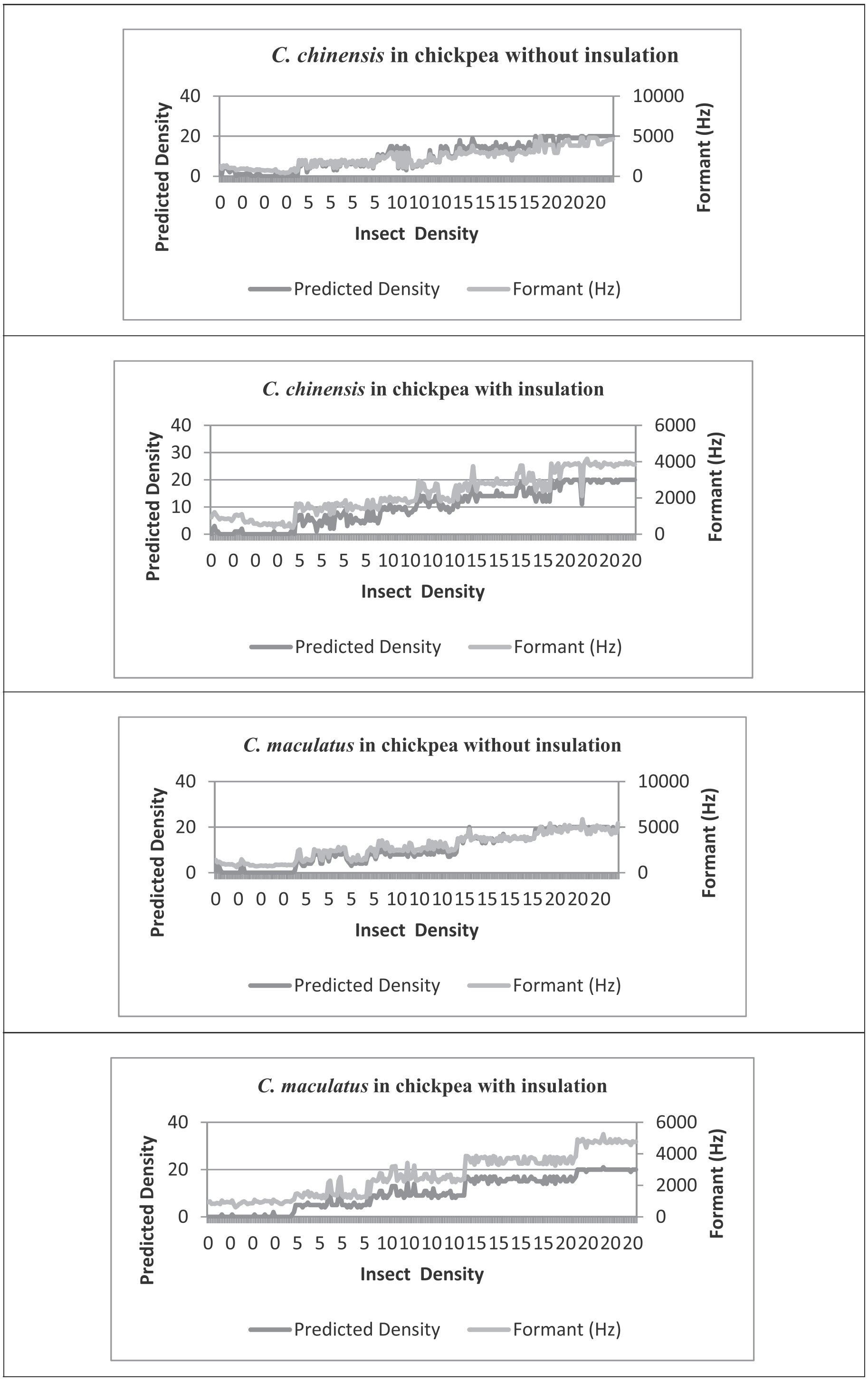

Fig. 2. Relation among actual insect density with formant and predicted density in chickpea without and with insulation.

the negative points which indicates that the model predicted insect densities slightly higher than the actual. In the case of insect density value of 10, similar pattern of distribution of insect density values was observed. For insect density value of 15, more values were orienting towards the positive points. In case of insect density value of 20, a symmetric pattern was observed. Since the density residual values for all the case are lower than ±6, it can be concluded that the model is fairly accurate with slightly low precision.

Similar pattern of distribution of residual density and predicted density values along the horizontal point zero was observed for *C. chinensis* with insulated condition in chickpea for the training and validation dataset. Plots of *C. maculatus* showed the distribution of values more toward the negative points in all the cases of insect density modeling, which indicated the good fitting of model.

In all the plots except validation plot of *C. chinensis* in green gram for with insulation condition, more values were clustered towards the negative values. Distribution of density values of

Table 1
Statistical fitness measures of model for insect density of *C. chinensis* and *C. maculatus* in bulk stored chickpea with and without insulated condition.

Statistical Measures	*C. chinensis*				*C. maculatus*			
	Training		Validation		Training		Validation	
	Without Insulation	With Insulation	Without Insulation	With Insulation	Without Insulation	With Insulation	Without Insulation	With Insulation
R^2	0.90	0.95	0.89	0.94	0.95	0.95	0.94	0.94
RMSE	2.23	1.69	2.29	1.60	1.58	1.55	1.73	1.72
MAD	1.56	1.12	1.57	1.10	1.18	0.97	1.27	1.07
Sum Freq.	166	167.00	84	83.00	200.00	166.00	50.00	84.00

Note: R^2 = Coefficient of determination, RMSE = Root mean square error, MAD = Mean absolute deviation, Freq. = Frequency.

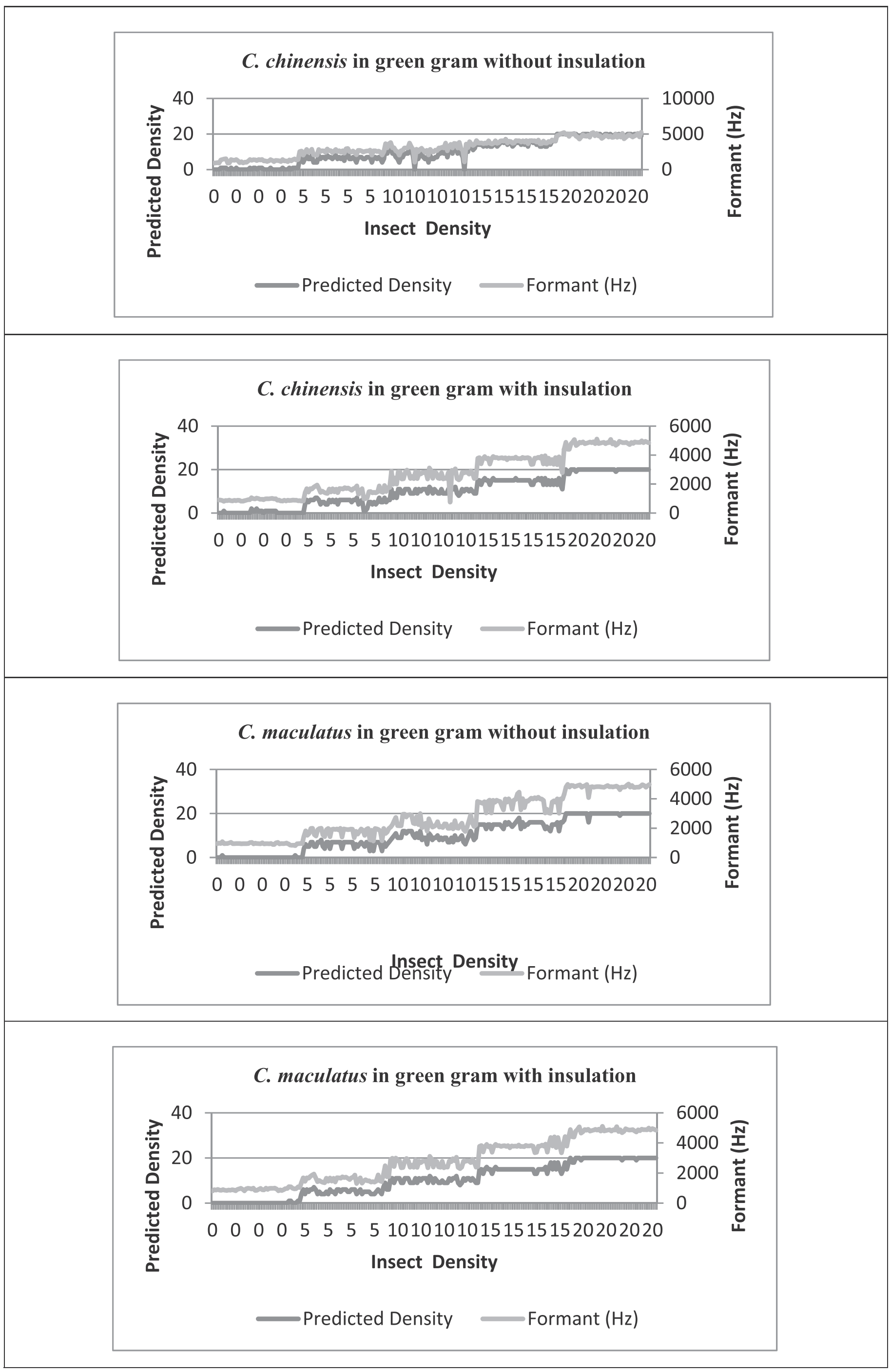

Fig. 3. Relation among actual insect density with formant and predicted density in green gram without and with insulation.

Table 2
Statistical fitness measures of model for insect density of *C. chinensis* and *C. maculatus* in bulk stored green gram with and without insulated condition.

Statistical Measures	*C. chinensis*				*C. maculatus*			
	Training		Validation		Training		Validation	
	Without Insulation	With Insulation	Without Insulation	With Insulation	Without Insulation	With Insulation	Without Insulation	With Insulation
R^2	0.94	0.98	0.91	0.98	0.97	0.99	0.97	0.98
RMSE	1.75	0.96	2.08	0.97	1.20	0.82	1.31	0.89
MAD	1.23	0.68	1.40	0.64	0.81	0.56	0.92	0.60
Sum Freq.	167.00	167.00	83.00	83.00	167.00	166.00	83.00	84.00

Note: R^2 = Coefficient of determination, RMSE = Root mean square error, MAD = Mean absolute deviation, Freq. = Frequency.

C. maculatus in green gram without insulation at insect density value of 15 was more towards the positive points and in the rest of insect densities more distribution was shown towards negative points. While in the case of with insulation, symmetric pattern was observed for all the density values of insect.

3.5. Models for the prediction of insect density on the basis of insect sound formant

Development of model for the linking of insect formant with insect density by ANN included the 30 hidden nodes. Equations of ANN model for chickpea and green gram for *C. chinensis* and *C. maculatus* without insulation and with insulation are given below.

Equation for the *C. chinensis* in chickpea without insulation is given as:

Insect density = 3.14 + 0.42*H1-1.25 * H2 + … … … …+ 36.28 * H30 Eq. (B.1)

Equation for the *C. chinensis* in chickpea with insulation is given as:

Insect density= (−22.86) + (−10.38) *H1 + (−4.79) *H2 + …..+ 11.59 * H30 Eq. (B.2)

Equation for the *C. maculatus* in chickpea without insulation is given as:

Insect density = 8.66 + 4.06*H1+3.08*H2+ … … …. . + −1.76 *H30 Eq. (B.3)

Equation for the *C. maculatus* in chickpea with insulation is given as:

Insect density = 6.40+-0.16*H1+-0.87 * H2 + … ……. +-4.51 * H30 Eq. (B.4)

Equation for the *C. chinensis* in green gram without insulation is given as:

Insect density = 13.92+-63.65*H1 + −42.99 * H2 + … …. + −72.39 * H30 Eq. (B.5)

Equation for the *C. chinensis* in green gram with insulation is given as:

Insect Density = 500.29+-29.60*H1+-4.12*H2 + ……..+ 421.25 * H30 Eq. (B.6)

Equation for the *C. maculatus* in green gram without insulation is given as:

Insect Density = 201.74+-944.71*H1+-168.09*H2 … … …. + 18.03 * H30 Eq. (B.7)

Equation for the *C. maculatus* in green gram with insulation is given as:

Insect Density=(-52.70)+ 0.52 *H11+ −0.48 * H12 + …… …. .+ −3.12 * H30 Eq. (B.8)

4. Discussion

4.1. Development of model for assessing the insect density using captured sound pattern

Low error in both the dataset of without and with insulated condition stored chickpea infested with *C. chinensis* and *C. maculatus* indicates that a good model was built for the prediction of insect density on the basis of insect sound formant. In the similar way, low RMSE was obtained in the prediction of infestation caused by *Sitophilus granarius* and *S. oryzae* in stored wheat and rice, respectively (Mishra et al., 2018; Srivastava et al., 2019). Other fitness measures mean absolute deviation of ANN model was used to evaluate the variability present in the data set of training and validation. Low values of MAD indicated the good fitting of model.

Similar pattern was followed for describing the authenticity of prediction model was signified by statistical fitness measures R^2, RMSE and MAD for *C. chinensis* and *C. maculatus* in bulk stored green gram without and with insulated condition. All the statistical parameter indicated that ANN model fitted very well for the prediction of bruchids density on the basis of sound formants.

Similar statistical fitness measures were used by several researchers. High R^2 (0.96 and 0.98) for the prediction of uric acid and protein content in infested wheat caused by *Sitophilus granarius* by applying multiple linear regression (MLR) was achieved (Mishra et al., 2018). In another research of identification and differentiation of insect infested rice grain varieties with FTNIR spectroscopy and hierarchical cluster analysis, high percentage of accuracy (93.10−99.74%) of classification was obtained (Srivastava et al., 2018). In the classification of rice grains infested by *S. oryzae*, high R^2 of 0.97 and 0.99 and low RMSE values of 2.08 and 1.05 was obtained (Srivastava et al., 2019). The adaptability of ANN with back propagation MLP approach was used to classify the *Rhyzopertha dominica* infestation in stored rice and found 98.9% of accuracy and overall relative error of ANN training and testing was 0.092 and 0.286, respectively (Srivastava et al., 2019).

In the current research, for all the cases of modeling of bruchids sound formant with bruchids density, it was observed that R^2 values above 0.90 were obtained for all the models except the R^2 value of validation dataset of non-insulated stored chickpea infested with *C. chinensis*. Maximum (0.99 and 0.98) and minimum R^2

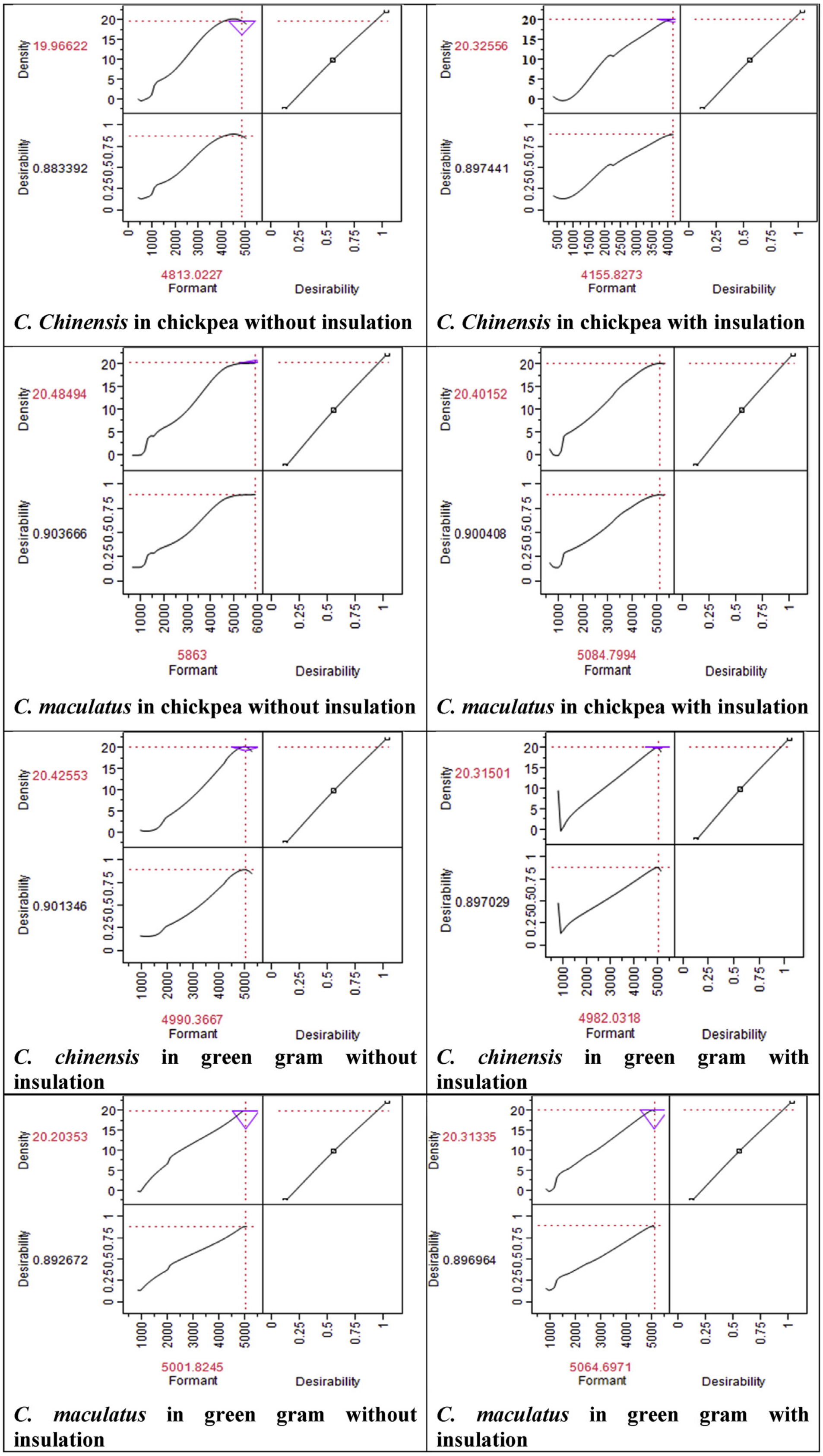

Fig. 4. Plots of prediction profiler with desirability function.

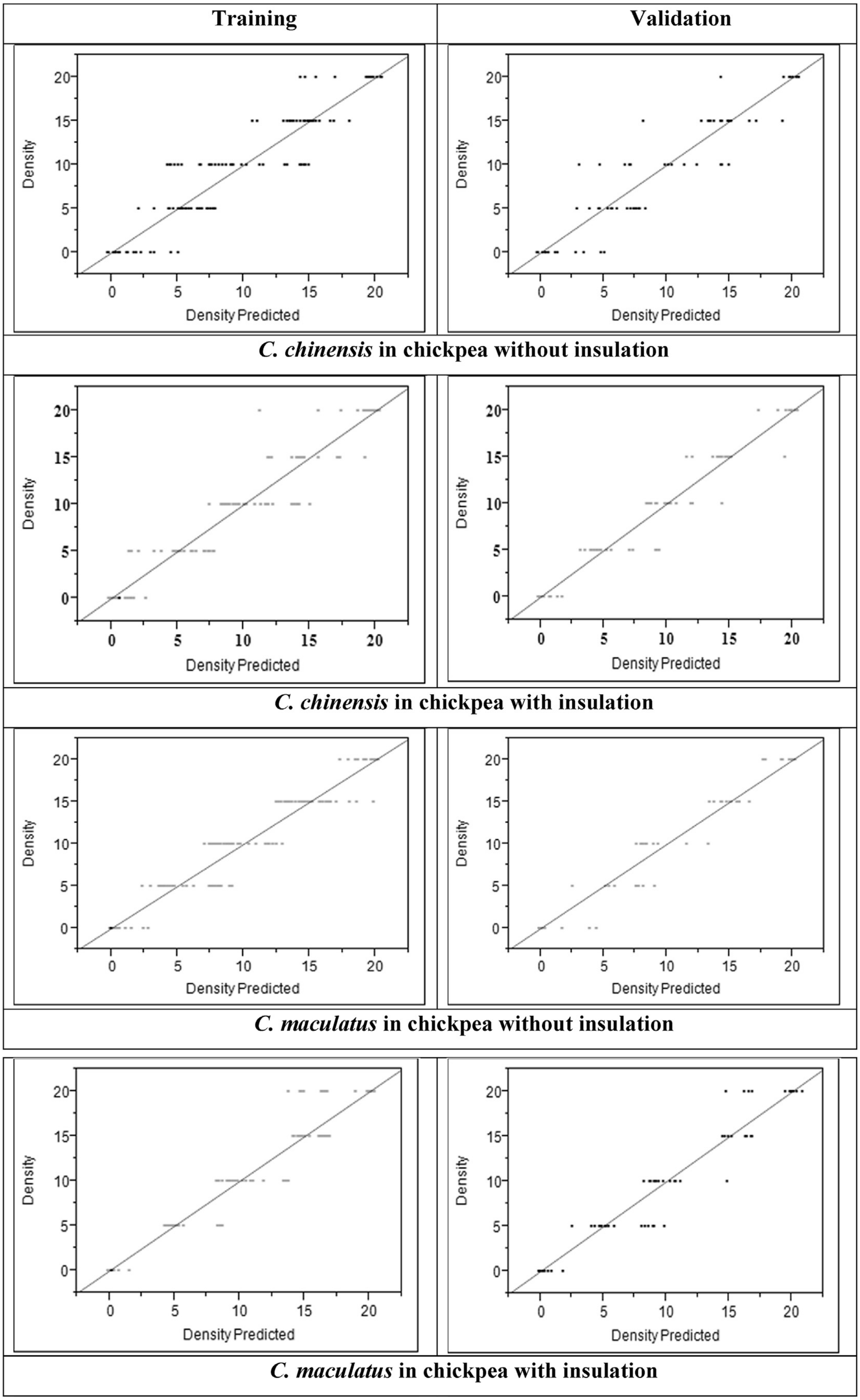

Fig. 5. Plot of actual density versus predicted density of training and validation dataset.

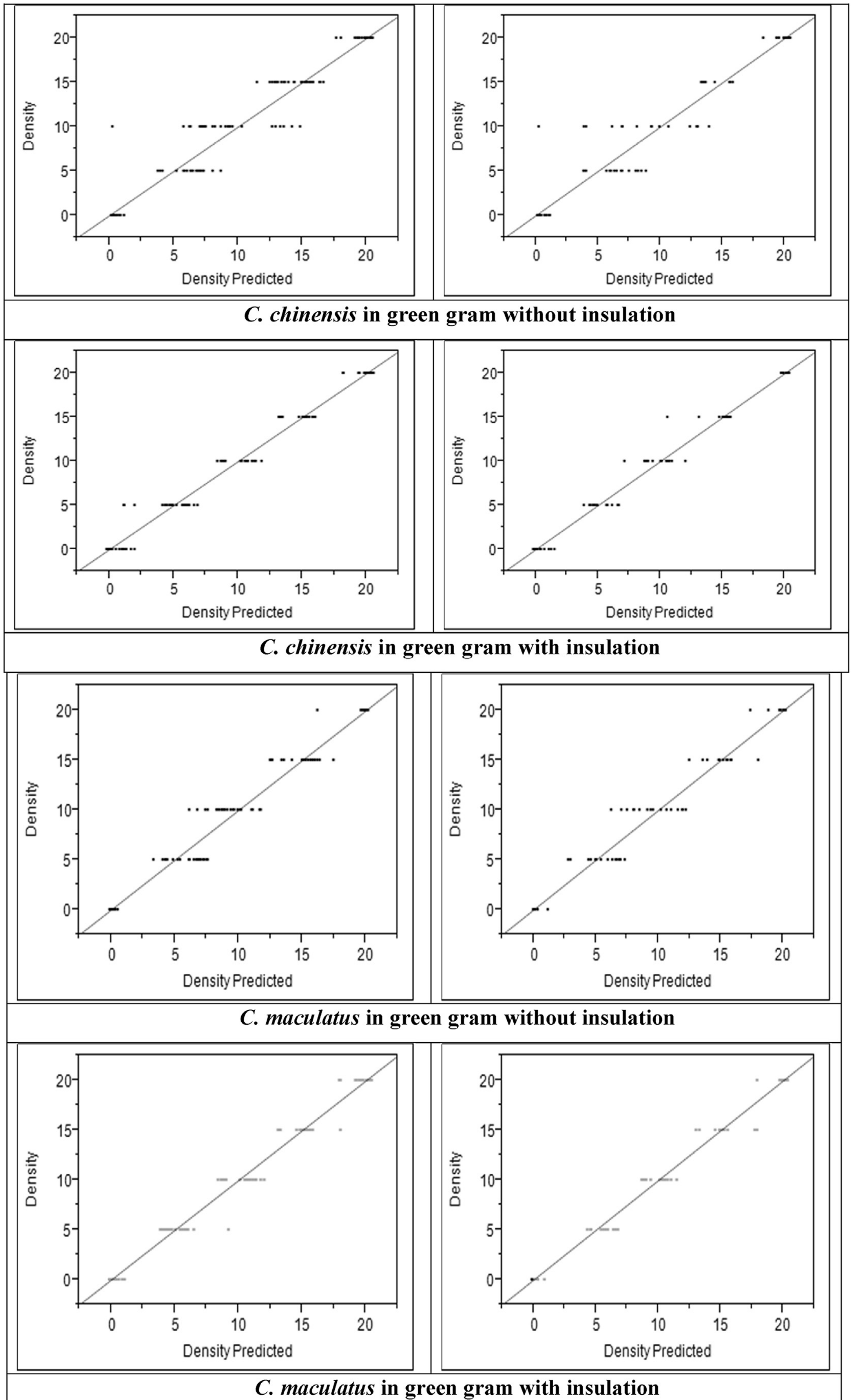

Fig. 5. (*continued*).

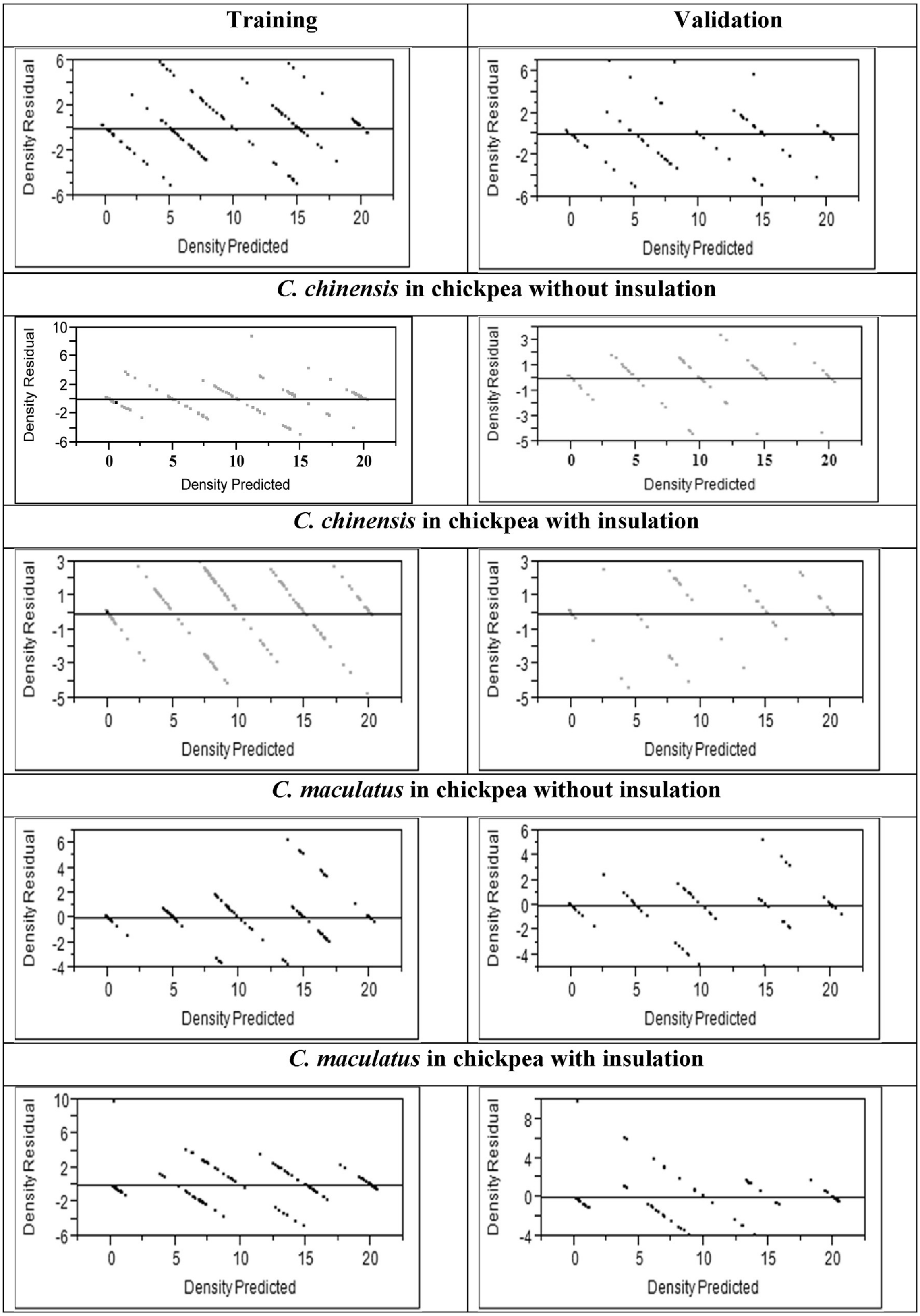

Fig. 6. Evaluation of model accuracy and precision for prediction of insect density using training and validation dataset.

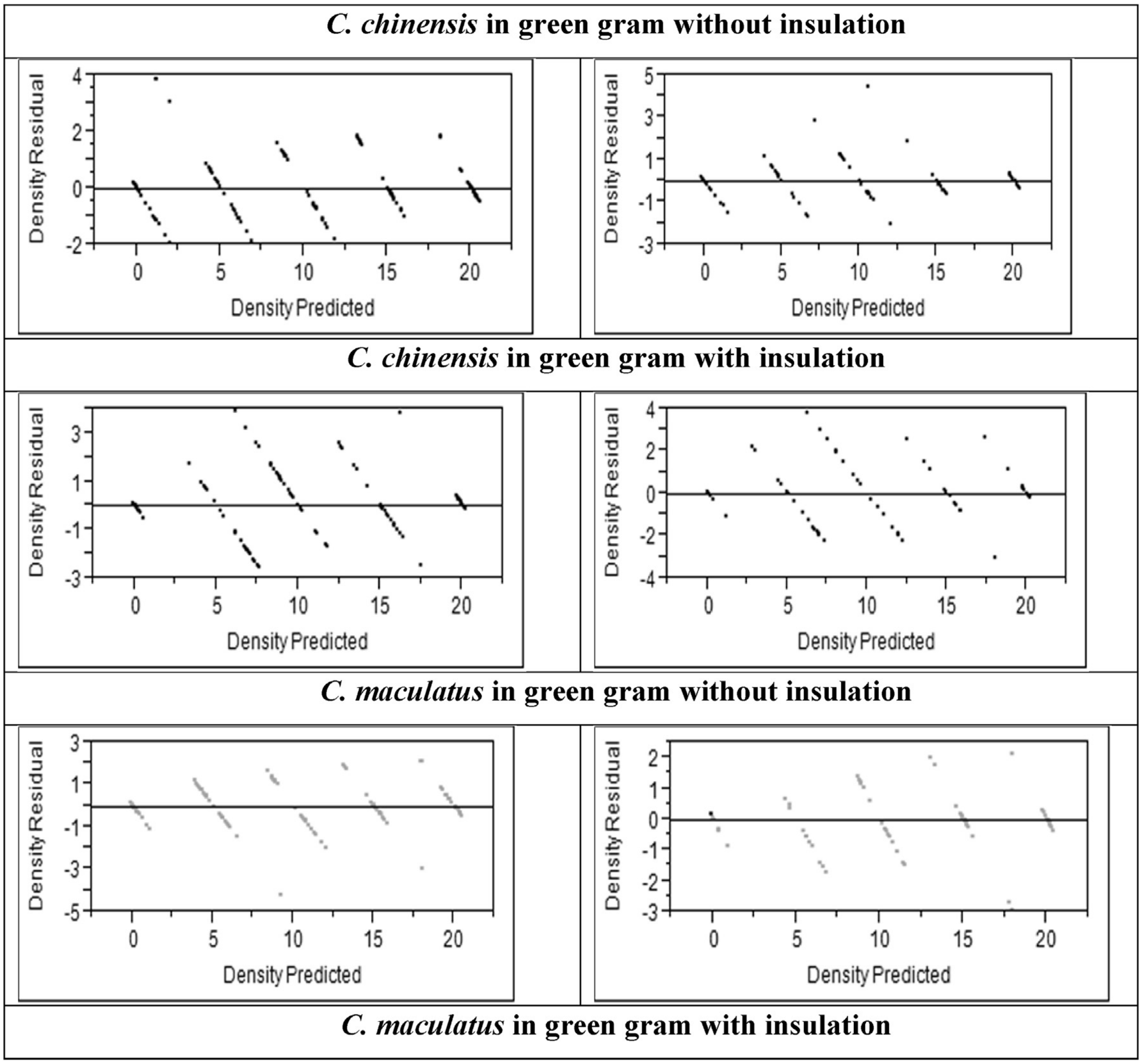

Fig. 6. (*continued*).

(0.90 and 0.89) values were obtained for the insulation condition of green gram in the case of *C. maculatus* and non-insulated stored chickpea infested by *C. chinensis*, respectively. Least values (0.82 and 0.89) high (2.23 and 2.29) of RMSE were obtained for training and validation under sound insulated stored green gram infested with *C. maculatus* and without insulation stored chickpea infested with *C. chinensis*, respectively. Maximum (1.56 and 1.57) and minimum (0.56 and 0.60) values of MAD were achieved for chickpea infested with *C. chinensis* stored with insulation and sound insulated stored green gram infested by *C. maculatus.* According to aforementioned results, maximum R^2, low RMSE and MAD values were obtained for the insulated condition of green gram infested by *C. maculatus.* Hence, it is concluded that ANN model could accurately predict the insect density under insulation condition for both the insects considered under this investigation. The results further verified that bioacoustic detection technique with ANN provides a reliable and accurate insect monitoring technique.

In the development of ANN model for assessing the density of *C. chinensis* and *C. maculatus* with formant with and without insulated condition stored chickpea, more values of data were used by the training dataset to understand the pattern of values. More accuracy was achieved in insulated condition due to less interference caused by background noise. Similar results were obtained in the identification of rice infested by *R. dominica* (Srivastava et al., 2019).

In the charts of actual density versus predicted density for training and validation dataset, data resembles near by the diagonal line, which indicated that similar values were obtained for the prediction of insect density. Symmetrical distribution along the diagonal line indicates the strong correlation between the actual and predicted values of insect density. Bell et al. (2013) also reported the same plots for the prediction of insect migration density and speed. Charts of residual density versus predicted density also indicated the good fitting of model for all the cases by more orienting the data values towards the negative points. Similar plots were used for predicting the migration of insect density and speed in daytime convective boundary layer (Bell et al., 2013).

5. Conclusions

A bioacoustic detection system with artificial neural network to predict the insect infestation level in bulk stored food legumes was adopted to formulate insect density prediction models employing ANN technique. Higher accuracy (R^2) and low RMSE values of training and validation data of *C. chinensis* and *C. maculatus* in bulk stored chickpea and green gram without and with insulation were achieved successfully. In all the cases of insulated condition, low RMSE could be obtained. The ANN model developed for *C. maculatus* under insulation using training dataset in bulk stored green gram showed maximum accuracy whereas minimum accuracy was observed for the model developed for *C. chinensis* in chickpea stored without insulation using the validation dataset. High accuracy obtained for the developed model of all the cases of insects in both the food legumes confirmed that models work well for the prediction of insect density on the basis of sound formant parameter. Least RMSE was obtained for the model developed to predict *C. maculatus* in sound insulated stored green gram for the training and validation dataset. On the basis of statistical fitness measures, it can be concluded that best model was obtained for the *C. maculatus* for green gram under insulated condition. Hence, it may be concluded that ANN gave accurate prediction results for the prediction of insect density. Detection of *C. maculatus* in green gram under insulated condition might be better than the other cases of detection due to the more acoustic activity caused by big size bruchids and less interference due to background noise. The results further bolstered the hypothesis that bioacoustic detection technique with ANN could provide a reliable and accurate insect monitoring technique. Prediction of bruchids density by adopting ANN might be helpful to reduce the fumigation treatments and also reduce the post-harvest losses. Although the performance under insulated conditions was better, the performance of model under un-insulated condition was not bad and hence the model could be employed in un-insulated bins with the developed acoustic detection system. The technique may further be adopted for bulk storage of selected legumes to assess the growth of insect population in bulk storage as a decision support system in a grain storage facility.

CRediT authorship contribution statement

Km. Sheetal Banga: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Nachiket Kotwaliwale:** Supervision, Conceptualization, Visualization, Data curation, Writing - review & editing. **Debabandya Mohapatra:** Supervision, Conceptualization, Visualization, Writing - review & editing. **V. Bhushana Babu:** Supervision, Conceptualization, Visualization, Formal analysis, Writing - review & editing. **Saroj Kumar Giri:** Supervision, Conceptualization, Visualization, Writing - review & editing. **Praveen Chandra Bargale:** Supervision, Conceptualization, Visualization, Writing - review & editing.

Declaration of competing interest

No conflict of interest.

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Appendix A. Supplementary data

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