

Precision Agriculture Research Program

Introduction

Canada is producing more than 50% of the world's wild blueberry crop. Fruit losses during harvesting are consequence of complex interactions between mechanical parameters, crop characteristics, weather conditions, soil structure, operator skills and field topography. Understanding and predicting these relationships can aid in better berry recovery during mechanical harvesting.

Wild blueberry growers are facing increased harvesting losses with their existing harvesters due to changes in crop conditions caused by improved management practices emphasizing the need to study the harvesting dynamics and to identify the sources responsible for losses. Therefore, the objectives of this work were to:

- Develop a predictive model by employing the artificial neural network (ANN) and multiple regression (MR) techniques, and
- To evaluate the potential and efficiency of the developed models against independent datasets.

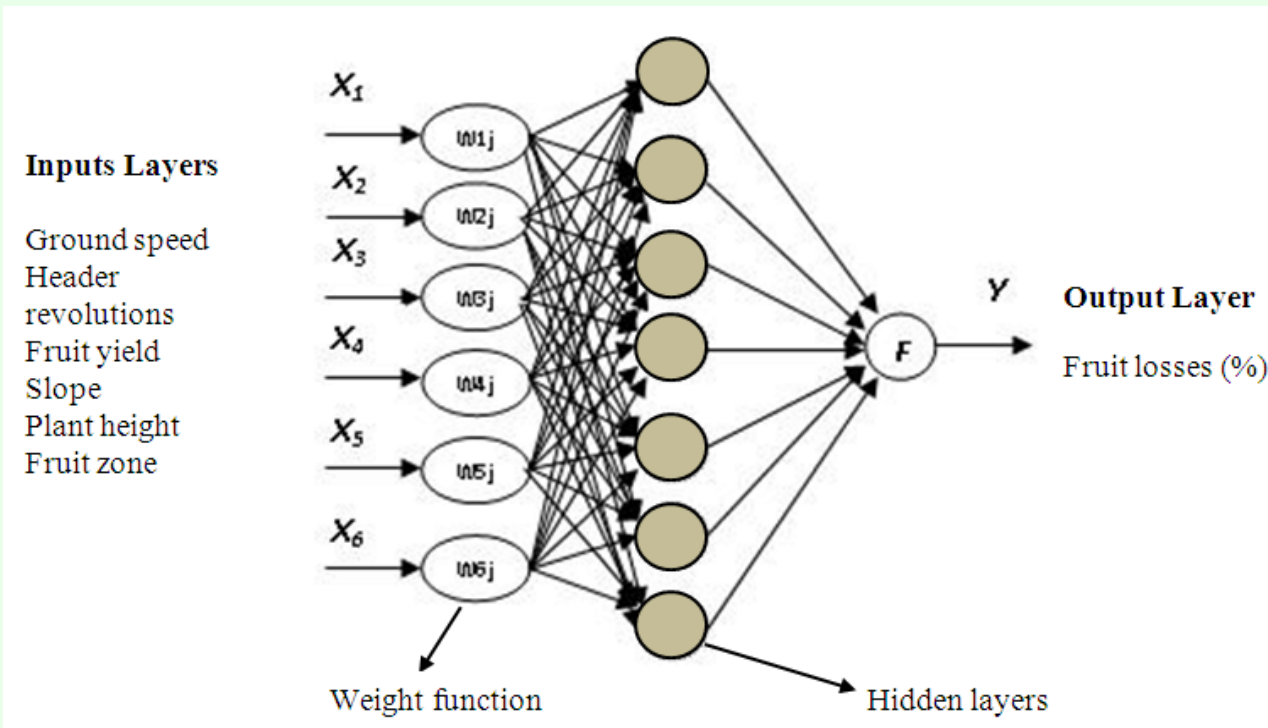


Fig: Multilayer artificial neural network model.

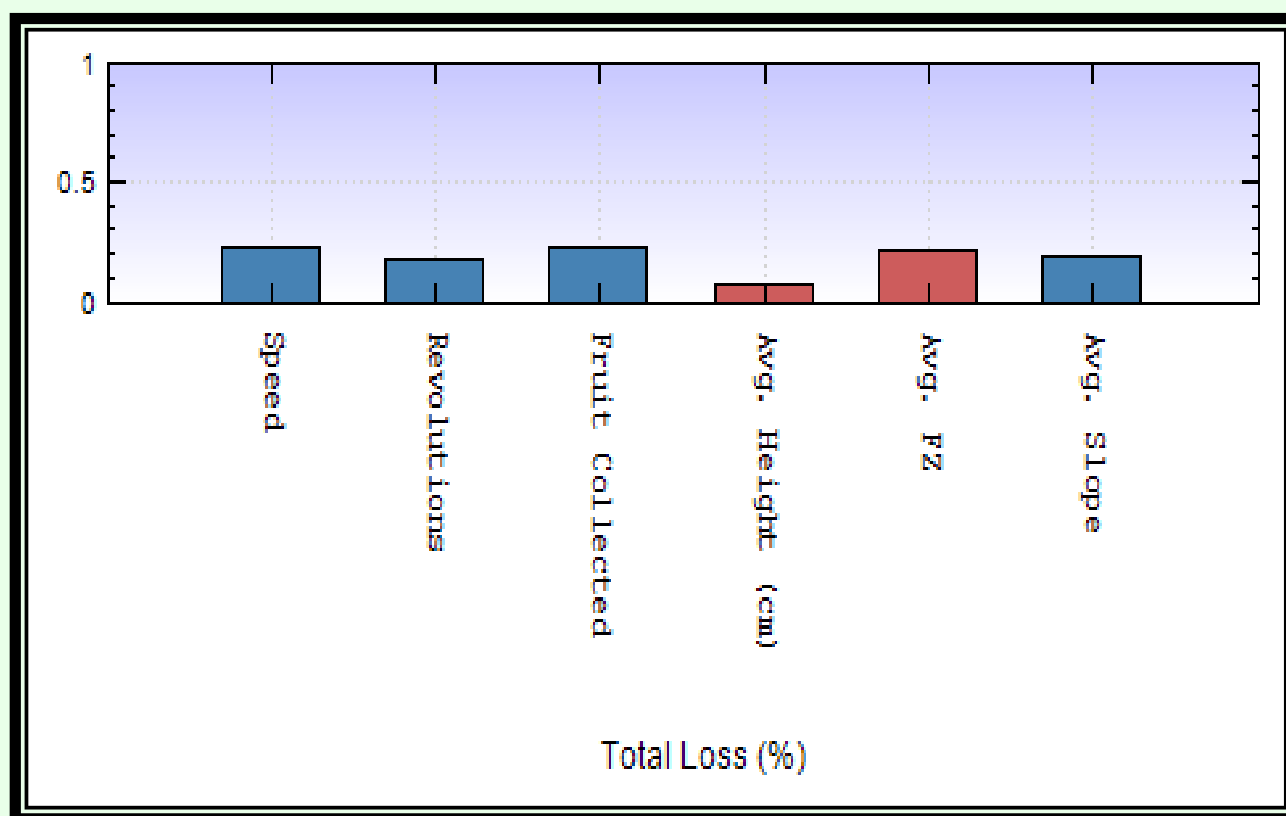
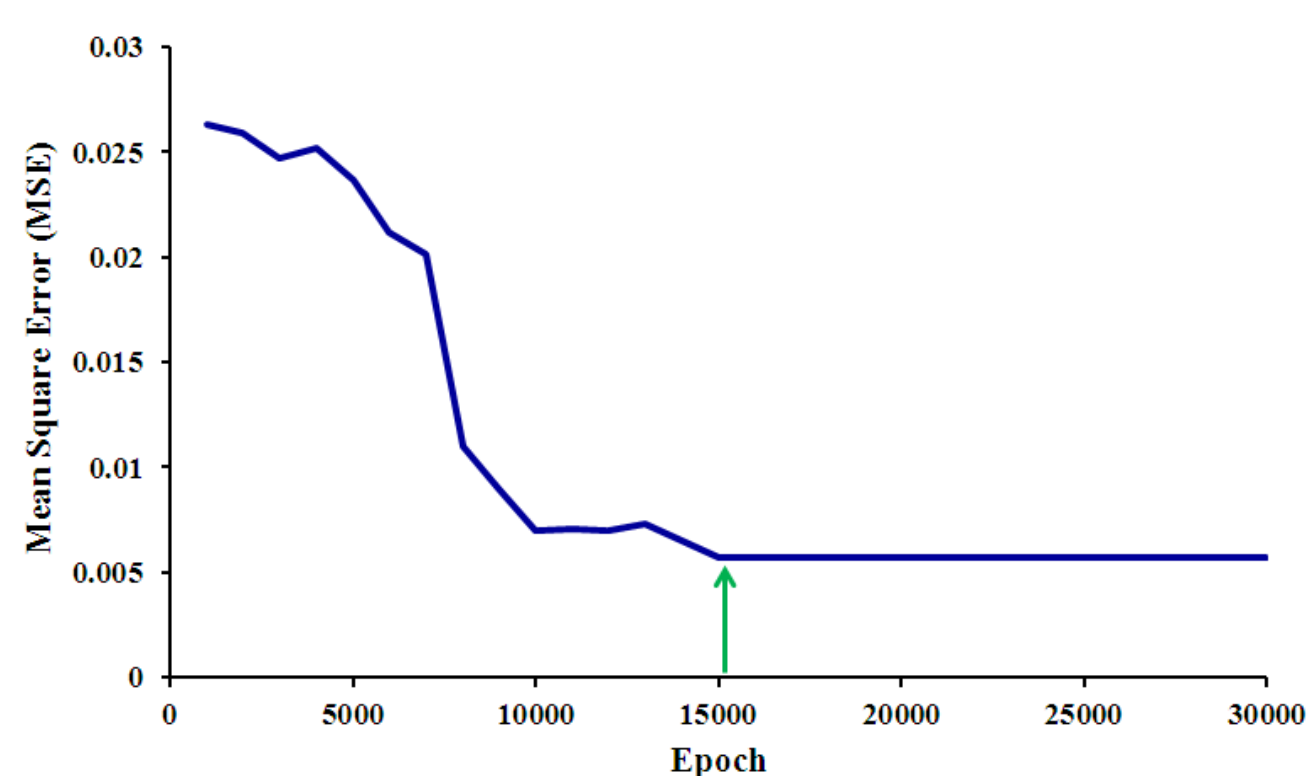


Fig: Correlation analysis using Peltarion Synapse software.

Table: Input selection using factorial ANOVA.

Source	Training Dataset		Validation Dataset	
	Total Losses (kg ha ⁻¹)	Total Losses (%)	Total Losses (kg ha ⁻¹)	Total Losses (%)
Speed	NS	NS	NS	NS
Revolution	NS	NS	NS	NS
Speed x Revolutions	*	*	*	*



Determination of the optimum epoch.

Methodology

Four wild blueberry fields were selected and completely randomized factorial (3 x 3) experiments were conducted. Yield plots (0.91 x 3 m) were made at each field to collect total fruit yield and total losses from each plot within selected fields. The harvester was operated at specific levels of ground speed (1.20, 1.60 and 2.00 km h⁻¹) and head rotational speed (26, 28 and 30 rpm). The slope, plant height, and fruit zone were also recorded from each plot.

The collected data were normalized for model development, training and validations. Correlation analysis was performed to identify the factors affecting the fruit losses during harvesting. Seven modeling architectures were developed using Peltarion Synapse software to find a suitable mathematical function, epoch, hidden layer, function layer, step size and momentum rule to articulate the performance of the developed networks in terms of the mean square error (MSE), root mean square error (RMSE) and coefficient of efficiency (CE). The trained architecture was extracted using the deployment postprocessor of the Peltarion Synapse software to make a separate and stand-alone WorkArea0.dll (.NET dynamic linking library). A DOS prompt based C# (Microsoft, Redmond, Wash.) program was developed to predict and validate external data using WorkArea0.dll and save processed result as a comma separated value (CSV) file.

Table: Comparison of ANN vs. MR Model

ANN Model					
Dataset	Model Structure	R ²	MSE	RMSE	CE
Training Dataset		0.835	0.006	0.075	0.801
Internal Validation	2 W (6/12 and 12/6) and 2 F (6/6 and 12/12) layers	0.858	0.006	0.075	0.811
External Validation		0.627	0.013	0.114	0.556
MR Model					
Training Dataset	Total Loss (%) = 0.137 +	0.461	0.019	0.138	-0.561
Internal Validation	0.0325 Ground Speed + 0.0435 Revolutions +	0.594	0.016	0.126	0.322
External Validation	0.304 Fruit Yield + 0.201 Plant Height - 0.146 Fruit Zone + 0.424 Slope	0.372	0.022	0.147	-0.130

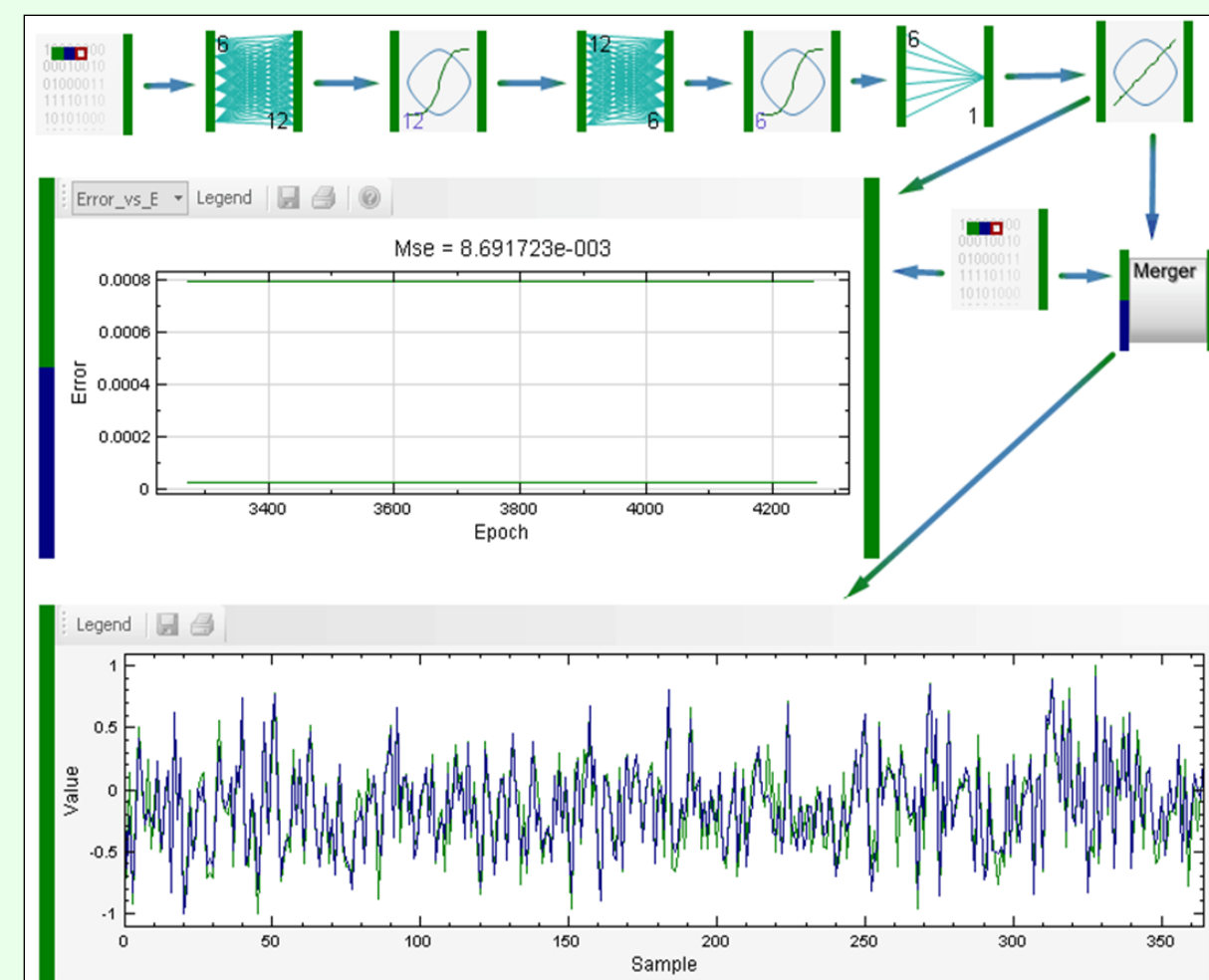


Fig: Optimal configurations of the proposed ANN model.

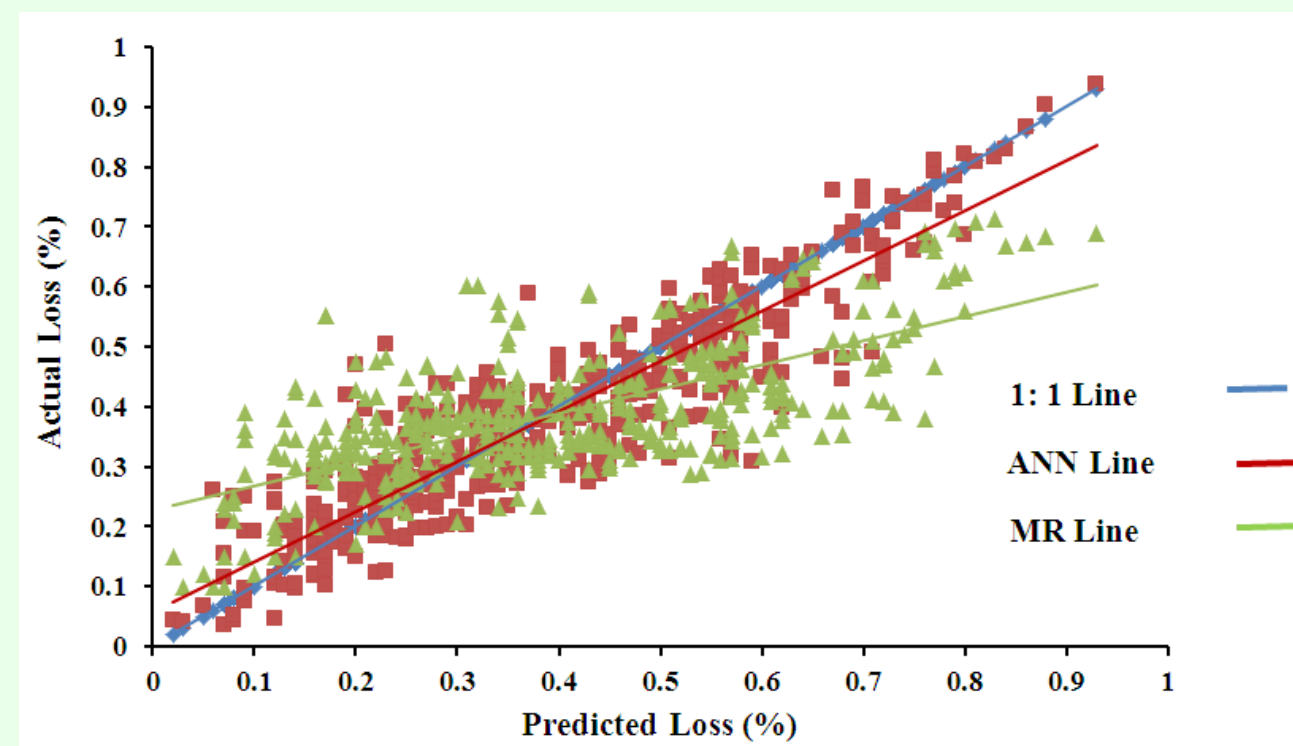


Fig: Actual vs. predicted values for training data.

Results

✓ Results suggested that fruit yield, plant height, fruit zone, slope, selected levels of ground speed and header rpm can be used as input variable to model the fruit losses during harvesting.

✓ Results of MSE and RMSE indicated that the Tanh-sigmoid transfer function between the hidden layer and output layer was the best fit for this study.

✓ Results of scatter plot among the MSE and epoch reported that an epoch size of 15000 was appropriate to predict fruit losses.

✓ Developed model using Peltarion Synapse software was able to accurately predict fruit losses during harvesting as function of different input variables.

✓ This study will help to identify the factors responsible for fruit losses and to suggest optimal harvesting scenarios to improve berry picking efficiency and recovery.

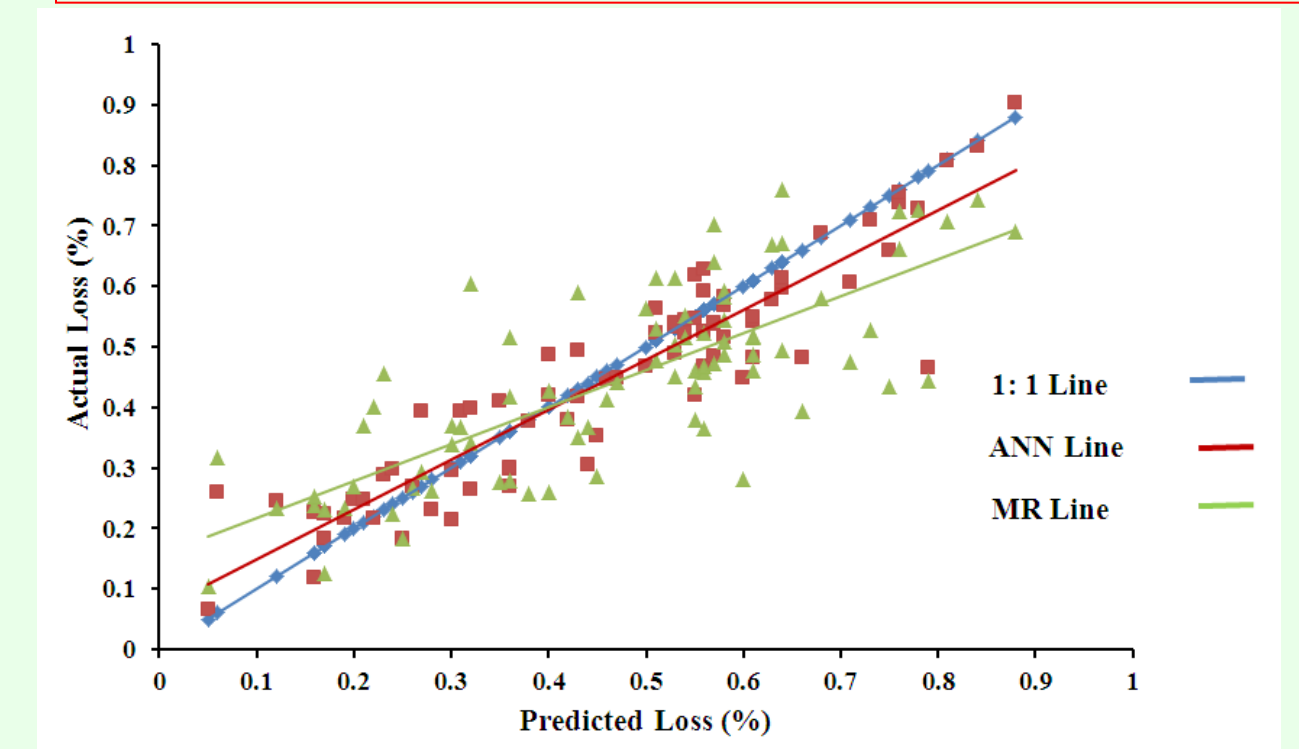


Fig: Actual vs. predicted values for verification data.

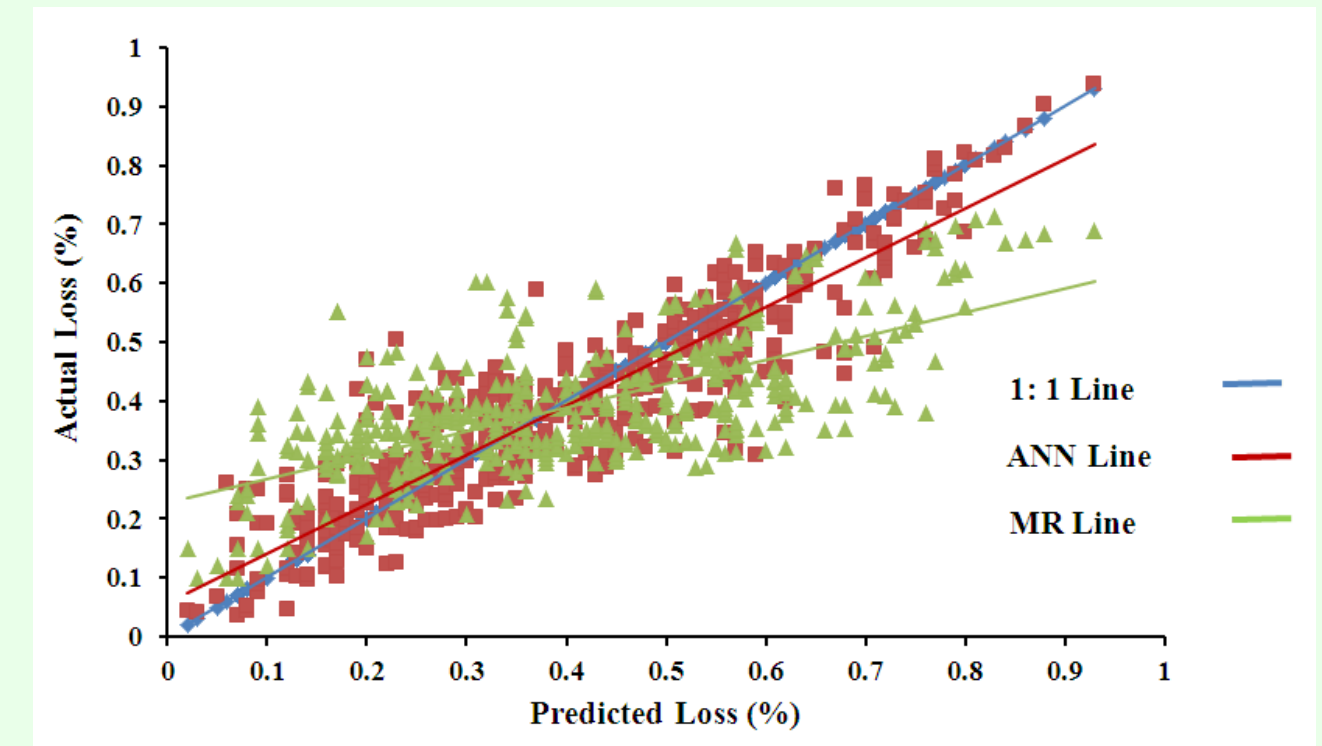


Fig: Actual vs. predicted values for verification data.

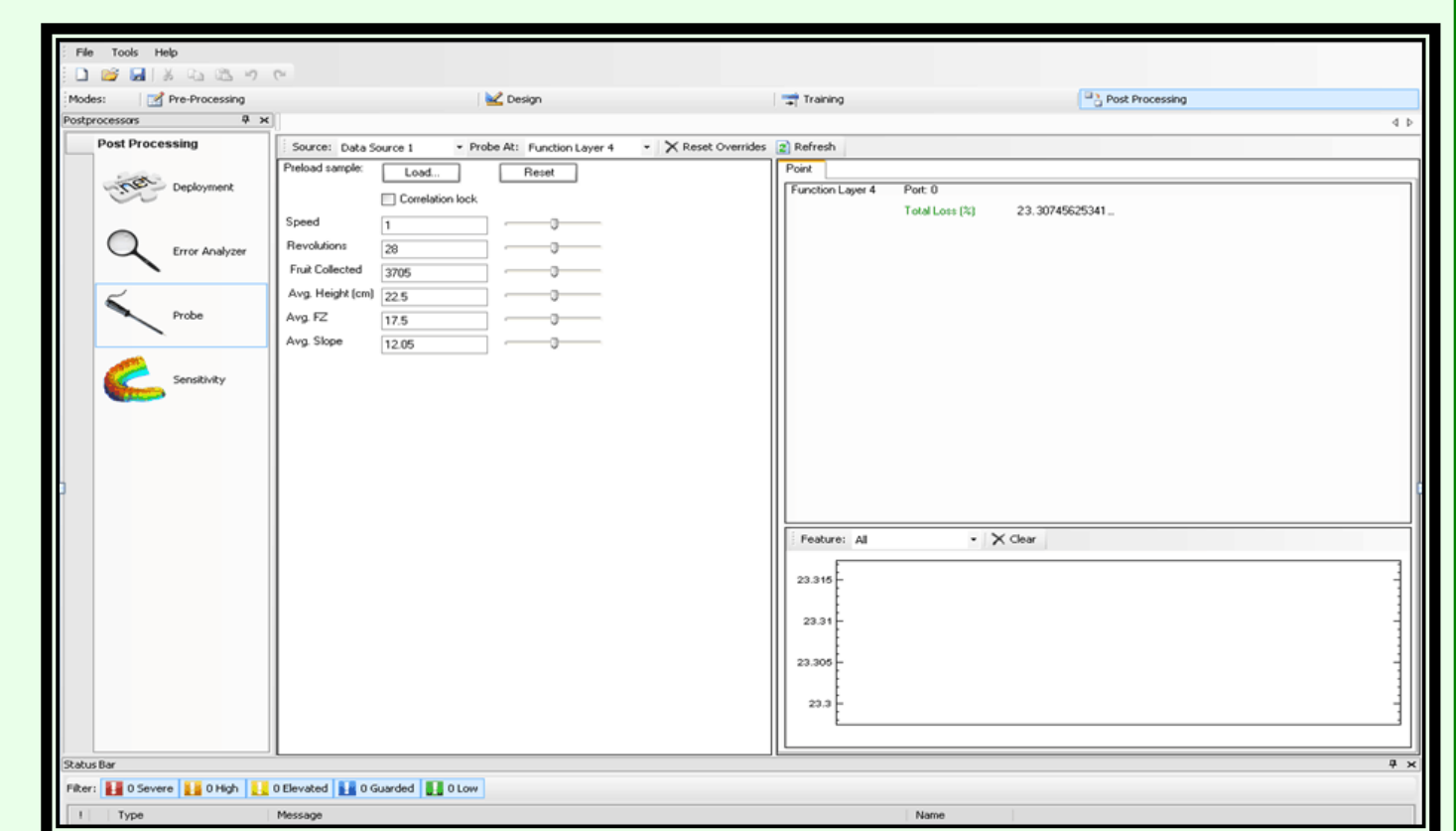


Fig: Interface to predict fruit losses.

Future Work

In future, inclusion of intensive mechanical, climatic and biological data in the model for multiple years will enable us to develop a robust interface using C# programming language, which will help the farmer community to make appropriate harvesting recommendations to reduce fruit losses during harvesting.