

# Artificial Wavelet Neural Network For Paddy Crop Yield Prediction

M.Sivasubramanian<sup>1</sup>, S. Meenakshi<sup>2</sup>, V. Prema<sup>3</sup>

<sup>1</sup>Assistant Professor, Department of Computer Science, JP College of Arts & Science, Ayikudi – Tenkasi 627 852, Tirunelveli, Tamil Nadu, India.

<sup>2</sup>Assistant Professor, Department of Computer Science, Government Arts and Science College, Kadayanallur, Tirunelveli, Tamil Nadu

<sup>3</sup>Assistant Professor and Head, Department of Computer Applications, JP College of Arts & Science, Ayikudi – Tenkasi 627852 Tamil Nadu, India.

---

## ABSTRACT

India's economy is based primarily on agriculture. Agronomic yield is influenced by organic, economic, and seasonal factors. As a result, crop yield estimation is a very difficult task. Numerous investigations have been conducted in agriculture to forecast crop yield using different techniques ranging from statistical to machine learning models. This article intends to propose a reliable and accurate model to perform paddy crop yield prediction. Data pertaining to the paddy crop are collected and then preprocessed. Two neural networks namely Feed Forward Neural Network (FFNN) and Wavelet Artificial Neural Network (WANN) are built and trained using the preprocessed data to anticipate paddy crop yield. A few metrics are employed to assess and compare the efficacy of the designed models. Numerical results demonstrated that the developed model, WANN offers higher performance than that of FFNN model as well as past approaches reported in the literature.

**Keywords:** Crop yield, feed forward neural network, paddy, prediction, and wavelet artificial neural network

## 1. INTRODUCTION

Agriculture is the main source of livelihood for the majority of people in India. The agriculture sector is a key building block for the development of the nation since it depends directly or indirectly on a significant number of farmers, middlemen, private businesses, and public sectors in the crop venture [1][2]. Farmers only consider agriculture to be viable when a strong crop year comes with a very high yield, which essentially encourages lucrative prices. Therefore, it is essential for them to predict crop production in advance in order to manage their farms and make wise decisions about marketing.

Crop Yield Prediction (CYP) is dependent on a number of variables like cultivation area, irrigation, weather, and soil quality etc. Over the past years, researchers have been developing crop yield prediction methods to accurately anticipate crop yields using data

gathered from farms and enhance agricultural statistics [3][4]. However, there is no standardized dataset for crop yield prediction, and it varies depending on the location, crop types, irrigation techniques, and meteorological conditions. Recently, researchers are adopting soft computing models to obtain precise yield prediction utilizing the agricultural data that is currently available. In soft computing, Machine Learning (ML) models are crucial for attaining higher prediction accuracy. Despite the fact that there have been considerable developments in ML and realization in many domains, the application of ML models has some limitations. Prediction accuracy of the ML models highly depend on optimal design of the model and data quality.

Artificial Neural Network (ANN) is the most commonly used ML model for CYP due to its ability to learn the relation between input and output variables through training process. The literature reports a number of techniques for predicting various crops, including wheat [3], paddy [4] and kiwi [5]. For accurate agricultural yield models, researchers contrasted statistical methods with ANN models. Wavelet ANN (WNN) is a class of ANNs that combines ANN and wavelets and has been used successfully to prediction problems. No research study has analyzed the predictive power of WANN for CYP. This article uses Feed Forward Neural Network (FFNN) and WANN to build a paddy CYP model and analyzes the performance of the introduced models. The effectiveness of the proposed models is also evaluated in comparison to older models, and the best model for forecasting paddy crop production is suggested.

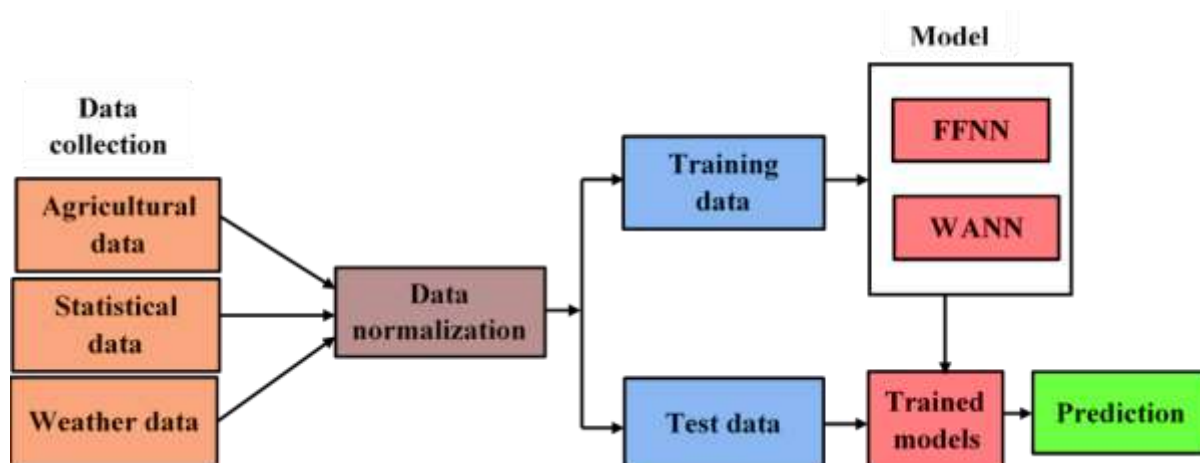
## **2. LITERATURE SURVEY**

Gopal and Bhargavi [1] built a hybrid model to predict paddy crop yield by combining ANN and Multiple Linear Regression (MLR). In this model, the MLR was used to initialize the parameters of the ANN. The ANN model was developed and trained with back propagation algorithm to predict crop yield. A paradigm for crop yield prediction was developed by Mariappan et al. [2]. Authors investigated the impact of many factors such as soil type, irrigation, climate and fertilizer etc. on crop yield prediction. Safa et al. [3] proved the power of ANN to forecast crop yield that the statistical methods. Rad et al. [4] predicted yield of Iranian paddy cultivars using ANNs. Abrougui et al. [6] examined the soil properties and crop yield employing MLR and ANN. Random Forest (RF) was applied as a predictive modelling to forecast crop yield production. Soil type, pH value, climate parameters, and rainfall were used as features to predict crop yield.

## **3. PROPOSED CROP YIELD PREDICTION METHOD**

Agricultural, statistical, and metrological data are sourced and preprocessed before applied to prediction model. Figure.1 depicts the overall structure of the proposed scheme for paddy crop yield prediction in Tamilnadu. The presented model consists of several processes are as follows:

- ❖ Data collection
- ❖ Data normalization and
- ❖ Proposed ANNs for prediction



**Figure.1 Overall processes of the developed model**

### 3.1 DETAILS OF DATA

The crop related data such as weather, statistical, agriculture production data are sourced from the metrological, statistical and economics, and agricultural departments of Tamilnadu over the span of 25 years from 1997 to 2021. The weather data has climatological features like solar radiation, mean rainfall, minimum and maximum temperature. The agricultural data comprises of cultivation area, irrigation details, and fertilizers details. As a results, 15 features including planting area (hectare), number of tanks, canal length, number of wells, production (tons), mean rain fall in mm, solar radiation (W/m<sup>2</sup>), minimum, maximum and average temperature (°C), phosphorus, potassium, and nitrogen used (kg), soil moisture, and yield (ton/hectare). Study area of the agricultural data collected in Tamilnadu is shown in Figure.2.

### 3.2 DATA NORMALIZATION

The gathered data are preprocessed to make it suitable for prediction task. The data is cleaned employing missing value treatment method [1] and the normalized into a common range between 0 and 1 using min-max method.

$$y' = \frac{y - \min(y)}{\max(y) - \min(y)} \quad (1)$$

Where,  $y'$ - scaled value,  $y$ -input value, min-minimum value and max-maximum value



**Figure.2 Study area considered in this work**

### 3.3 FEED FORWARD NEURAL NETWORK

ANN is one of the widely utilized modes for agriculture production prediction [1][3] due to its capability to model the nonlinear relationship between input and output variables. In this investigation, the FFNN is designed with three layers namely input layer, one hidden layer, and an output layer. The input layer has the 14 neurons which represents the number of input features, one hidden layer with 24 hidden neurons in each layer, and an output layer with single neuron representing predicted value, as shown in Figure.3. Input data is passed from input layer, hidden layer followed by output layer. The output of the hidden layer,  $S$  is expressed as,

$$S_j = \sum_{i=1}^p x_i w_{ij} + b_j \quad (2)$$

$$S = A(S) = A\left(\sum_{i=1}^p x_i w_{ij} + b_j\right) \quad (3)$$

Where,  $x$ -input,  $b$ -bias,  $w_{ij}$ -weight between input and hidden layer, and  $A$ -activation function. Trial and error approach is adopted for choosing number of hidden layers and its neurons. The hidden layer output is multiplied with weight and added with bias. The resultant value is fed as input to the output layer which gives the predicted value,  $Y$ . The predicted value can be defined as,

$$Y = A(S) + b \quad (4)$$

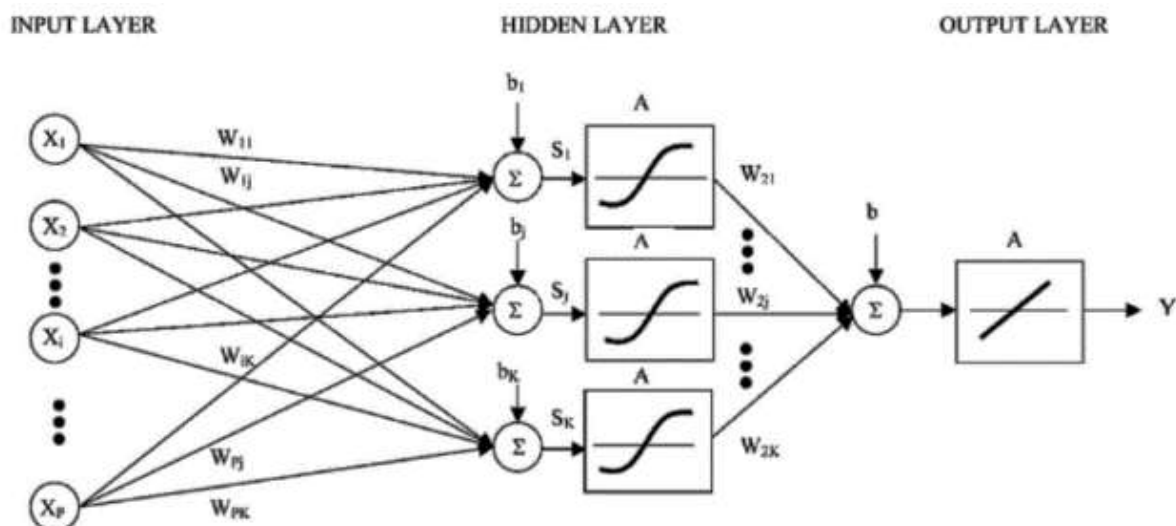


Figure.3 FFNN developed for paddy yield prediction

### 3.4 Wavelet Artificial neural network

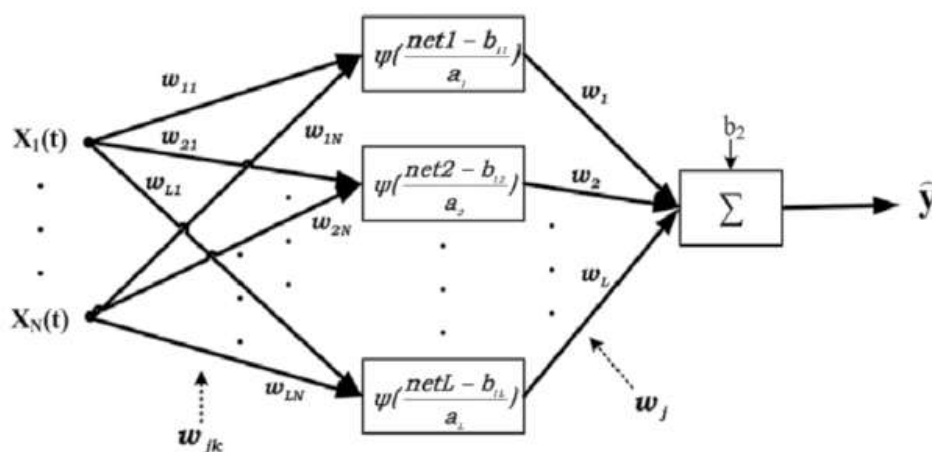


Figure.4 WANN designed for paddy crop yield prediction

Wavelet networks are feedforward networks utilizing wavelets as activation functions. Wavelet networks substitute the sigmoid activation components of the classical feedforward artificial neural networks (ANNs) with wavelets transform function. In wavelet neural networks, both the translation (position) and the dilation are tuning besides weights. The utilization of wavelet node outcomes in efficient networks are optimally approximated and estimated for nonlinear and nonstationary functions. The architecture of the AWNN developed to anticipate paddy crop yield production is illustrated in Figure.4.

The WANN model can be expressed as,

$$\hat{y}(t) = \sum_{j=1}^L w_j \psi \left( \frac{\sum_{n=1}^N w_{jn} x(t) - b_j}{a_j} \right) + b_2 \quad (5)$$

Where,  $y$ -predicted value,  $x$ -input,  $w$ -weight,  $a$ -scale parameter,  $b$ -translational parameters,  $b_2$ -bias, and  $\psi$ -mother wavelet. Morlet wavelet is used as mother wavelet.

#### 4. RESULTS AND DISCUSSION

The research work implemented two ANN models, FFNN and AWNN for anticipating paddy crop yield prediction. The proposed models have been validated using MATLAB software. In this section, numerical outcomes of the introduced models are given. Paddy crop related data were collected and then 14 attributes were taken as features. Prediction performance of the introduced models was assessed by computing the following metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Square Error (MSE), and coefficient of determination ( $R^2$ ).

$$RMSE = \sqrt{\frac{\sum_{p=1}^M (Y_p - Y'_p)^2}{M}} \quad (6)$$

$$MAE = \left( \frac{\sum_{p=1}^M |Y_p - Y'_p|}{M\bar{Y}} \right) \quad (7)$$

$$MSE = \frac{1}{M} \sum_{p=1}^M (Y_p - Y'_p)^2 \quad (8)$$

$$R^2 = \left\{ \frac{1}{M} * \frac{\sum_{p=1}^M (Y_p - \bar{Y}) * (Y'_p - \bar{Y}')}{(\sigma_Y - \sigma_{Y'})} \right\}^2 \quad (9)$$

The FFNN and WANN was developed and trained to predict paddy crop yield prediction. The predicted values versus actual values of the test data of FFNN and WANN is illustrated in Figure.5 and Figure.6 respectively. As shown in Figure.5 and Figure.6, it is observed that the predicted values using WANN is closer to actual values which indicates less error.

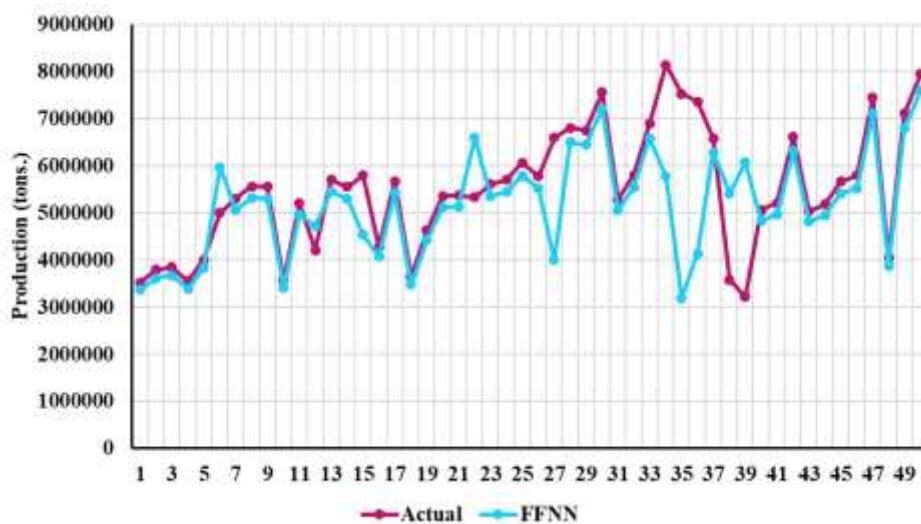
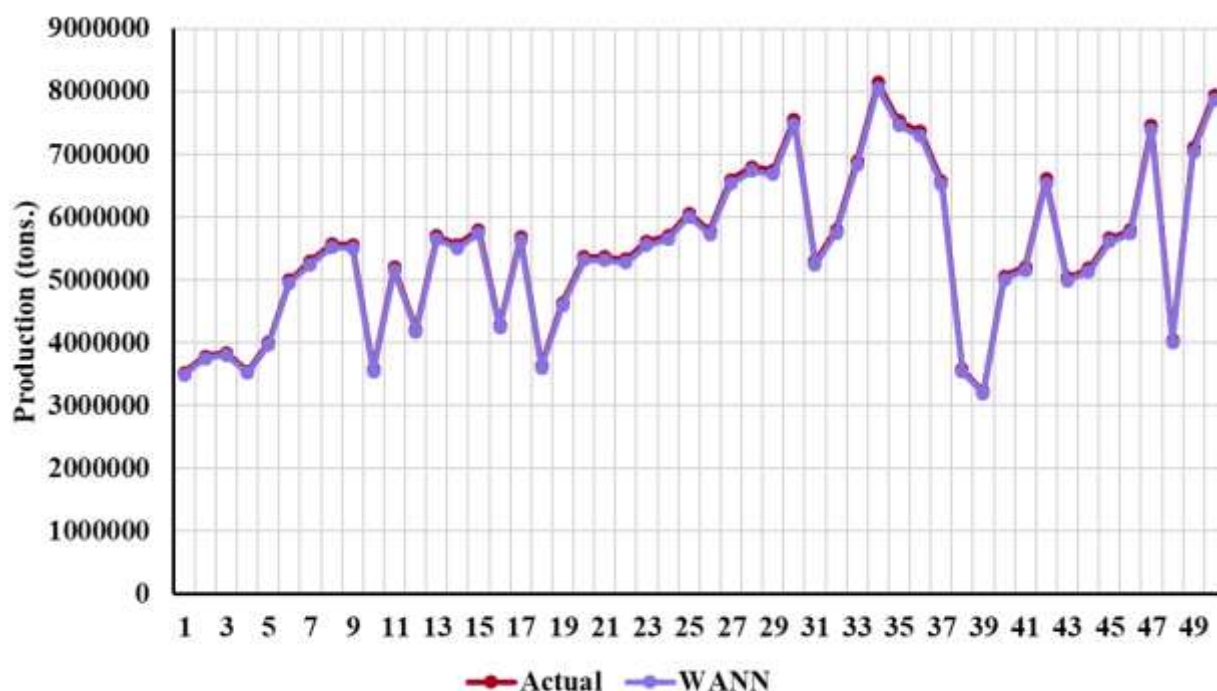


Figure.5 Actual Vs. predicted yields for FFNN



**Figure.6 Actual Vs. predicted yields for WANN**

Table.1 Prediction comparison between different approaches

Models	KNN [2]	GRNN [9]	SVR[10]	HYBRID [1]	RF [7]	FFNN	WANN
<b>MSE</b>	0.016	0.052	0.009	0.002	0.007	0.019	0.0001
<b>RMSE</b>	0.127	0.229	0.099	0.051	0.085	0.141	0.01
<b>MAE</b>	0.089	0.127	0.065	0.041	0.055	0.093	0.001
<b>R2</b>	0.87	0.986	0.92	0.99	0.93	0.847	1

Effectiveness of the introduced FFNN and WANN was evaluated by computing RMSE, MAE, MSE, and  $R^2$  and was reported in Table.1. Performance measuring metric values of K-nearest neighbor (KNN), Generalized Regression Neural Network (GRNN), Support Vector Regression (SVR), hybrid, Random Forest (RF) were also given in Table.1 from the past approaches for comparing the efficacy of the introduced models. From the Table.1, it is inferred that the KNN, GRNN, SVR, hybrid, RF, and FFNN produces MSE value as 0.016, 0.052, 0.009, 0.002, 0.007, and 0.019 but WANN gives MSE value as 0.0001 which proves closer prediction. It is noted that the introduced WANN achieves less error compared to the past approaches. The MAE of the WANN model is 0.001. In addition to this, the introduced WANN model has high  $R^2$  of 1 when compared to other models. Pictorial representation of Table.1 is given in Figure .7- Figure.10.

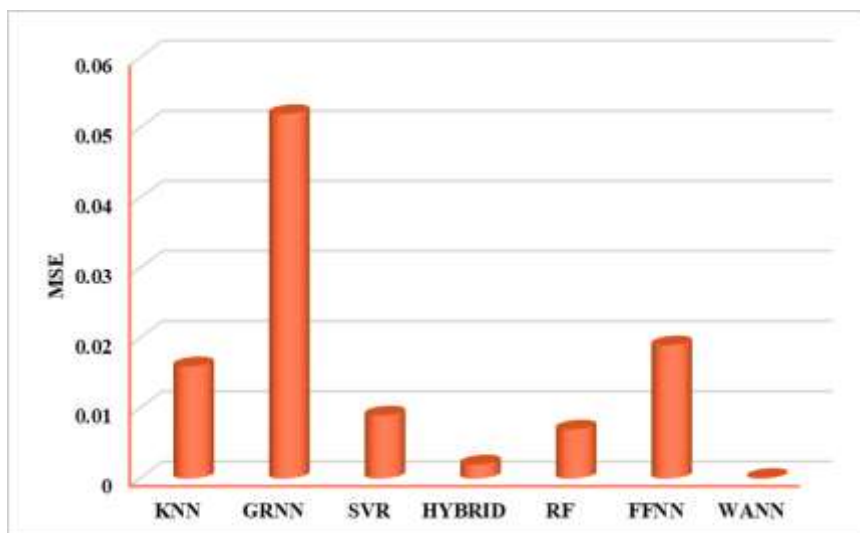


Figure.7 MSE comparison of various CYP methods

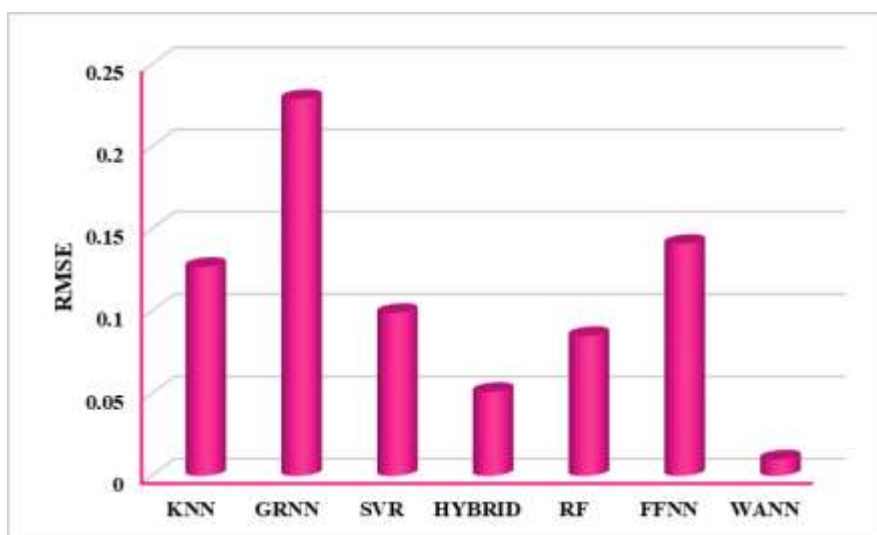


Figure.8 RMSE comparison of various CYP methods

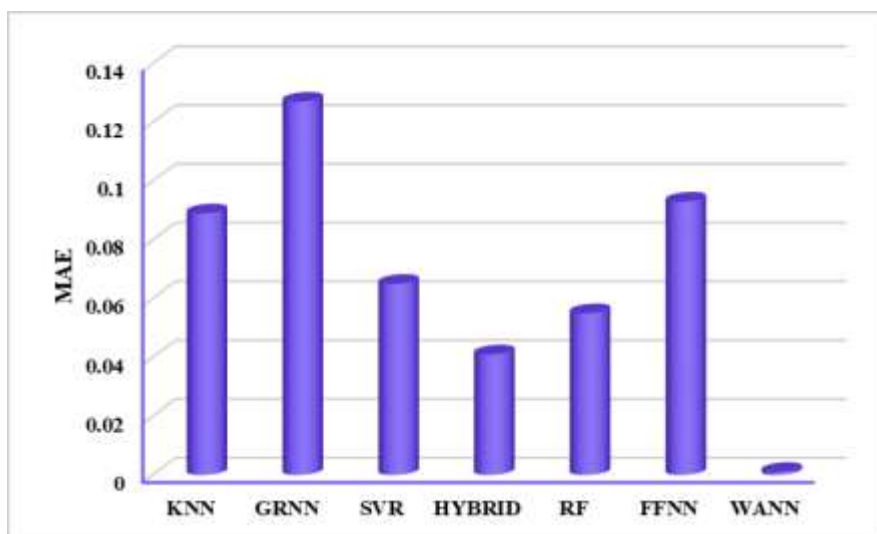
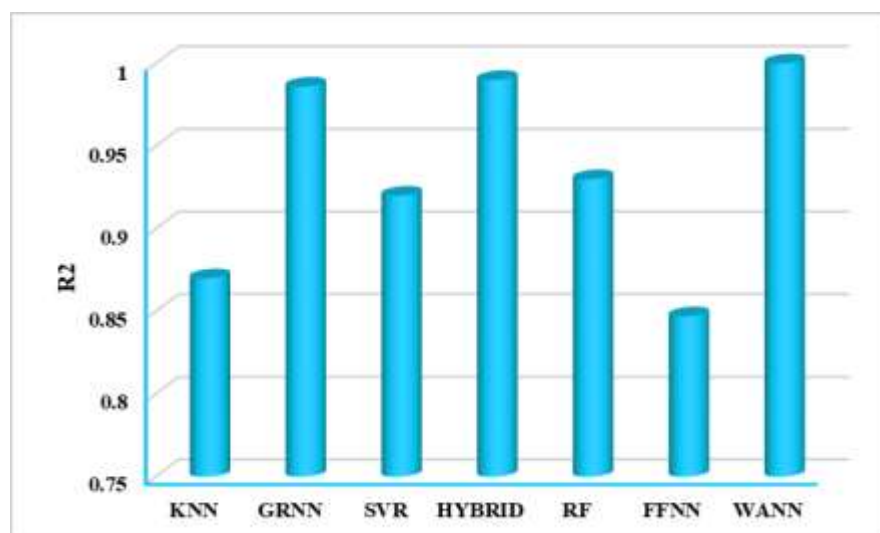


Figure.9 MAE comparison of various CYP methods





**Figure.10** R<sup>2</sup> comparison of various CYP methods

## 5. CONCLUSION

In this article, two machine learning models was designed to anticipate the accurate paddy crop yield. Crop yield prediction for Tamilnadu can be made by fusing agricultural, statistical, and weather data. Feed forward neural network and artificial wavelet neural network was designed and trained to predict paddy crop yield. Prediction performance of the FFNN and AWNN was evaluated by utilizing MSE, RMSE, MAE, and R<sup>2</sup>. Experimental outcomes were compared with other machine learning models, GRNN, KNN, RF, hybrid, and SVR in order to show its validity. Empirical analysis demonstrated that the introduced WANN model achieves better results than FFNN as well as other machine learning models.

## REFERENCES

1. Gopal, P.S.M., and Bhargavi, R., 2019. A novel approach for efficient crop yield prediction, *Computers and Electronics in Agriculture*, 165, 1-9.
2. Mariappan, A.K. and Ben Das, J.A., 2017. A paradigm for rice yield prediction in Tamilnadu, *Proceedings of the 2017 IEEE International Conference on Technological Innovations in ICT for Agriculture and Rural Development*, 18-21.
3. Safa, M. and Samarasinghe, S., 2011. Determination and modelling of energy consumption in wheat production using neural networks: "A case study in Canterbury province, New Zealand. *Energy* 36 (8), 5140-5147.
4. Rad, A.T, Khojastehpour, M., Rohani, A., Khoramdel, S. and Nikkhah, A., 2017. Energy flow modelling and predicting the yield of Iranian paddy cultivars using artificial neural networks. *Energy* 135, 405-412
5. Soltanali, H., Nikkhah, A. and Rohani, A., 2017. Energy audit of Iranian kiwifruit production using intelligent systems. *Energy* 139, 646-654.
6. Abrougui, Khaoula, Gabsi, Karim, Mercatoris, Benoit, Khemis, Chiheb, Amami, Roua, Chehaibi, Sayed, 2019. Prediction of organic potato yield using tillage systems and soil properties by artificial neural network (ANN) and multiple linear regressions (MLR). *Soil Tillage Res.* 190, 202-208

7. Suresh, N., Ramesh, N. V. K., Inthiyaz, S., Priya, P. P., Nagasowmika, K., Kumar, K. V. N. H., ... Reddy, B. N. K. (2021). Crop Yield Prediction Using Random Forest Algorithm. Proceedings of the 2021 7<sup>th</sup> International Conference on Advanced Computing and Communication Systems, 279-282
8. Gopal, P.S. M, andBhargavi, R., 2019. Optimum Feature subset for optimizing crop yield prediction using filter and wrapper approaches. Appl. Eng. Agri. 35 (1), 9–14.
9. Joshua,V.,Priyadharson,S.M. and Kannadasan,M Exploration of machine learning approaches for paddy yield prediction in eastern part of Tamilnadu,Agronomy,2021,11,1-19.
10. Gopal, P.S.M., andBhargavi, R., 2019. Performance evaluation of best feature subsets for crop yield prediction using machine learning algorithms. Appl. Artificial Intelligence 33 (7), 621–642