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A Performance Benchmarking of ML and DNN Models in Sorghum Yield Estimation for South India

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Abstract: ***The agriculture sector is extremely vulnerable to the consequences of climate change, leading to reduced quantity and nutritional quality of crop yields. The application of innovative techniques contributes to the modernization of agricultural practices and enhances productivity, quality, and food security. The accurate and reliable estimation of crop yields based on climate, soil, and crop-related data can guide/assist farmers in planning and managing agricultural activities in a better way. Nowadays, deep learning techniques are widely being explored for agricultural yield predictions due to their ability to address both linear and non-linear components of the data. The present work assesses the predictive capabilities of a tensor-flow-based deep neural network (DNN) in predicting yields of the jowar crop in the southern state of India. Comparatively better prediction accuracy was demonstrated by the DNN when compared to the performances of four other machine learning models. The DNN used the meteorological, soil, and crop data of the growing season of jowar for 15 years of duration and presented promising prediction results with R^2 values of 0.88. The work incorporates the novel approach of using the SHAP (SHapley Additive exPlanations) framework to identify the contribution of the most significant feature towards prediction.***

Keywords: Crop yield, Deep neural network, Jowar yield, Random Forest, Support Vector Regressor, Prediction

1. Introduction

Climate change, extreme climatic variability, and loss of arable lands due to urbanization have majorly affected agricultural yields and are the major causes of food security in recent years. Agriculture has been associated with the production of food crops whose demand continues to rise by 59% – 98% by 2050 (Valin et al., 2014). The jowar (sorghum) is the cereal crop grown in the arid and semi-arid tropics of Africa and Asia and is the major staple food of most populations in developing countries like India. It also serves as an important source of fodder, animal feed, and industrial raw material. However, the country's yields of jowar have significantly reduced in the past decades. India is one of the major jowar-producing countries, with Karnataka state, ranked second contributing 18.51% to the total production. Rice, wheat, and ragi are the other major crops along with cash crops such as sugarcane, pepper, coffee, cotton, tobacco, and cardamom grown either in the Kharif or Rabi seasons in the state. Nevertheless, it was reported that the state suffers from extremely low yields with respect to the increasing areas of cultivation. Despite the incessant advancements in agriculture fields over the years, yields have remained low in the state. Such decreased trends in agricultural production have affected the country's trade policies at the global level. An accurate prediction of crop yields may help farmers decide on suitable agrarian factors to combat food scarcity issues in the changing climatic conditions (Ansarifar et al., 2021). Various statistical methods in data mining techniques have successfully achieved the underlying task of yield prediction.

Controlled factors include the farming methods used by the farmer during cultivation. Uncontrolled factors, on the other hand, include weather and soil conditions that affect the plant's growth at different physiological stages. Things in the surroundings are found to have the most significant effect on crop growth. Also, agricultural experts are looking for ways to make crops more productive while having less of an effect on our natural resources. These efforts are called Climate Sustainable Agricultural practices. So, if we want to make accurate predictions about crop yield and keep farming from hurting our natural resources too much, it is needed to fully understand how these external factors affect crop yield. Agricultural yields are dependent on various factors such as climate conditions, soil characteristics, cultivation area, usage of fertilizers, irrigation methods, and past yield of the crops. It is very challenging to get a precise estimation technique for yield prediction of the crops with the available parameters as input features. Nonetheless, several statistical models exist employing numerous weather parameters and soil data to predict yields of major and economical crops. Recent advances in the field of data science, machine learning/deep learning techniques, and sensor-based smart agriculture have been promising for farmers toward enhanced agrarian production.

Among the four algorithms, ANN, SVR, K-NN, and RF with different feature subsets, RF predicted the yield of paddy with higher accuracy (PS and M.G., 2019). Three regression-based algorithms such as multivariate polynomial regression, support vector machine regression, and random forest were used in corn yield prediction by developing a relationship between various climatic parameters and corn yield (Shah et al., 2018). The 4 regression-based algorithms, random forest regression, gradient boosted tree regression, LASSO regression, and stacked generalization ensemble methods were used to predict wheat yield from climate parameters (Anbananthen et al., 2021). Long-term agro-met-spectral variables were used to predict cotton yields at 3 different growing seasons in the Maharashtra state in India using the Random Forest approach, which gave faster and more precise results (Prasad et al., 2021). (Han et al., 2020) focused on the applicability of RF, Gaussian Process Regression (GPR), and SVM models to predict yields of wheat using a combination of remote sense, climate, and soil data in China. RF model exhibited the best generalization abilities among the 3 models. The hybrid Multiple Linear Regression (MLR)-ANN demonstrated more accurate results than the ANN, MLR, SVR, k-NN, and RF models used for predicting paddy yields (Gopal and Bhargavi, 2019). (Guo et al., 2021) proposed yield prediction models for rice using regression and a combination of traditional machine learning methods such as backpropagation neural network (BP), support vector machine (SVM), and random forest (RF). The study demonstrated the relative importance of phenological variables to climatic variables. The potential of RF was demonstrated to estimate mango fruit yields in response to water availability under different irrigation regimes in Northern Thailand (Fukuda et al., 2013). Four RF models based on ten-day irrigation and rainfall data precisely estimated the mango yields. The early season sugarcane yields were accurately predicted by the RF models in northeastern Australia which enabled farmers to plan better harvesting and milling operations (Everingham et al., 2016). RF was proved to be extremely good at predicting yields of wheat, maize, and potato at regional and global scales when compared to the multiple linear regressions (MLR) method (Jeong et al., 2016). The capacity of the RF algorithm to forecast cotton crop yield utilizing long-term agrometeorological variables was assessed throughout the growing season in India (Prasad et al., 2021). The RF model was able to produce reliable and accurate prediction results in the final yields of the crop.

Artificial Neural Network (ANN), a computing system inspired by biological neural networks has been extensively used in yield estimations of several primary crops. The ANN was used to predict the rice yield and investigate the non-linear relationship between the yield and the influencing factors as demonstrated by (Gandhi et al., 2016). A data fusion model of self-organizing maps with neural networks explained the accurate prediction of wheat yield and its spatial distribution by visualizing the correlations between soil, crop data, and yield (Pantazi et al., 2016). In addition, Convolution Neural Networks (CNN)-Long Short-Term Memory (LSTM) network models estimated wheat yield, and the uncertainty analysis on yield prediction was carried out (Wang et al., 2020). (Wolanin et al., 2020) evaluated the DNN model for wheat yield prediction followed by an assessment of the impact of environmental conditions. (Zannou and Houndji 2019) discussed the Tensor Flow-based CNN approach to detect the sorghum ears from the image and hence estimate its yields. The DNNs made reasonably accurate predictions of corn yields based on environmental data and genotype (Khaki and Wang 2019).

ANN has been a reliable and powerful model for predicting sugarcane yields ever since in India (Kumar et al., 2015). The neural network results were improved by reducing over-fitting and the stacking ensemble of ANN produced more promising sugar cane yield predictions (Fernandes et al., 2017). The ANN provided better yield predictions of sugarcane than the Multivariate Linear Regression (MLR) model from the remote sensing data images described by (Rahimi Jamnani et al., 2019). The Deep Neural Network (DNN) outperformed the counter models in predicting sugarcane yield, however, showed overfitting of training data (Srikamdee et al., 2018).

Motivation: The present study assesses the yield predictions of jowar, one of the predominant crops grown in the Bijapur district of Karnataka state. Jowar is the second-largest food crop after rice for the people in the Northern parts of the state. However, Bijapur, a leading producer of jowar, showed a negative production trend due to decreasing cultivation lands (Satishkumar and Kammardi 2014). Furthermore, there is a decline in yield production due to irregular rainfall patterns and changing climatic conditions prevailing in the state (Rajegowda et al., 2009).

2. Materials and Methods

2.1 Study Region

The present research work is carried out for Bijapur of Karnataka state in India, where varieties of major and commercial crops are predominantly produced. The district employs a different style of farming based on the range of crops grown there as well as the geography and physiography of the region. The geographical location of the district is shown in Figure 1. Bijapur is situated in the interior part of the Deccan Peninsula characterized by a semi-arid climate. The dry weather with deep black and red soils is favourable for growing jowar crops. Belgaum lies in the northwestern part of the state and has a tropical savanna climate. Varying textures and depths of black and red soils, lateritic soils, and alluvial soils can be found in the district. Bijapur district has an annual temperature that varies between 25^{o} C to 38^{o} C and annual rainfall varies between 591 mm to 760 mm. The main crop grown in Bijapur is jowar and other supporting crops due to dry weather conditions.

2.2 Dataset Acquisition

District-wise data for the growing season of the jowar crop for 15 years (1999-2014) is obtained from the Global Weather Data for SWAT (https://globalweather.tamu.edu/) and International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) (https://www.icrisat.org). The various attributes of the dataset are the independent variables, and the yield is the dependent variable. The complete details of the dataset are given in Table 1. Various machine learning and deep neural network-based yield prediction models were developed, and performance comparison was done using historical data on climate, soil, fertilizer, and crop production data for a period of 15 years.

Table 1: Details of the input dataset

Attributes	Units of measurement
Temperature (Average)	^{o}C
Precipitation	mm
Reference Evapotranspiration (Average)	mm/day
Solar Radiation	W/m^2
Mean Relative Humidity	%
Area	acres
Past Yield	Tons
Fertilizer N	Tons
P	Tons
K	Tons
Soil pH	-

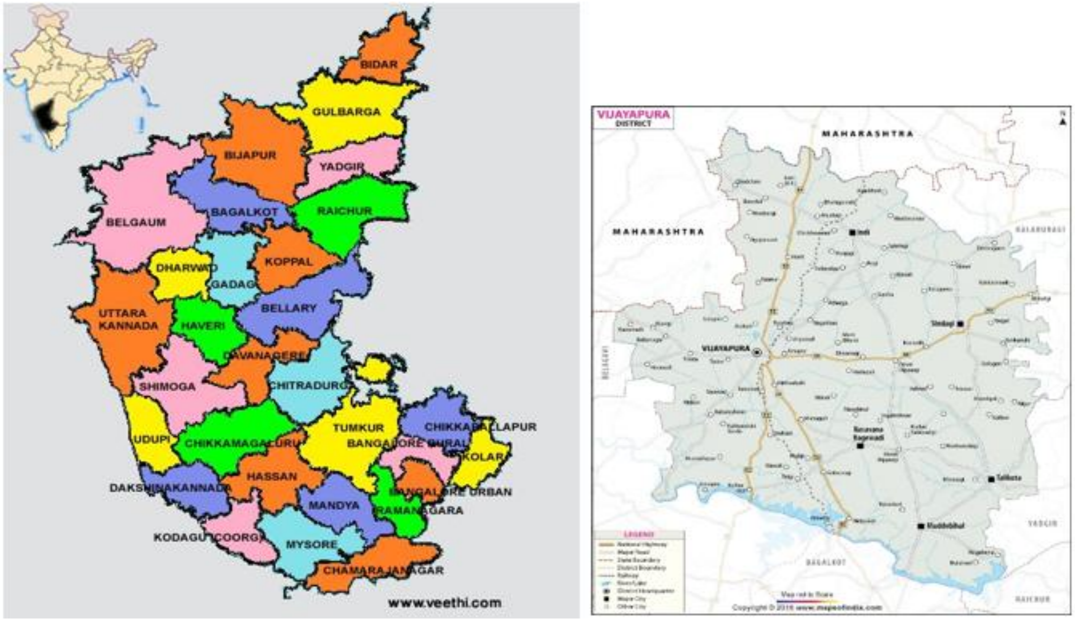

Figure 1: Location map of Bijapur in Karnataka

2.3 Dataset Pre-processing and Analysis

Various strategies are used to preprocess the data in preparation for training using machine learning algorithms. During the feature selection process, the columns 'Year' and 'Place' were excluded while retaining the other significant features for the training phase. A normalization technique known as the Min-Max scaling function is used to fit the given dataset in the range [0,1]. The dataset is then partitioned into two subsets: 80% training set, which is used for training the machine learning models, and the remaining 20% test set is used to evaluate the performance of trained models. Three statistical metrics, Coefficient of Determination (R^2), Root Mean Squared Error ($RMSE$), and Mean Absolute Percentage Error ($MAPE$) were used to assess the performances of the various models. The methodology of the prediction process is given in Fig. 2.

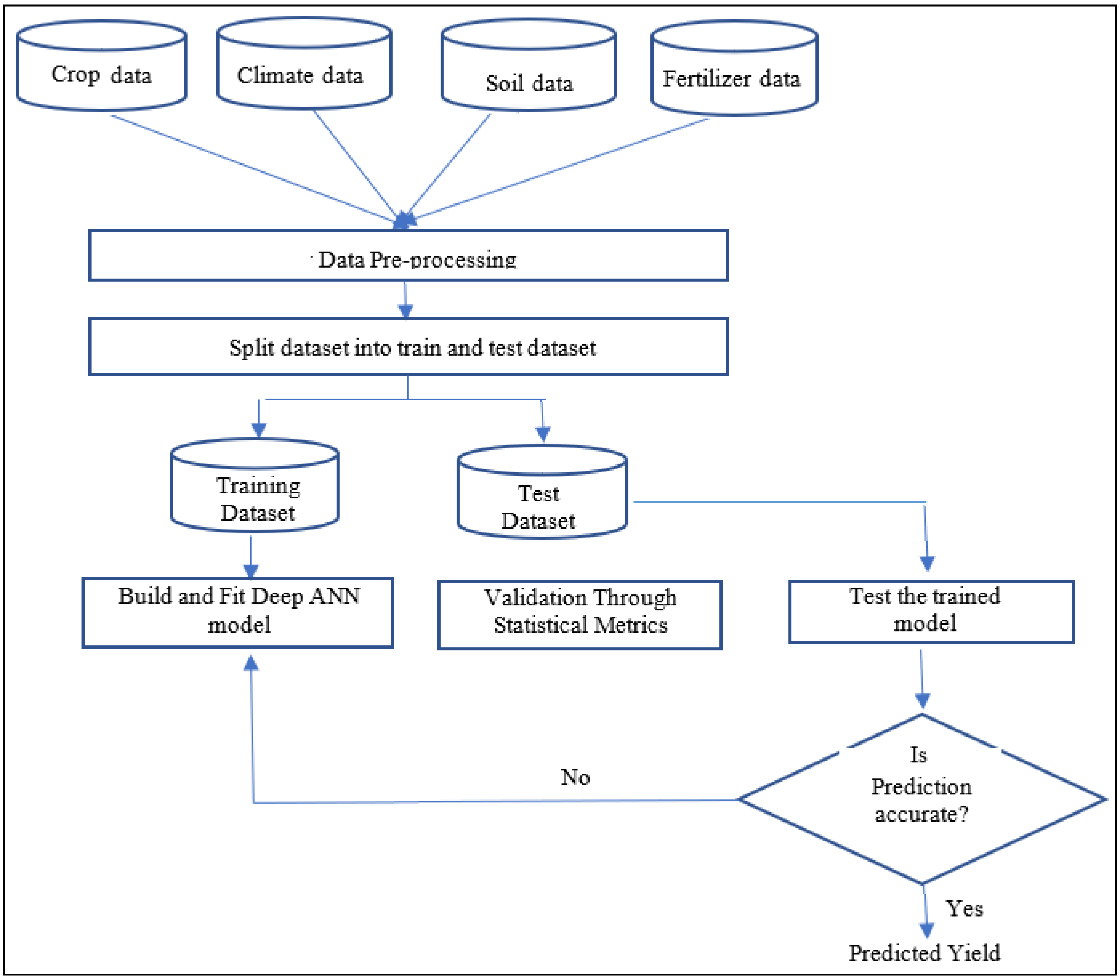

Figure 2: Yield Prediction Process

3. Yield Prediction Models

In agriculture, data mining is widely employed to predict yield estimations. The extensive collection of a 15-year agriculture dataset is analysed using data mining to transform it into a structured format for future use. Numerous researches have demonstrated that machine learning is a crucial decision-support tool for predicting agricultural productivity. With the use of machine learning, the farmers may get precise recommendations with respect to crop yields and provide insight on how to lower the agricultural loss. This study examines three Machine Learning Models: support vector regression, neural networks, and random forests. These methods were selected because of the size of the dataset and the nature of the target variables. Each model is built based on the known target variable and fitted according to the model parameters to increase the prediction accuracy. The accuracy of the model will be found out with respect to the output of the model to that of actual target variables values observed. A good model fit indicates that the model approximates the results if the inputs are unknown. Among the proposed models, the Random Forest is the non-parametric model, and the deep neural network is the parametric model for our predictive analysis of crop yield.

3.1 Yield Prediction using Deep ANN

A deep neural network (DNN) is an improved version of ANN with several layers between input and output (Schmidhuber, 2015). These network works are better than multivariate regression models. The backpropagation algorithm is used to train artificial neural networks. The neural network is made up of nodes or units which are the basic structures. The architecture of a DNN comprises one input layer, two hidden layers, and one output layer as depicted in Figure 3. A deep learning model consists of 11 neurons in the input layer, 4 neurons in the hidden layer, and 1 neuron in the output layer. A non-linear activation function, the hyperbolic tangent activation function (Tanh) is used which gives a stronger gradient value during training. The loss function is minimized by using the stochastic gradient descent (SGD) optimization function. Factors such as epoch size and batch size also influence the performance of the neural network architecture. As the system goes deeper, it pulls out more complex traits, which makes it very accurate. If the right variables are given, it is known to be a ubiquitous approximator function. This means that it can guess almost any feature, but it is hard to pick the right values. The model is developed using Python implementation of "Keras" (version 2.3.0) which is built on the "TensorFlow" (version 2.0.0) framework on a cuDNN (The NVIDIA CUDA® Deep Neural Network library). In the current approach, a linear stack of several neural network layers is built using the sequential module from the Keras package.

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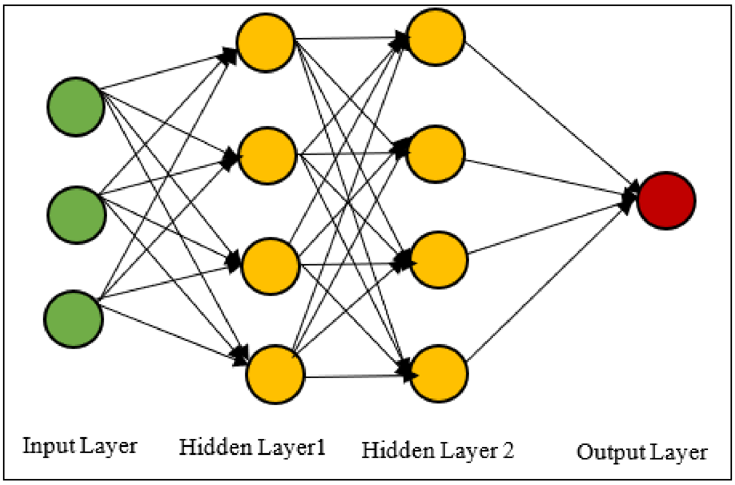

Figure 3: The general structure of a deep neural network

The performance of the deep neural networks is compared with the random forest as both can handle interactions between variables and can model data with nonlinear correlations between variables.

3.2 Yield Prediction Using Random Forest Regressor

Random Forest is a supervised learning-based algorithm that is used both for classification and regression. The random forest creates decision trees from various data samples and predicts from each subset by voting to give better predictions. It uses a bagging-based ensemble method to solve a regression problem. The bagging method combines different models to create an optimized system that is more accurate. The structure of the random forest is shown in Figure 4. It works well and generates more powerful and accurate predictions when there are non-linear relationships between the variables. However, there are chances of overfitting, hence the number of trees in the model must be chosen carefully.

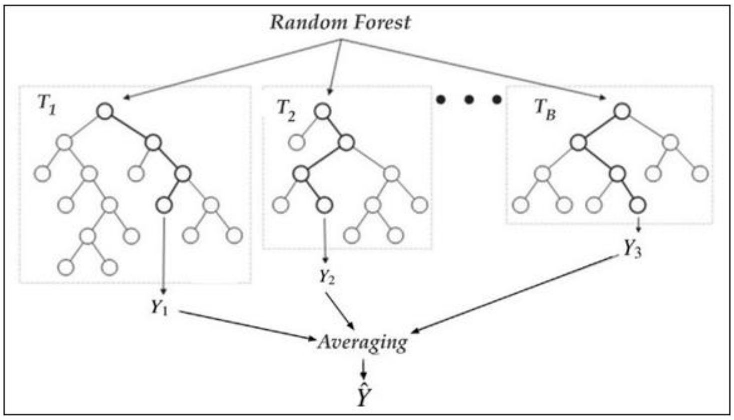

Figure 4: Structure of a Random Forest (Nguyen et al., 2013)

3.3 Yield Prediction Using Support Vector Regressor

Support Vector Machine, developed by Vapnik and his collaborators, is a simple and efficient supervised algorithm to solve classification and regression problems as Support Vector Classification (SVC) and Support Vector Repressor (SVR) (Vapnik et al., 1996). The SVR uses the concept of a hyperplane and margin and the SVR model only requires a small portion of the training data since the cost function that was used to build the model ignores any training data that is close (within a threshold ε) to the model prediction. In the present work, SVR is used for solving a non-linear regression problem of yield prediction using the radial basis function (RBF) kernel function. In SVR, ε- tube is the margin and the hyperplane is the plane that passes through as many data points as possible within the ε- tube as illustrated in Figure 5. SVR handles overfitting more effectively than other regressor models.

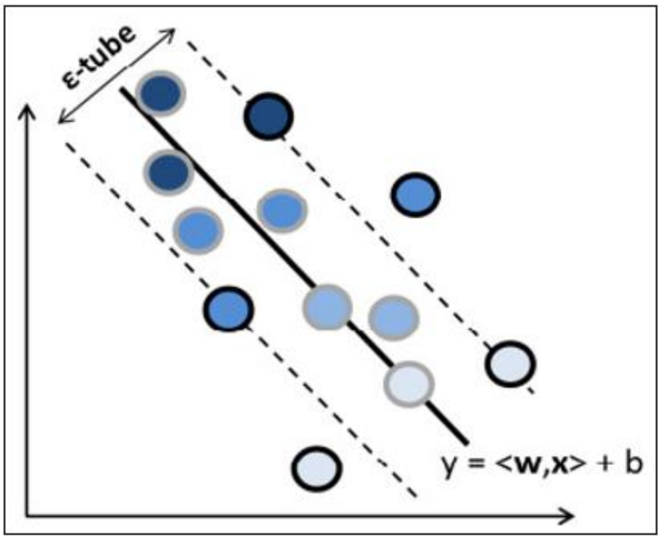

Figure 5: Support Vector Regressor (Rodríguez-Pérez Rodríguez-Pérez and Bajorath, 2022)

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4. Model Performance

The various statistical evaluation metrics used in the present work are Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). The sample standard deviation of the variations between expected and actual values is called the Root Mean Squared Error, or RMSE. It is defined as

$$RMSE = \sqrt{(1/n)}\ \sum_{i=1}^{n}(ETcalcualted - ETpredicted)2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The Mean Absolute Error (MAE) is calculated by dividing the sum of absolute differences between the actual value and the predicted value divided by the number of observations. It is defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|ETcalcualted - ETpredicted| \quad \ldots\ldots\ldots\ldots(2)$$

The coefficient of determination (R^2) determines the closeness of the predicted value to the actual value and is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(ETcalculated - ETpredicted)2}{\sum_{i=1}^{N}(ETcalculated - meanETpredicted)2} \quad \ldots\ldots(3)$$

5. Results and Discussions

5.1 Predicting the Jowar Yield in Bijapur

The deep ANN models were developed to predict yields of jowar crop in Bijapur district in Karnataka from 2004 - 2019. The neural network was repeatedly trained using various hyper-parameters, including learning rate, epoch size, batch size, number of layers, number of nodes per layer, and gradient descent, to achieve the optimum performance. The best way to understand the model generalization is to compare the training loss to the validation loss over a number of epochs. The lower values of validation loss compared to the training loss indicate that the model can predict the validation set more easily than the training dataset. Mean Squared Error (MSE) loss, the most common loss function is calculated as the average of the squared differences between the predicted and actual values. The training MSE decreases gradually whereas the validation error is very low and much less than the training error as shown in Figure 6. Figure 7 shows graphs of the training and validation RMSE versus the number of epochs for the model. It follows from the figure that RMSE decreases rapidly with the increasing number of epochs. The coefficient of determination (R^2) value for the prediction is observed to be 0.87. The results of desirable predictions are visualized through the scatter plots that show the plot of actual vs. the predicted jowar yields (Figure 8).

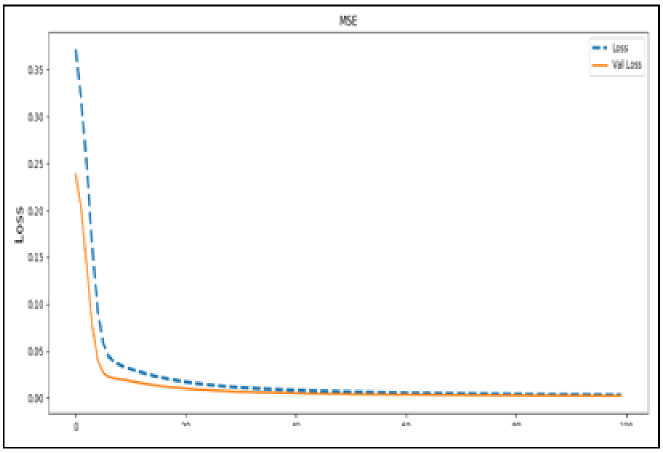

Figure 6: Loss in the jowar dataset using 100 epochs

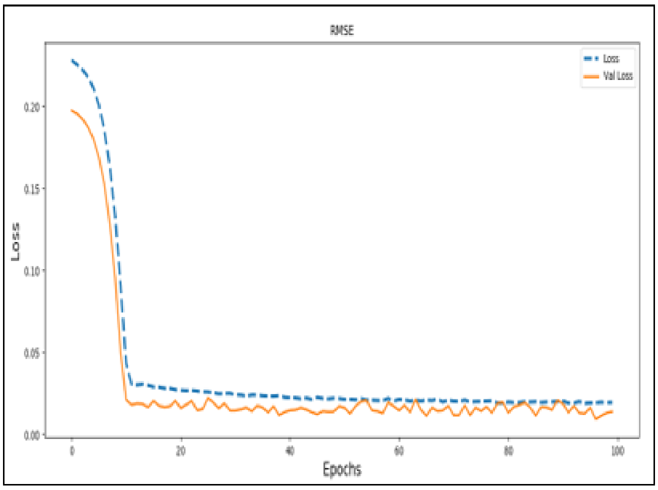

Figure 7: RMSE Loss Curve for 100 epochs while running the DNN model for jowar yield

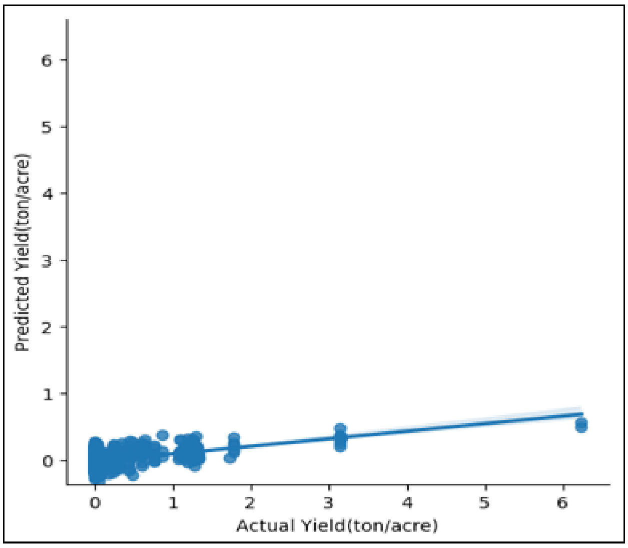

Figure 8: Actual vs predicted Jowar yields

5.2 Feature Importance in DNN using SHAP (SHapley Additive exPlanations)

The SHAP tool is used to explain the model's prediction by assessing the contribution of each feature to the outcome. It shows which feature has contributed the most in making predictions through a visual representation. (Lundberg and Lee 2017) initially proposed the SHAP algorithm in his work to consider SHAP values as a unified measure of feature importance. The present work incorporates the novel approach of using the SHAP framework to demystify the black box nature of DNN.

Due to the black-box nature, DNNs don't give any information about the significance of the features. SHAP framework works on the core principle that a feature's impact is dependent on the dataset as a whole rather than on the single feature. Therefore, SHAP retrains the model over all the combinations of features under consideration to determine the impact of each feature on the target variable using combinatorial calculus (referred to as SHAP value). The average absolute value of a feature's impact on a target variable serves as a measure of its significance. The formula for calculating the SHAP value of feature F is given by (Lundberg and Lee 2017) as

$$\mathrm{SHAP}_{\mathrm{feature}}(\mathrm{x}) = \sum_{set:feature€set} \left[|set| \times \binom{F}{|set|}\right] - 1[Predict\ set(x) - Predict\ set\backslash feature(x)]$$

In the present work, we plot the SHAP values of each feature for each sample to gain an understanding of which features are most crucial for the model. The summary plot shown in Figure 8 uses SHAP values to display the distribution of the effects that each feature has on the model output. Features are sorted by the sum of SHAP value magnitudes across all samples. The features are listed in order of importance, starting with the most significant. "P" (Potassium) is the most important feature, as seen in Figure 9. As the value of this feature goes high, it has a more positive influence on the target variable. The lower value of the feature implies a negative contribution to the target. The feature values are represented by color, with red indicating high and blue indicating low. The x-axis of the plot talks about the risk, the positive side indicates there is a risk, and the negative side implies there is no risk. From Figure 9, the low value of "P" determines there is a risk, and a higher value indicates there is no risk. Figure 10 depicts the bar plot showing eleven features in order of importance based on the mean absolute value of the SHAP values for each feature.

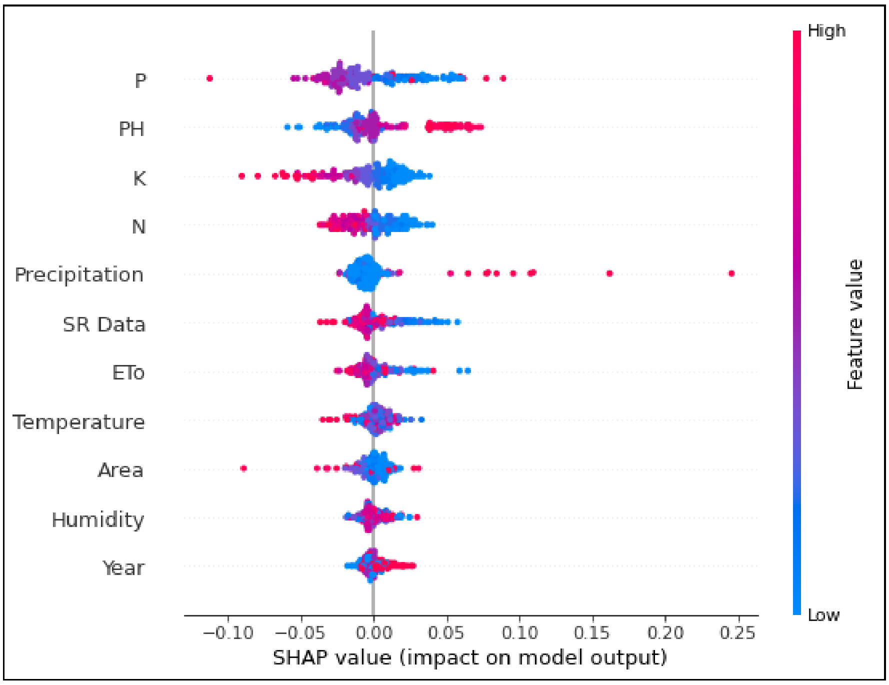

Figure 9: SHAP values' impact on jowar prediction model output

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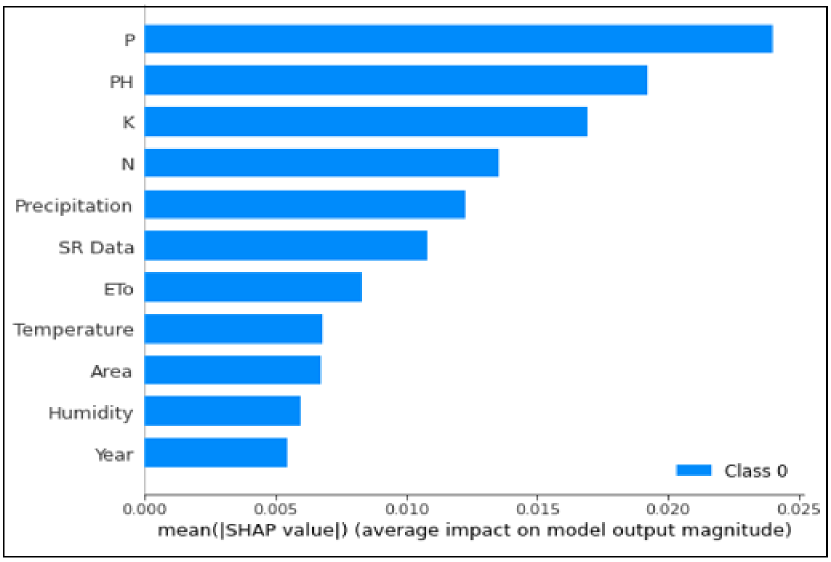

Figure 10: Feature Importance of jowar Prediction

The dataset is randomly divided into a training set and a test set for building four machine-learning models, with the training set being the set with the most data. Despite the test dataset's short size, there is a risk that some crucial details may have been overlooked, which may have improved the model. Furthermore, the K-fold cross-validation is used to solve the volatility issues of the climate datasets. Specifically, the issues of temporal dependency of input variables caused due to the implicit dependence on prior observation that led to frequent changes in mean and variance, are handled through a forward chaining process. The performances of the four models with the training and validation set are compared as given in Table 2. The visual representation of the various metrics such as MAE, MSE, RMSE, and R^2 are analyzed as given in Figure 11.

Table 2: Performance evaluation comparison among the four models

Model	Training Dataset				Validation Dataset			
	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE	R^2
Deep Neural Network	0.18	0.03	0.15	0.82	0.14	0.02	0.18	0.88
Artificial Neural Network	0.32	0.08	0.34	0.68	0.20	0.07	0.34	0.71
Random Forest	0.61	0.67	0.81	0.25	0.63	0.59	0.75	0.39
SVR	0.54	0.36	0.67	0.52	0.46	0.32	0.57	0.59

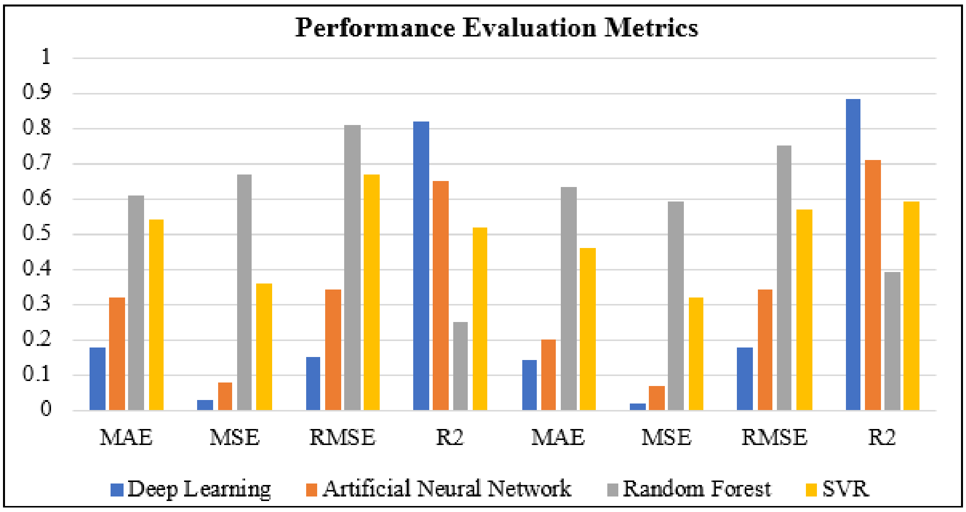

Figure 11: Performance metrics analysis of four models

5.3 Prediction Accuracy Metrics

The reasonability of the proposed models is assessed by evaluating their performance against various execution measures or specialized assessment criteria. The overall performance of the various models in estimating the crop yields can be measured by the prediction accuracy. The accuracy can be measured through the Mean Absolute Percentage Error (MAPE) metric and is defined as the average absolute percentage difference between predicted values and actual values. To ensure a fair evaluation of the model error metrics to estimate yield, two distinct sets of the aforementioned four models were created for training and validation. The hyperparameter optimization for the proposed models is conducted using a manual selection strategy for each relevant model. The primary goal of manual hyperparameter selection is to adjust the model's capacity to align with the complexity of the target job. The determination of hyperparameters, such as the learning rate, number of hidden units, optimizer, activation function, and dropout values, is contingent upon the extent to which the training process and cost function effectively minimize test error. The lowest MAPE value of 18% by the DNN model indicates that the model can predict yields more accurately than the other potential models as given in Table 3. The corresponding bar chart of accuracy and MAPE of the four models is shown in Figure 12.

Table 3: Accuracy and MAPE measure of the four models

Model	Accuracy Measure	MAPE (%)
DNN	95.6	18
ANN	91.4	21
RF	87.2	42
SVR	82.8	47

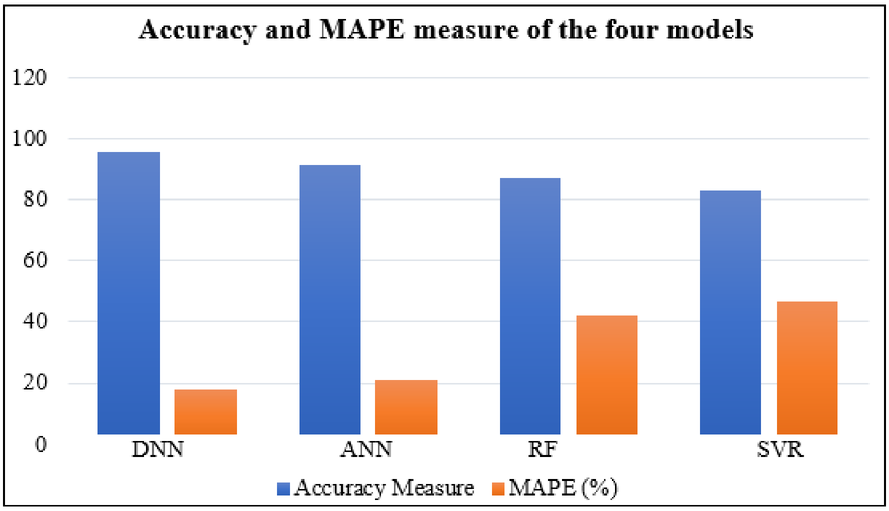

Figure 12: Bar chart of accuracy and MAPE of four models

6. Conclusion

The current study assessed the efficacy of four machine learning models and the neural network models to estimate the yields of the jowar crop in Karnataka using climatic and agricultural data gathered over the growing season of 15 years. The results have shown that the validation loss is smaller than the training loss, indicating that the validation set can be predicted by the model more easily than the training set. The DNN models outperformed the other four machine learning models with an R^2 value of 0.88 during yield predictions of jowar. The lowest MAPE value obtained by the DNN model shows a more accurate prediction compared to other models. According to the SHAP framework, P (Potassium) is the most significant factor influencing the yield predictions of jowar in the district. Using this novel method in deep learning models, it is feasible to quantify the contribution of each feature in the dataset to the prediction of the model.

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