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Research Paper

Comparison of machine learning classification algorithms based on weather variables and seed characteristics for the selection of paddy seed

DHINAKARAN SAKTHIPRIYA AND THANGAVEL CHANDRAKUMAR*

Department of Applied Mathematics & Computational Science, Thiagarajar College of Engineering, Madurai 625015, Tamil Nadu.
**Corresponding author email: t.chandrakumar@gmail.com*

ABSTRACT

Selection of seed is very crucial for the farmers before the start of the crop season. In this study therefore, an attempt has been made to compare various machine learning (ML) classification techniques for paddy seed forecast for cultivation in three major paddy producing taluk of Madurai district, Tamil Nadu viz Thirumangalam, Peraiyur, and Usilampatti. Five machine learning classification techniques viz. K-nearest neighbour (KNN), decision tree (DT), naive bayes (NB), support vector machine (SVM), and logistic regression (LR) used in this study were compared based on weather data and seed characteristics for the better predictions of a paddy seed. Various measures were used to evaluate the algorithms, including F1-score, accuracy, precision, and recall. The findings indicated that the KNN (K-Nearest Neighbour) gave a better accuracy, precision, recall, and F1-score values of about 0.99, 0.94, 1.0, and 0.96 correspondingly. It gave the best result of the paddy seed selection which may be helpful for the farming community in getting higher yield and profit.

***Keyword*:** Paddy seed, K-nearest neighbour (KNN), Decision tree (DT), Naive bayes (NB), Support vector machine (SVM), Logistic regression (LR)

Rice (*Oryza sativa)* is widely cultivated crop throughout the world and is also known as Asian rice. Sufficient paddy seed quality is imperative to enable producers to achieve optimal crop yields. The selection of paddy seed is a critical stage in the overall cultivation procedure. In order to determine the optimal paddy seed for cultivation, experts depend on their own expertise and consider various characteristics of the kernel, including its morphological structure, shape, texture, and colour. They classified a specific variety of paddy seed that originated in a particular region during the inspection. Variations in agricultural productivity across different regions can be ascribed to a multitude of factors, encompassing technological aspects (such as managerial decisions and weeds), biological factors (such as weeds, insects, pests, and illnesses) and environmental factors (such as weather, soil fertility, terrain, and water quality) (Gopal *et al.,* 2019).

Using agricultural yield prediction, Kavita and Mathur (2020) argue that technology can help farmers boost their output. It is determined that the primary objective is to forecast agricultural yield using area, yield, production, and irrigated area. Using machine learning, agricultural productivity has been estimated using decision trees, linear regression, lasso regression, and ridge regression. Nain *et al.,* (2021) have derived prediction models for rice yield in Karnal district, Haryana. Specifically, the performance of multiple linear regression, principal component analysis, and discriminant function analysis to be evaluate the most effective method among these approaches for accurately predicting rice yield before harvest in the specified geographical area. Formerly, researchers estimate the predictive models for soybean yield across different districts: Almora, Udham Singh Nagar, and Uttarkashi. Among these districts, the PCA-SMLR-ANN, SMLR-ANN, and PCA-ANN models emerged as the most effective predictors for soybean yield in each respective district, (Khan *et al.,* 2023).

Das *et al.,* (2018) evaluated six different multivariate models (SMLR, PCA-SMLR, ANN, PCA-ANN, LASSO, ELNET) for prediction of rice yield using long-term weather variables and the suggested LASSO model can be used for west coast of India. Setiya and Nain (2021) developed a regression model that can be used in the prediction of rice crop yield based on the variability in rainfall (mm), maximum temperature (^{0}C), minimum temperature (^{0}C) and solar radiation over the area of study. The models were

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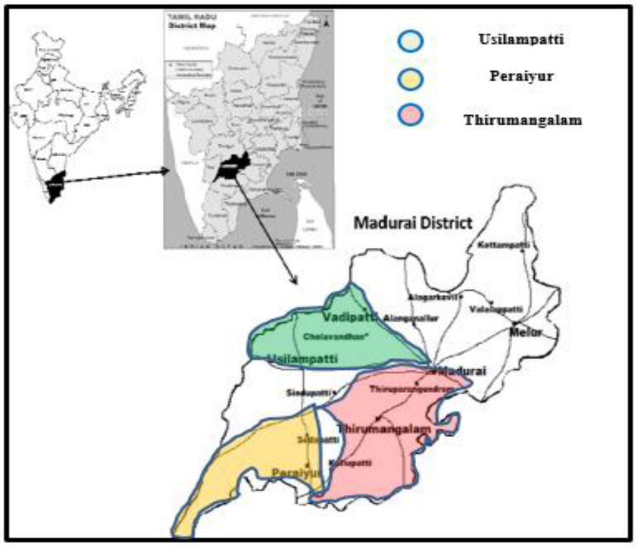

Fig. 1: Map of study area

developed based on the yield and weather data of 15 years and the statistical analysis was performed with the help of Statistical Package for Social Sciences (SPSS) software. Sridhara *et al.,* (2023) examined the application of the stepwise linear regression method, supervised machine learning algorithms (support vector machines (SVM) and random forest (RF)), shrinkage regression approaches (least absolute shrinkage and selection operator (LASSO) or elastic net (ENET)), and artificial neural network (ANN) model for pigeon pea yield prediction using long-term weather data in India during 2023.

In the past research, several studies have mainly focused on the comparison related to weather variables for the prediction of crop yields using machine learning algorithm. But for the paddy seed selection, no research was carried out using machine learning algorithms. Hence in this study, five different machine learning algorithms (K-Nearest Neighbor, Decision Tree, Naive Bayes, Support Vector Machine, and Logistic Regression were used for generating regional-scale predictions of paddy seed-using weather and paddy seed characteristics variables in taluks of Madurai district in Tamilnadu.

MATERIALS AND METHODS

Description of data

The experiment was carried out in three Paddy Research Centres of Tamil Nadu Agricultural University, located in three taluks namely Thirumangalam, Peraiyur and Usilampatti of Madurai district (Fig. 1). In year 2022, paddy was grown in 4000 hectares in the study area and 20000 tonnes of paddy was harvested.

For analysis purpose, twenty years (2002-2022) of agricultural statistics pertaining to rice: 11 Paddy seed characteristics variables, primarily focusing on durations (short, medium, and long duration), average yield, minimum and maximum days, seed types, grain weight, grain type, colour, parentage & other special characteristics shown in Table 1 (1-11), were obtained from the web portal of the Department of Agritechnology of Madurai, Tamilnadu (https://agritech.tnau.ac.in/expert_system/paddy/TNvarieties.html). The data on weather variables (starting month, ending month, rainfall actual, rainfall normal, temperature minimum, temperature maximum, district) shown in Table 1 (12-18) were collected from and the web portals of Tamil Nadu Agriculture Weather Network (http://tawn.tnau.ac.in/General/HomePublicUI.aspx). With a total of 10189 instances for 18 different variables included in the sample size were considered for this research study.

Methodology

Five Machine learning (ML) classification algorithms viz. K-nearest neighbours (KNN), support vector machine (SVM), decision tree (DT), naive bayes (NB), and logistic regression (LR) were compared using 16 years of data for training and 4 years of data for testing for both weather (7 variables) and paddy seed characteristic variables (11 variables). In this study, machine learning algorithms extract the data features, traits, or input variables (predictor). The model's intended result or prediction is represented by the output variable, which is also known as the target variable or label. Table 1 provides a list of the variables used as inputs (predictor) and outputs (target) in this study.

Machine learning algorithms

K-Nearest Neighbor (KNN): KNN is a supervised machine learning approach that employs distance metrics to classify novel data points in conjunction with training data. The utilization of this method attends to classification and regression issues (Khan *et al.,* 2023). It takes a classification algorithm's productivity (labels) and returns an integer value. A memory-based classifier, KNN keeps track of all the data points from training and uses them to make predictions about test data by comparing the input sample to each instance of training. It takes into account k training neighbors br that are closest to $b0$ in distance, where i = 1,...,. The algorithm assigns a label to a newly introduced data point $g0$ by means of a majority vote from its g neighbors (Oktoviany *et al.,* 2021; Khan *et al.,* 2023). The KNN technique is utilized to iterate through different values of n at corresponding times and subsequently selects a that effectively minimizes the number of errors.

Decision tree (DT): Decision tree classifiers use a greedy approach. A supervised learning algorithm, it uses a tree representation for characteristics and class labels. The primary application of decision trees is the construction of training models for the purpose of predicting the value or class of target variables. This model is trained using decision rules derived from historical data (Cai *et al.,* 2022). According to Pallathadka *et al.,* (2023), this method is recursive and needs to be performed for each sub-tree that begins its root at different nodes.

Naive bayes (NB): Yudianto *et al.,* (2021) state that this technique can quickly and accurately predict outcomes by assuming that the properties of the input data are conditionally independent with respect to the class. In statistics, naive Bayes classifiers are simple models that use the Bayes theorem for probability. Despite the

Table 1: Paddy seed and weather factors

S. No	Variable name	Variable ID	Variable type	Description
1	Paddy seed name	RCN	Target	Ruling varieties based on duration (short/medium/long/hybrid), collection of paddy name
2	Parentage	PT	Predictor	Hybrid seeds
3	Period	PD	Predictor	Period (duration) (Short/Medium/Long)
4	Maximum duration	MaxD	Predictor	Duration based on no. of days Max-160 days
5	Minimum duration	MinD	Predictor	Duration based on no. of days Min-94
6	Average yield	AY	Predictor	Average Yield of Paddy (Kg/ha)
7	Grain weight	GW	Predictor	Grain weight
8	Grain type	GT	Predictor	Grain Type (Long/short/medium- Bold/Slender, small) etc.
9	Habit	HT	Predictor	Habit of the crop (semi-dwarf/semi-dwarf, semi-erect/semi-dwarf, slightly open), etc.
10	Rice colour	RC	Predictor	Colour of the rice
11	Special feature	SF	Predictor	Additional features of the paddy crop
12	Starting month	SM	Predictor	Starting month of season
13	Ending month	EM	Predictor	Ending month of season
14	Rainfall actual	RFA	Predictor	Rainfall actual ratio
15	Rainfall normal	RFN	Predictor	Rainfall normal ratio
16	Temperature minimum	Tmin	Predictor	Temperature (10 – 12 ^{0}C)
17	Temperature maximum	Tmax	Predictor	Temperature (36 – 38 ^{0}C)
18	District	DT	Predictor	District list in south Tamil Nadu

naive Bayes classifier's oversimplification of complex concepts, it is widely employed in many real-world applications, including the agriculture sector (Vikram *et al.,* 2021).

Support vector machine (SVM): A robust machine learning technique, Support Vector Machine is employed for a variety of applications, including linear and nonlinear classification, regression, and outlier detection (Ju *et al.,* 2021). When we are attempting to locate the hyperplane that provides the greatest degree of separation between the various classes that are present in the target feature, SVM algorithms prove to be highly effective (Dang *et al.,* 2021).

Logistic regression (LR): Binary classification is accomplished by the utilization of logistic regression, which employs the sigmoid function. This function accepts the inputs as independent variables and generates a probability value that falls between 0 and 1. It is utilized for the purpose of describing data and providing an explanation of the relationship that exists between a single dependent binary variable and one or more independent variables that are of the nominal, ordinal, interval, or ratio level (Cedric *et al.,* 2022).

Performance testing of machine learning algorithms

The performance of various ML classification algorithms was categorized based on accuracy, precision, recall, F1-score and presented according to different zones (Madurai Thirumangalam Taluk, Madurai Peraiyur Taluk, and Madurai Usilampatti Taluk. The formulae used for calculating the performance parameters are as follow;

$$Accuracy\ (Acc) = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision\ (P) = \frac{TP}{TP+FP}$$

$$Recall(R) = \frac{TP}{TP+FN}$$

$$F1 - Score(F1) = 2\left(\frac{Precision - Recall}{Precision + Recall}\right)$$

Where, TP= True Positive, TN=True Negative, FP=False Positive, FN= False Negative

RESULTS AND DISCUSSION

Madurai Thirumangalam taluk

The values of prediction accuracy statistics of all algorithms for Madurai Thirumangalam taluk can be found in Table 2. At first, we used the Accuracy value—which ranges from 0.86 for SVM to 0.99 for KNN—to compare the algorithms' performance on the training data. The second metrics Precision value, is ranging from 0.81 for DT to 0.94 for KNN. The third metrics Recall value, is ranging from 0.86 for SVM to 1.0 for KNN. The final measurement of F1-score value, is ranging from 0.86 for SVM to 0.96 for KNN. In this study Madurai Thirumangalam taluk get the result ranging from 0.86 for SVM and 0.96 for KNN and it is found that KNN classification algorithm performed better compared to the other ML algorithms (SVM, LR, NB, DT) for paddy seed selection in Madurai Thirumangalam taluk.

Table 2: Comparison of ML-model validation analysis in different taluks of Madurai

Taluks	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Thirumangalam	**KNN**	**99**	**94**	**100**	**96**
	SVM	86	85	88	86
	LR	91	92	89	90
	NB	87	84	92	88
	DT	88	81	91	89
Peraiyur	**KNN**	**98**	**94**	**100**	**96**
	SVM	84	84	88	86
	LR	90	90	89	90
	NB	82	80	82	88
	DT	86	81	91	89
Usilampatti	**KNN**	**99**	**94**	**100**	**96**
	SVM	86	81	88	86
	LR	91	91	89	90
	NB	87	90	92	88
	DT	88	87	91	89

Table 3: Comparisons of Training and Testing data splitting accuracy

Data splitting range (in)		Accuracy (%)					Precision (%)				
Training (%)	Testing (%)	KNN	SVM	LR	NB	DT	KNN	SVM	LR	NB	DT
25	75	49.33	49.33	49.33	69.32	66.66	38.40	42.80	39.79	14.15	55.55
30	70	55.71	64.28	71.42	79.50	77.14	48.75	57.41	62.79	07.38	63.84
35	65	73.84	70.76	67.69	86.35	81.53	63.08	59.10	58.71	09.15	72.75
40	60	80.00	78.33	60.00	87.25	85.00	80.95	76.77	53.11	13.34	80.21
45	55	80.00	80.00	76.36	92.00	83.63	82.36	74.43	79.27	18.49	77.95
50	50	78.00	62.00	78.00	90.52	84.00	83.60	67.10	83.23	18.29	80.62
55	45	80.00	82.22	77.77	87.88	84.44	86.08	78.51	79.51	18.14	79.95
60	**40**	**93.50**	**87.50**	**82.50**	**85.71**	**87.50**	**91.27**	**83.95**	**80.83**	**78.48**	**78.48**
65	35	85.71	77.14	60.00	91.25	85.71	85.23	73.09	62.85	17.85	78.43
70	30	76.66	73.33	83.33	89.25	83.33	75.83	68.44	75.44	11.77	74.36
Training (%)	Testing (%)	Recall (%)					F1_Score (%)				
25	75	49.33	49.33	49.33	93.33	66.66	41.24	41.11	42.31	56.82	58.45
30	70	55.71	64.28	71.42	71.49	77.14	49.76	59.18	66.29	71.42	68.96
35	65	73.84	70.76	67.69	76.93	81.53	66.96	63.49	62.09	75.54	75.52
40	60	80.00	78.33	60.00	15.00	85.00	77.39	74.03	55.99	32.27	81.06
45	55	80.00	80.00	76.36	18.18	83.63	79.26	75.37	74.47	52.07	79.59
50	50	78.00	62.00	78.00	16.00	84.00	78.05	61.92	78.72	43.16	80.43
55	45	80.00	82.22	77.77	13.00	84.44	79.37	79.11	76.91	35.40	80.63
60	**40**	**92.35**	**87.50**	**82.50**	**87.50**	**87.50**	**88.52**	**85.42**	**79.75**	**73.50**	**82.30**
65	35	85.71	77.14	60.00	85.00	85.71	84.47	74.48	58.22	97.43	80.96
70	30	76.67	73.33	83.33	10.00	83.33	74.98	69.77	78.38	93.65	77.68

Madurai Peraiyur taluk

The values of prediction accuracy statistics of all algorithms for Madurai Peraiyur taluk Can be found in Table 2. Initially the performance of algorithms during training data was compared based on the Accuracy value, is ranging from 0.86 for SVM to 0.99 for KNN. The second metrics Precision value, is ranging from 0.84 for NB to 0.94 for KNN. The third metrics for Recall value, is ranging from 0.86 for SVM to 1.0 for KNN. The final measurement of F1-score value, which is ranging from 0.86 for SVM to 0.96 for KNN. In this study Madurai Peraiyur taluk get the result ranging from 0.86 for SVM and 0.96 for KNN and it is found that KNN classification algorithm performed better compared to the other ML algorithms for paddy seed selection in Madurai Peraiyur taluk.

Madurai Usilampatti taluk

Initially the performance of algorithms during training data was compared based on the Accuracy value, is ranging from 0.86 for SVM to 0.99 for KNN. The second metrics for Precision value, is ranging from 0.84 for NB to 0.94 for KNN. The third metrics for Recall value, is ranging from 0.86 for SVM to 1.0 for KNN. The final measurement of F1-score value, is ranging from 0.86 for SVM to 0.96 for KNN. In this study Madurai Usilampatti taluk get the result ranging from 0.86 for SVM and 0.96 for KNN and it is found that KNN classification algorithm performed better compared to the other ML algorithms for paddy seed selection in Madurai Usilampatti taluk.

Table 4: Results comparison with other models

S. No	Models	Crop	Region	Results	Ref
1	MLR	Paddy	Tamil Nadu, India	Accuracy=0.85	Gopal and Bhargavi (2019)
2	Boruta, SFFE, RFE,	All Crops	Tenkasi District, TamilNadu, India.	Accuracy=0.92	Suruliandi *et al.,* (2021)
3	MDI, Feal ect, RRelieif with DNN	Wheat	Henan Province, China	Accuracy=0.60	Fei *et al.,* (2022)
4	PSO-SVM, KNN, RF	All Crops	United States	Accuracy=0.97	Gupta *et al.,* (2022)
5	Bayes Net, LR, RF, NB, Multilayer Perception	All Crops	Kuwait	Accuracy=0.97	Elbasi *et al.,* (2023)
6	KNN, NB, DT, SVM, LR	Paddy	Madurai, TN, India.	Accuracy=0.99	Our proposed Research

We have also conducted that the 16 years data and 4 years data for training and testing with the ranges 25% to 75% and 30% to 70% respectively which is shown in Table 3. Effectiveness is measured by means of the Accuracy, Precision, Recall, and F1 Score.

Table 3 demonstrates that the optimal functionality of preference metrics implementing the various ML classification algorithms for this research is achieved when the training and testing data sets are split between 60% to 40%. This gets the highest value for each metric states for highlight the Accuracy value for 93.50, Precision value for 91.27, Recall value for 92.35 and finally F1-score value for 88.52 from KNN. The results signify that the KNN classification algorithm is superior to other ML classification algorithms strategies like SVM, NB, DT, and LR.

Our research shows that KNN is the best classifier model for ML Classifiers for predicting paddy seeds from Table 4. It has an accuracy value of 0.99 compared to other models like Boruta, SFFE, RFE, MDI, Feal, etc., along with RRelief with DNN, MLR, BayesNet, Multilayer Perception, RF, and PSO-SVM for different crops like paddy, wheat, and more, that have been suggested by other researchers.

CONCLUSION

This research aims to find the best ML algorithms for paddy seed selection. Based on dataset paddy seed characteristics and weather variables, five ML systems were tested for paddy seed selection. The KNN (K-nearest neighbour) method was the best paddy seed selection predictor model for Madurai district of Tamil Nadu followed by SVM. The KNN has improved Accuracy, Precision, Recall, and F1-Score values of 0.99, 0.94, 1.0, and 0.96. It provides the best paddy seed selection, helping farmers increase output and profit. This research study only examined weather and paddy seed characteristic variables, but in the future, more traditional paddy seed variables (Soil nutrients, Disease Resistance, Pest Resistance, Yield Potential, Grain Quality, Genetic Purity and Environmental Adaptability and Water Availability etc.,) shall be addressed and evaluated using advanced machine learning algorithms such that (Deep learning, ANN, Ensemble learning, Graph based models like GNN etc.,) for different geographic regions in India.

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