OPEN ACCESS
International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-4, November 2019

Rice Yield Forecasting using Support Vector Machine

Sunil Kumar, Vivek Kumar, R. K. Sharma

Abstract: ***In the domain of Soft Computing, Support Vector Machines (SVMs) have acquired considerable significance. These are widely used in making predictions, owing to their ability of generalization. This paper is about the development of SVM based classification models for the prediction of rice yield in India. Experiments have been conducted involving one-against-one multi classification method, k-fold cross validation and polynomial kernel function for SVM training. Rice production data of India has been sourced from Directorate of Economics and Statistics, Ministry of Agriculture, Government of India, for this work. The best prediction accuracy for the 4-year relative average increase has been achieved as 75.06% using 4-fold cross validation method. MATLAB software has been used for experimentation in this work.***

Keywords**:** ***Support vector machines, Rice yield, Forecasting, Training patterns***

I. INTRODUCTION

Nearly half the world has rice as staple diet. Hundreds of millions living in Asia, Africa and Latin America are dependent on rice that comprises the most important components of their diet [1]. In India, rice is a significant cereal crop. In 2015-16, the annual production was almost 104 tonnes and almost 43 million hectares was used for this purpose [2]. It has a significant task to carry out in the national food security scheme. Rice is a sturdy crop capable of adapting itself to a variety of ecosystems. More than 58% of the India's population depends on rice as a primary source of livelihood [3].Almost 41% of total food grain production in India comprises of rice. The emphasis is on accomplishing maximum crop yield at less cost. This becomes possible if the problems indicated by the crop yield indicators are detected early and tackled. This can be achieved with early discovery and management of issues related with crop yield pointers. Furthermore, these predictions can be utilized to increase crop yield at whatever point the potential for good developing conditions exists.

Manuscript published on November 30, 2019.
*Corresponding Author

Sunil Kumar*, Assistant Professor, Department of Management Studies, Kumaun University Campus, Bhimtal-253136, India,
Email:sunilarora29@gmail.com

Vivek Kumar, Professor, Department of Computer Science, Gurukula Kangri Vishwavidyalaya, Haridwar- 249404,India,
Email: vivekdcg@gmail.com

R.K. Sharma, Professor, Department of Computer Science and Engineering, Thapar Institute of Engineering & Technology, Patiala - 147004, India Email: rksharma@thapar.edu

Accurate forecasting may help stakeholders in taking appropriate and timely decision. In particular, people associated directly with rice production may avoid unpleasant surprises. Reliable and timely forecasts can provide important and useful inputs for planning towards attaining food security in India.

As such, the need of the hour is to build models that can accurately predict future agricultural production with the help of historical data and develop agriculture based decision support systems [4][5].Neural networks have significant applications in complex systems behaviour forecasting. Many applications have shown that artificial neural networks (ANNs) can serve as an effective mechanism for time-series forecasting and modelling [6]. Several studies outlined the development of models based on agronomics by using ANNs. Applications of Agronomic ANN facilitates the process of forecasting rice yield [7], wheat production forecasting [8], forecasting maize crop yield [9], weather based forecasting model for crops yield [10], yield forecasting [11], Agricultural Crop Yield Prediction [12], wheat yield prediction [13] and rice crop yield prediction [14].

Some of these studies, however, indicate that ANN has its own drawbacks as far as learning of patterns go. This is because agricultural yield data has high dimensionality, inconsistency and unpredictability in performance regarding noisy data frequently addressed in ANN. However, back-propagation (BP) neural network, the popular model of neural network, is limited by its use to select a enormous number of network parameters like pertinent input variables, hidden layer size, learning rate, momentum term, etc.

At least nine studies indicate that forecasting crop yield is possible through application of soft computing techniques under different climatic scenarios[12][13][15][16][17][18][19][20] [21].

Application of SVM in agricultural science research has been sparse. Tripathi *et al.* provided details regarding how SVM was executed for decrease in precipitation for changed environmental situations[21]. SVM Technique was utilized for estimation of demand and supply of pulpwood with the objective of restricting the generalization error [22]. The climatic conditions were used to feature contribution analysis to understand the crop response pattern for agricultural yield prediction by applying SVM[23]. SVM was applied for classification of agricultural datasets on basis of discretization[24]. Using SVM, aerial hyper spectral observations were used to assess the biophysical parameters of crops[25].Wang *et al*. compared regression analysis with SVM to predict wheat stripe rust [26]. Balakrishan *et al.* ensemble SVM models to project the crop production over a period of time (year 1990-2003) [27].

Gandhi *et al.* investigated SVM for rice yield forecasting for Maharashtra State of India (27 districts)[28]. The data of rice yield of these districts was subjected to Sequential Minimal Optimization (SMO) classifier.

SVM, a machine learning algorithm developed by Vapnik, is based principle of statistical learning theory[29]. SVM holds a lot of promise for classification with an added feature of structural and experimental risk minimization [30]. Also, it can map the features in high dimensional space while changing the complex problems into a linearly separable case.

This study has been based on the dataset of rice yield in India from the year 1950 to 2014. This paper envisages bringing to the fore the applicability of an SVM model to forecast yield of rice crop based on this data.

II. METHODOLOGY

A. SVMs and their applications

A.1 Basic Concepts

SVM is a critical classifier, characterized by an isolating hyperplane. In two-dimensional, a line dividing a plane in two parts – a hyperplane includes one class on either side.

SVMs create non-linear class boundaries. They operate essentially to construct a more complicated linear classifier called a hyperplane**.** In boundless dimensional space, SVM constructs a hyperplane. So, SVM is the method which is a particular type of linear model, known as the *maximum margin hyperplane*. This hyperplane maximizes the margin (a margin is a separation of line to the closest class points) between the decision classes. The vectors (cases) that define the hyperplane are the support vectors/data points/training data. The binary class boundaries are not defined pertinently by the other training examples.

Let us examine a situation that is a linearly separable case. A scenario of three-attribute in a hyperplane separating the binary decision classes may be depicted as:

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 \qquad (1)$$

Here y is the output, x_i indicates values of attribute, and w_i, the leaning function has four weights to learn. In (1), weights w_i are parameters for the hyperplane to decide. The maximum margin hyperplane may be elaborated with support vectors as follows:

$$y = b + \sum \alpha_i y_i \mathbf{x}(i).\mathbf{x} \qquad (2)$$

where y_i denotes the class value of training example $\mathbf{x}(i)$, ·(dot)indicates the dot product between the input ($\mathbf{x}$) and each support vector $\mathbf{x}(i)$. The vector $\mathbf{x}$ is a test example and the vectors $\mathbf{x}(i)$ indicate the support vectors. The coefficients b and α_i (for each input) must be estimated from the training data. The hyperplane in this equation is represented by b and α_i. Identifying support vectors and parameters b and α_i are indicative of a linearly restricted quadratic programming (QP) for the purpose of implementation.[36].

As stated above, SVM creates linear model for the implementation of nonlinear class boundaries by modifying the input variables to the high-dimensional feature space.A high-
dimensional version of (2) is simply depicted as follows in the case of nonlinearly separable:

$$y = b + \sum \alpha_i y_i K(\mathbf{x}(i), \mathbf{x}) \qquad (3)$$

Here, the function $K(\mathbf{x}(i),\mathrm{x})$ indicates the kernel function(KF). This KF is similar to learning function used in ANN. There are several distinct kernels for creating the dot products to build machines with distinct kinds of nonlinear decision boundaries in the input. The best model is selected which minimizes the estimate between distinct kernels. Commonly employed KFs are:

1) Linear Kernel: $K(u_i, u_j) = u_iu_j$
2) Polynomial: $K(u_i, u_j) = (\gamma u_iu_j + \mathrm{c})^d$
3) Radial basis function: $K(u_i, u_j) = \exp(-\gamma|u_I - u_j|^2)$
4) Sigmoid: $K(u_i, u_j) = tanh(\gamma u_iu_j + \mathrm{c})$

A separable case is represented by (3) where the coefficient α_i has a lower bound value of '0'. In non-separable case, the coefficients α_i may be induced by an upper bound C apart from the lower bound [31].

SVMs generate mapping functions for input-output from a collection of labelled training data [34]. These functions can be regression or classification. The KF $K(u_i, u_j)$ makes SVM a remarkable tool to map the input data *i.e.* linearly inseparable to a feature space *i.e.* high dimensional. Perhaps this attribute makes SVM perfect for assisting the construction of linear hyperplanes that would separate the classes. Moreover, Optimization of the bounding surface – ideal hyperplane distance shall lead to minimization of the chances of misclassification.

SVM, created originally for binary classification, is later efficiently expanded by joining many binary classifiers to classify various classes. One-against-all, one-against-one, and directed acyclic graph SVM (DAGSVM) are techniques which involve solution of several binary classifications. Several binary classifiers have to be constructed for multiclass SVM methods, One-against-all, the oldest technique, constructs k SVM models, where k is number of classes. Hence finding the ideal hyperplanes involves solving k quadratic programming issues. Another technique, one-against-one builds $(k(k\text{-}1))/2$ classifiers and each classifier is trained. The original data transfers data of pair of classes to the classifiers. The prediction of classes for the testing data (unseen data) is done by applying a majority vote scheme(Max Wins strategy) [35]). The training of the DAGSVM method is the similar to the one-against-one method. Moreover, the time taken in testing phase is less than time taken in one-against-one method [35].

The one-against-one technique is considered, despite its computational complexity, as the most regarded as the most appropriate technique for multiclass classification problems [35]. It was therefore chosen for development of the proposed model.

A.2 Prior applications of SVM

Due of its use in commercial applications and prevalent learning capability, the BP network was extensively employed in the field of time series forecasting.

Be that as it may, the Back-propagation network has numerous drawbacks including the requirement for network controlling parameters and the number of neurons in the hidden layer, and the peril of overfitting issue.
If we leave aside the upper bound *C* for the non-separable cases in linear SVM, there are no parameters to tune[32]. Moreover, overfitting with SVM unlikely to occur. While there are chances of overfitting being caused of extreme flexibility in the decision boundary, the maximum hyperplane is comparatively quite stable, giving very little flexibility[31].

The advantages of SVM failed to motivate the agricultural scientists to use it for agricultural forecasting studies.

B. Data Collection

Rice production data of India has been sourced from Directorate of Economics and Statistics, Ministry of Agriculture, Government of India [33].The data set encompasses the rice yield in India from the year 1950 to 2014.

C. Feature Extraction for Support Vector Machine

The extracted features should have all information, so that when the same is enhances the recognition capability of classifier.SVM classifier for the prediction of rice yield has been used. In order to implement SVM, the training and testing patterns have been developed as per the process outlined below: Instead of taking the raw yield data as a pattern, we have worked upon the relative increase in the yield, and formed the patterns, using the relative increase as input and output. We first calculated the yearly relative increase in the rice yield. As mentioned earlier, we have this yield for the period from 1950 to 2014. As such, we had 64 values. These values gave us 63 values of the relative increase in the rice yield. These have been taken as the input to SVM as described in next paragraph. We further calculated the four-year moving averages of the rice yield. Using these four year moving averages, we then calculated the relative increase in these moving averages. This relative increase in four year moving averages is used to model the output from the SVM. This modelling is done as per Table I.

Table-I: Relationship between relative four year moving average and SVM label

Relative four year moving average	Class label
(-4.5, -2.5]	Very Low Yield
(-2.5, -0.5]	Low Yield
(-0.5, 2.0]	Average Yield
(2.0, 4.0]	Moderate Yield
(4.0, 6.0]	High Yield
(6.0, 8.0]	Very High Yield

The first training pattern/support vector is now formed by taking first five years relative increase in the yield as input and first four year relative moving average as output. Similarly, next pattern is formed by taking next five years relative increase in the yield as input and second four year relative moving average as output. Using this strategy, we obtained 60 training/testing patterns.

Using a similar process, we have experimented with five year relative increase in the yield and four year relative moving averages of the yield. This modelling is done as per the following Table II.

Table- II: Relationship between relative five year moving average and SVM label

Relative four year moving average	Class label
(-3.5, -2.0]	Very Low Yield
(-2.0, -0.5]	Low Yield
(-0.5, 1.0]	Average Yield
(1.0, 2.5]	Moderate Yield
(2.5, 4.0]	High Yield
(4.0, 5.5]	Very High Yield

The classes are labeled as C1 - Very Low Yield, C2 – low yield, C3 – average yield, C4 - Moderate Yield, C5 – high yield, C6 - very high yield. Now these C1-C6 are identified as classifiers in both the cases *i.e.* 4 year relative and 5 year relative moving average.

D. Experiments

One-Against-One (OAO) multiclass SVM method has been used for classification. SVM Classification model is proposed, utilizing six binary SVMs for classification. The detection of a single class by a dedicated SVM is flagged as 0 or 1 to mark its presence. as shown in Fig. 1. Ever SVM training is carried out with inputs of classes of data that contain an input 1 as target and 0 for another classes.

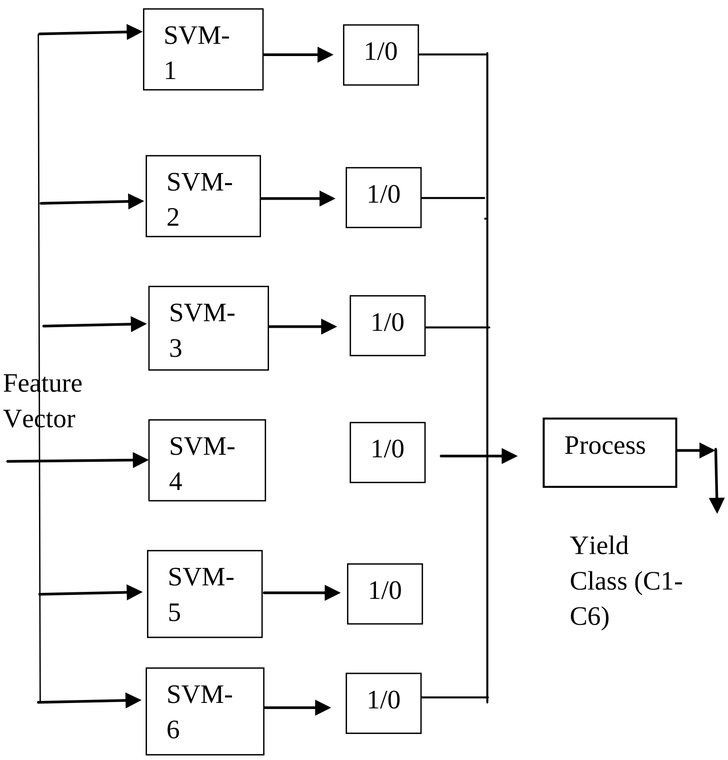

Fig. 1.Proposed SVMs classification model

The most widely used metric for deciding the capability of a model is the accuracy that it achieves. The accuracy of a model is defined as the achievement by the classifier achievement rate. In this work, the performance of SVM classification model is described in terms of the accuracy it achieves. *K*-fold cross validation method has been utilized so that overall data is utilized to develop the classification model. Here 3-fold cross validation, 4-fold cross validation and 5-fold cross validation method have been applied for experimentation. The original data was scaled using strategy of moving averages. Each feature component is independently normalized by linear scaling which ensures maintaining a balance between the larger and smaller values of input attributes and this in turn helps in reducing the prediction errors. The final prediction accuracy has been computed after averaging the accuracies obtained by all three folding strategies. The performance of classifiers that have been experimented was also calculated by constructing confusion matrices.

In this study, the polynomial KF is used for implementing the SVM. The degree *d* of this kernel function has been taken as 3. is the parameter for The soft margin cost function (*C*), also called as BoxConstraint parameter has been set to 0.2. The tolerance of termination criterion (*e*) has been set to 0.001.

III. RESULTS AND DISCUSSION

The SVM classification models were trained with values of learning parameters as explained in Section II. The results of different *k*-fold cross validations were recorded, and are being presented in Table III.

Table- III: The prediction accuracy for rice yield forecasting

Results based on four year relative increase			
k-fold	*3-fold*	*4-fold*	*5-fold*
Prediction Accuracy (%)	73.60	75.06	64.88
Results based on four year relative increase			
k-fold	*3-fold*	*4-fold*	*5-fold*
Prediction Accuracy (%)	64.70	56.70	53.55

A. Confusion Matrix

Various confusion matrices have also been obtained. Coordinates in confusion matrix represent row vector, column vector, and number of folds. The confusion matrices for best prediction accuracy are incorporated in Table IV.

Table- IV: Confusion matrices for accuracies of four year relative increase

Fold Accuracy	Confusion Matrix
SVM (1-against-1): accuracy = 78.57% SVM (1-against-1): accuracy = 0.00% SVM (1-against-1): accuracy = 0.00% SVM (1-against-1): accuracy = 0.00%	(:,:,1) = 0 0 0 0 0 0 1 0 0 0 0 0 0 0 5 1 0 0 0 0 0 3 0 0 0 0 0 1 2 0 0 0 0 0 0 1
SVM (1-against-1): accuracy = 78.57% SVM (1-against-1): accuracy = 75.00% SVM (1-against-1): accuracy = 0.00% SVM (1-against-1): accuracy = 0.00%	(:,:,2) = 1 0 0 0 0 0 0 0 1 0 0 0 0 0 6 0 0 0 0 0 2 2 0 0 0 0 0 0 3 0 0 0 0 0 1 0
SVM (1-against-1): accuracy = 78.57% SVM (1-against-1): accuracy = 75.00% SVM (1-against-1): accuracy = 80.00% SVM (1-against-1): accuracy = 0.00%	(:,:,3) = 0 1 0 0 0 0 0 1 0 0 0 0 0 0 6 0 0 0 0 0 1 3 0 0 0 0 0 0 2 0 0 0 0 0 1 0
SVM (1-against-1): accuracy = 78.57% SVM (1-against-1): accuracy = 75.00% SVM (1-against-1): accuracy = 80.00% SVM (1-against-1): accuracy = 66.67%	(:,:,4) = 1 0 0 0 0 0 0 0 1 0 0 0 0 0 4 1 0 0 0 0 1 2 1 0 0 0 0 1 2 0 0 0 0 0 0 1
Average Accuracy	**75.06**

In the experiments conducted in this work, it has been seen that the best prediction accuracy for 4-years relative increase is 75.06% using 4-fold cross validation method.

IV. CONCLUSION

In the past, a good amount of work has been done on the forecasting of rice yield. The development of soft computing models that provide an exact or even a good approximation to crop yield for next year(s) will immensely contribute to the encouragement of farmers and other interested holders. These models will improve the quality of decision making in connection to domestic sustenance and international trade. The importance of rice in India and world cannot be underestimated. Development of a suitable forecasting model valid across all agro climatic zones for the yield of rice crop shall have far reaching beneficial outcomes.

The efficacy of SVM in predicting the yield of rice crop has been demonstrated in this paper. SVM-based classification models have been developed for the forecasting of rice yield in India. SVM classification models have been tested using 3-fold, 4-fold and 5-fold cross validation methods, one-against-one multi classification method. The dataset encompasses the rice yield in India from the year 1950 to 2014.

Retrieval Number: D7239118419/2019©BEIESP
DOI:10.35940/ijrte.D7236.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

The best prediction accuracy for 4-year relative average increase has been obtained as 75.06% using 4-fold cross validation method. This is not a very high accuracy; however, it is believed that this can be improved by redefining training patterns, considering other KF. The learning parameters can also be optimized using particle swarm optimization or other related techniques. This work can also be explored further for yield prediction of other crops.

REFERENCES

1. YOSHIDA, S. (1981). Fundamentals of Rice Crop Science. Los Banos, Philippines: International Rice Research Institute, available: http://books.irri.org/9711040522_content.pdf.
2. Annual Report 2016-17, Department of Agriculture and Cooperation, Ministry of Agriculture & Farmer Welfare, Government of India, available: http://agricoop.nic.in/sites/default/files/Annual_rpt_201617_E.pdf.
3. Gain Report on Global Agricultural Information Network, India Grain and Feed Annual, USDA Foreign Agricultural Service, 2014, available: https://gain.fas.usda.gov/Recent%20GAIN%20Publications/Grain%20and%20Feed%20Annual_New%20Delhi_India_2-23-2017.pdf.
4. Y.W. Jame and H.W. Cutforth, "Crop growth models for decision support systems," *Canadian Journal of Plant Science.*, vol. 76, pp. 9-19, 1996, doi: 10.4141/cjps96-003.
5. W. Stephens, T. Middleton, "Why has the uptake of decision support systems been so poor? Crop-Soil Simulation Models: Applications in Developing Countries." In R. B. Matthews, W. Stephens, eds., pp. 129–147.Wallingford, UK:CAB International, 2002, doi: 10.1079/9780851995632.0000
6. G. Zhang, B.E. Patuwo, M.Y. Hu, Forecasting with artificial neural networks: the state of the art, *Int. J. Forecasting*, vol 14, pp. 35-62, 1998, available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.138.4828&rep=rep1&type=pdf.
7. Kumar, A., Ramasubramanian, V., and Agrawal, R., "Forecasting rice yield using neural networks," in *Proc. 3rd Indian International Conference on Artificial Intelligence (IICAI-07)*, pp. 1510-1516, December 17-19, 2007, available : https://dblp.org/rec/conf/iicai/KumarVA07.
8. Adesh K. Pandey, A.K. Sinha, V.K. Srivastava, "A Comparative Study of Neural-Network & Fuzzy Time Series Forecasting Techniques – Case Study: Wheat Production Forecasting," *Journal of Computer Science and Network Security*, vol. 8, no. 9, pp. 382-387, 2008, available: http://paper.ijcsns.org/07_book/200809/20080956.pdf.
9. Rama Krishna Singh and Prajneshu, "Artificial Neural Network Methodology for Modelling and Forecasting Maize Crop Yield," *Agricultural Economics Research Review*, vol. 21, pp. 5-10, 2008, available: https://ageconsearch.umn.edu/record/47354/files/2-RK-Singh.pdf.
10. Ratna Raj Laxmi and Amrender Kumar, "Weather based forecasting model for crops yield using neural network approach", *Statistics and Applications*, vol. 9, no. 1&2, pp. 55-69, 2011 (New Series), available: https://pdfs.semanticscholar.org/7c6e/22b5a86ce83150af7ba913df9268075f372d.pdf.
11. Baral S., Kumar Tripathy A., Bijayasingh P., "Yield Prediction Using Artificial Neural Networks. In Das V.V., Stephen J., Chaba Y., eds. *Computer Networks and Information Technologies. CNC 2011. Communications in Computer and Information Science*, vol. 142, Springer, Berlin, Heidelberg, March 10-11, 2011, doi: 10.1007/978-3-642-19542-6_57.
12. Miss. Snehal S. Dahikar, Dr. Sandeep V. Rode, "Agricultural Crop Yield Prediction Using Artificial Neural Network Approach," *International Journal Of Innovative Research in Electrical, Electronics, Instrumentation And Control Engineering*, vol. 2, no. 1, pp. 683-686, January 2014, available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.429.1195&rep=rep1&type=pdf.
13. Vikas Lamba, V.S. Dhaka, "Wheat Yield Prediction Using Artificial Neural Network and Crop Prediction Techniques (A Survey), "*International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, vol. 2, no. 9, September 2014, available: https://www.ijraset.com/fileserve.php?FID=938.
14. Gandhi, N., Petkar, O., & Armstrong, L. J., "Rice crop yield prediction using artificial neural networks," in *Proc. Technological Innovations in ICT for Agriculture and Rural Development (TIAR), IEEE*, pp. 105-110, 2016, doi: 10.1109/TIAR.2016.7801222.
15. R. Medar, V. Rajpurohit, "A survey on data mining techniques for crop yield prediction", *International Journal of Advance Research in Computer Science and Management Studies*, vol. 2, no. 9, pp. 59-64, 2014, available: http://www.ijarcsms.com/docs/paper/volume2/issue9/V2I9-0026.pdf.
16. S. Bejo, S. Mustaffha and W. Ismail, "Application of artificial neural network in predicting crop yield: A review", *Journal of Food Science and Engineering*, vol. 4, pp.1-9, 2014 available: https://www.researchgate.net/publication/283570924_Application_of_Artificial_Neural_Network_in_Predicting_Crop_Yield_A_Review.
17. W. Guo and H. Xue, "An incorporative statistic and neural approach for crop yield modelling and forecasting", *Neural Computing and Applications*, vol. 21, pp. 109-117, 2012, available: https://www.researchgate.net/publication/220372630_An_incorporative_statistic_and_neural_approach_for_crop_yield_modelling_and_forecasting/download.
18. W. Guo and H. Xue, "Crop yield forecasting using artificial neural networks: A comparison between spatial and temporal models", *Mathematical Problems in Engineering*, pp.1-7, 2014, doi: 10.1155/2014/857865.
19. D. Ramesh and B. Vardhan, "Analysis of crop yield prediction using data mining techniques", *International Journal of Research in Engineering and Technology*, vol. 4, no. 1, pp. 470-473, 2015, available: https://www.academia.edu/21226449/ANALYSIS_OF_CROP_YIELD_PREDICTION_USING_DATA_MINING_TECHNIQUES.
20. G. Yengoh and J. Ardo, "Crop yield gaps in Cameroon", AMBIO, Springer, vol. 43, pp. 175-190, 2014, doi: 10.1007/s13280-013-0428-0.
21. S. Tripathi, V.V. Srinivas and R.S. Nanjundiah, "Downscaling of precipitation for climate change scenarios: a support vector machine approach", *Journal of Hydrology*, vol. 330, no. 3, pp. 621-640, 2006, doi: 10.1016/j.jhydrol.2006.04.030.
22. V. Anandhi and R.M. Chezian, "Support Vector Regression in forecasting", *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 2, no. 10, October 2013, available: https://www.ijarcce.com/upload/2013/october/79-H-anandhi_venugopal_-SUPPORT.pdf.
23. S. Brdar, D. Culibrk, B.Marinkovic, J.Crnobarac and V. Cmojevic, "Support Vector Machines with Features Contribution Analysis for Agricultural Yield Prediction", *Annual Research & Review in Biology*, vol. 4, no. 24, pp. 4246-4258, 2014, available: http://ktios.net/brdar/radovi/2011%20-%20Support%20Vector%20Machines%20with%20Features%20Contribution%20Analysis%20for%20Agricultural%20Yield%20Prediction.pdf.
24. A. Bharadwaj, S. Dahiya, and R. Jain, "Discretization based Support Vector Machine (D-SVM) for Classification of Agricultural Datasets", *International Journal of Computer Applications*, vol. 40, no. 1, pp. 8-12, 2012, doi:10.5120/4918-7139.
25. Karimi, Y & Prasher, Shiv & Madani, A & Kim, S.," Application of support vector machine technology for the estimation of crop biophysical parameters using aerial hyperspectral observations," *Canadian Biosystems Engineering*, vol. 50, pp. 7.13-7.20, 2008, available: http://www.csbe-scgab.ca/docs/journal/50/c0715.pdf.
26. Wang, Haiguang & Ma, Zhanhong, "Prediction of wheat stripe rust based on support vector machine," in *Proc. Seventh International Conference on Natural Computation*, pp. 378-382, July 26-28, 2011, doi: 10.1109/ICNC.2011.6022095.
27. Nararyanan Balakrishan and Dr. Govindarajan Muthukumarsamy, "Crop production- enable machine learning model for prediction," *International Journal of Computer Science and Software Engineering (IJCSSE)*, vol. 5, no. 7, pp. 148-153, July 2016, available: http://ijcsse.org/published/volume5/issue7/p5-V5I7.pdf.
28. N Gandhi, LJ Armstrong, O Petkar, AK Tripathy, "Rice crop yield prediction in India using support vector machines," in *Proc. 13th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pp. 1-5, July 13-15, 2016, doi: 10.1109/JCSSE.2016.7748856.
29. V.N. Vapnik, Statistical Learning Theory, Wiley, New York, 1998, available:

http://read.pudn.com/downloads161/ebook/733192/Statistical-Learning-Theory.pdf.
30. C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995, doi: 10.1023/A:1022627411411
31. I.H. Witten, E. Frank, Data Mining Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kaufmann Publishers, San Francisco, CA, 2000, available: https://sigmodrecord.org/publications/sigmodRecord/0203/bookreview2-geller.pdf.
32. H. Drucker, D. Wu, V.N. Vapnik, Support vector machines for spam categorization, *IEEE Trans. Neural Networks*, vol 10, no 5, pp. 1048–1054, 1999, doi: 10.1109/72.788645
33. Agricultural Statistics At a Glance 2015. Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India. *http://eands.dacnet.nic.in/At_Glance_2010/4.6 (A).xls,* June 07, 2016.
34. C. Saunders, M.O. Stitson, J. Weston, L. Bottou, and A. Smola, Support vector machine-reference manual, 1998, available: https://eprints.soton.ac.uk/258959/1/SVM_Reference.pdf.
35. C. W. Hsu and C. J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Transactions on Neural Networks*,vol. 13, no. 2, pp. 415–425, 2002, doi: 10.1109/72.991427
36. Kyoung-jae Kim, "Financial time series forecasting using support vector machines," *Neurocomputing*, vol. 55, pp. 3017-319, 2003, available: https://doi.org/10.1016/S0925-2312(03)00372-2.

AUTHORS PROFILE

Sunil Kumar is a Ph.D. in Computer Science from Gurukula Kangri Vishwavidyalaya, Haridwar, India. He was awarded MCA degree by Indira Gandhi National Open University, New Delhi. His career in academies spans over 27 years. Presently he is working as Assistant Professor in the Department of Management Studies, Kumaun University, Nainital. His research interests include machine learning and computer networks. Dr. Sunil's publications in national and international journals and in the form of book chapters have been widely appreciated and cited.

Vivek Kumar is a Ph.D. from Gurukul Kangri University, Haridwar, India and Masters in Applied Mathematics (1985-1987) and Computer Applications (1987-1988) from University of Roorkee (now IIT), Roorkee, India. His research interests include Machine Learning, distributed computing and wireless adhoc networks.

Rajendra Kumar Sharma received his Ph.D. degree in mathematics from IIT Roorkee (earlier, University of Roorkee, Roorkee), India in 1993. He is currently working as a Professor at Thapar Institute of Engineering and Technology, Patiala, India, where he teaches, among other things, statistical models and their usage in computer science. He has been involved in the organization of a number of conferences and other courses at Thapar Institute of Engineering and Technology, Patiala. His main research interests are Statistical Models in Computer Science, Machine Learning, and Pattern Recognition.