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RESEARCH ARTICLE

An enhanced support vector machine bbased multiclass classification method for crop prediction

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Abstract

Crop type classification is a fundamental task in precision agriculture, enabling informed decision-making for crop management and resource allocation. Support vector machines (SVMs) have emerged as robust and effective tools for multiclass classification tasks. This study explores the application of SVM-based multiclass classification techniques to accurately categorize various crop types based on remote sensing data. The SVM algorithm is employed to create decision boundaries that maximize the margin between different crop classes while minimizing classification errors. To enhance classification performance, various kernel functions such as linear, polynomial, and radial basis functions are evaluated to capture complex relationships within the data. The proposed SVM-based approach is compared with other commonly used classification methods to assess its superiority in terms of accuracy, precision, recall, and F1 score.

Keywords: Crop type classification, Multiclass, Support vector machine.

Introduction

Agriculture, as one of the cornerstones of human civilization, has evolved with the integration of technological advancements over the years. Among these advancements, the fusion of machine learning (ML) and deep learning (DL) techniques has brought about a transformative shift in the realm of crop classification. Accurate and timely identification of different crop types plays a pivotal role in modern agriculture, enabling efficient resource allocation, optimized yield prediction, and sustainable land management. The ability to differentiate between various crops through automated processes not only enhances productivity but also reduces labor-intensive tasks, contributing to increased overall agricultural efficiency, Kaya, A., Keceli, A. S., Catal, C., Yalic, H. Y., Temucin, H., & Tekinerdogan, B. (2019), Zhong, L., Hu, L., & Zhou, H. (2019).

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Traditional methods of crop classification have relied on manual inspection, which is time-consuming and susceptible to human error. The advent of ML and DL has revolutionized this process by enabling automated and accurate crop classification using diverse sources of data, including satellite imagery, remote sensing data, and sensor networks. Machine learning techniques, such as support vector machines (SVMs), random forests, and decision trees, provide a foundation for robust crop classification by learning complex patterns from data. On the other hand, deep learning techniques, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated exceptional capabilities in capturing intricate spatial and spectral features present in agricultural data, Dokic, K., Blaskovic, L., & Mandusic, D. (2020, December), Dang, C., Liu, Y., Yue, H., Qian, J., & Zhu, R. (2021), Moreno-Revelo, M. Y., Guachi-Guachi, L., Gómez-Mendoza, J. B., Revelo-Fuelagán, J., & Peluffo-Ordóñez, D. H. (2021).

The utilization of ML and DL techniques for multiclass crop classification presents a host of opportunities and challenges. The inherent variability in crop appearance due to factors like growth stage, lighting conditions, and environmental variations necessitates the development of models that can generalize across diverse scenarios. Moreover, the availability of large-scale datasets, combined with the computational power required for training deep neural networks, poses challenges in terms of data pre-processing, feature extraction, and model optimization, Jain, S., & Dharavath, R. (2023), Kianat, J., Khan, M. A., Sharif, M., Akram, T., Rehman, A., & Saba, T. (2021), Poornappriya, T. S., & Gopinath, R. (2022), Poornappriya, T. S., & Selvi, V. (2020).

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As the agricultural sector strives to meet the challenges posed by a growing global population and changing climate conditions, the fusion of machine learning and deep learning techniques holds the promise of revolutionizing crop classification. By enabling precise and automated identification of crop types, these techniques contribute to informed decision-making, sustainable land management, and ultimately, food security, Sood, S., & Singh, H. (2021), Sood, S., & Singh, H. (2021), Kalimuthu, M., Vaishnavi, P., & Kishore, M. (2020, August), Priyadharshini, D., Gopinath, R., & Poornappriya, T. S. (2020), Priyadharshini, D., Gopinath, R., & Poornappriya, T. S. (2020), Priyadharshini, D., Gopinath, R., & Poornappriya, T. S. (2020).

Related Works

This research study aims to assist novice farmers by utilizing machine learning, an advanced technology in crop prediction, to provide guidance on selecting suitable crops for cultivation. The Naive Bayes algorithm, which is a supervised learning technique, proposes a methodology for its implementation. The collection of seed data for crops occurs at this location, taking into account specific parameters such as temperature, humidity, and moisture content. These factors contribute to the favorable conditions necessary for the effective growth of crops. Furthermore, with the software, there is ongoing development of a mobile application specifically designed for the Android operating system. Users are prompted to input factors like as temperature, and their location is automatically retrieved by the program to initiate the prediction procedure, Patil, P., Panpatil, V., & Kokate, S. (2020).

The system was developed utilizing machine learning algorithms with the objective of enhancing agricultural practices for the benefit of farmers. The suggested approach aims to provide recommendations for the most appropriate crop selection for a given land area, taking into consideration factors such as soil composition and meteorological conditions. Additionally, the system offers information pertaining to the necessary substance and quantity of fertilizers, as well as the requisite seeds for cultivation. Therefore, with the implementation of the suggested approach, farmers have the ability to cultivate a novel crop variety, potentially leading to an increase in their profit margin while also mitigating the risk of soil pollution, Nischitha, K., Vishwakarma, D., Ashwini, M. N., & Manjuraju, M. R. (2020).

The objective of this study was to identify the optimal model for crop prediction, with the intention of assisting farmers in making informed decisions regarding crop selection, taking into account weather conditions and soil nutrient levels. This study conducted a comparative analysis of commonly used algorithms, namely K-nearest neighbor (KNN), decision tree, and random forest classifier, employing two distinct criteria, Gini and Entropy, Rao, M. S., Singh, A., Reddy, N. S., & Acharya, D. U. (2022).

Agriculture plays a crucial role in driving economic growth. The maintenance of a healthy biosphere is contingent upon this factor. A diverse array of agricultural products plays a crucial role in several facets of human existence, upon which individuals heavily rely. Farmers are required to effectively adapt to the challenges posed by climate change while simultaneously fulfilling the increasing requirements for greater quantities of food with enhanced nutritional value. To enhance agricultural output and growth, farmers must possess knowledge of the prevailing climatic circumstances, which informs their decision-making process regarding the cultivation of appropriate crops within those specific environmental elements. The implementation of internet of things (IoT) technology in the context of Smart Farming has demonstrated significant enhancements to the overall efficiency and effectiveness of the Agriculture system through the real-time monitoring of fields. The system effectively monitors and regulates many variables, like as humidity, temperature, and soil conditions, providing accurate and immediate real-time observations. The application of machine learning techniques in the agricultural domain aims to enhance crop productivity and quality. The utilization of relevant algorithms on the collected data has the potential to facilitate the recommendation of appropriate crops, Gupta, A., Nagda, D., Nikhare, P., & Sandbhor, A. (2021).

Machine learning (ML) plays a vital role in obtaining practical and effective solutions for the problem of crop yield. Supervised Learning in Machine Learning enables the prediction of a target or outcome based on a predetermined set of predictors. In order to obtain the desired outcomes, it is necessary to create an appropriate function that incorporates a collection of variables. This function will effectively transfer the input variable to the intended output. The process of crop yield prediction involves utilizing historical data to forecast the anticipated yield of a specific crop. This historical data encompasses various parameters, including temperature, humidity, pH levels, rainfall, and the specific crop being analyzed. It provides us with an indication of the optimal projected crop that can be cultivated under specific field weather circumstances. The task of making predictions can be accomplished through the utilization of a machine learning algorithm known as Random Forest. The system will generate crop predictions with the highest level of accuracy. The random forest approach is employed to generate an optimal crop yield model while minimizing the number of models considered. Predicting crop yield in the agricultural sector is highly advantageous, Kumar, Y. J. N., Spandana, V., Vaishnavi, V. S., Neha, K., & Devi, V. G. R. R. (2020, June).

The present study aims to develop a Deep Recurrent Q-Network model, which is a deep learning algorithm based on Recurrent Neural Network architecture, to predict crop yield using the Q-learning reinforcement learning method.

The data parameters are used to feed the successively stacked layers of a Recurrent Neural Network. The Q-learning network establishes an environment for predicting agricultural productivity by utilizing input parameters. The mapping of output values from a Recurrent Neural Network to Q-values is achieved through the utilization of a linear layer. The reinforcement learning agent utilizes a hybrid approach, combining parametric features and a threshold mechanism, to effectively forecast crop yield. Ultimately, the agent obtains a comprehensive score based on its executed actions, aiming to minimize errors and maximize the accuracy of its predictions. The suggested model demonstrates a high level of efficiency in predicting crop production, surpassing the performance of existing models. This is achieved by effectively conserving the original data distribution, resulting in an accuracy rate of 93.7%, Elavarasan, D., & Vincent, P. D. (2020).

The authors conducted a systematic review that involved the extraction and synthesis of features utilized for the prediction of crop yield, specifically focusing on the cytochrome P450 enzyme system (CYP). Additionally, a diverse range of methodologies has been developed to analyze crop yield prediction, including approaches derived from artificial intelligence. The primary constraints associated with neural networks pertain to the decrease in relative error and diminished predictive efficacy in the context of Crop Yield. In a similar vein, the limitations of supervised learning methods became apparent when attempting to capture the complex relationship between input and output variables in the context of fruit grading or sorting. Numerous research were proposed to enhance agricultural development, with the objective of establishing a precise and effective framework for crop classification. This framework encompasses various aspects, including crop yield estimation based on meteorological conditions, identification of crop diseases, and categorization of crops according to their growth stages. This study investigates the application of machine learning (ML) techniques in the domain of crop yield estimation. It offers a comprehensive examination of the accuracy of these techniques through a detailed analysis, Reddy, D. J., & Kumar, M. R. (2021, May).

This work employs machine learning techniques to forecast the yields of four commonly farmed crops across several regions in India. Once the prediction of crop production is conducted with site-specificity, the application of inputs, such as fertilizers, can be adjusted accordingly based on the anticipated requirements of the crop and soil. In this work, Machine Learning methodologies are employed to construct a trained model that facilitates the identification of patterns within data, specifically for the purpose of crop prediction. This work focuses on the application of machine learning techniques to forecast the yields of the four most commonly farmed crops in India. The crops encompassed in this category are maize, potatoes, rice (paddy), and wheat, Pant, J., Pant, R. P., Singh, M. K., Singh, D. P., & Pant, H. (2021). The integration of agronomic concepts of crop modeling with machine learning techniques was employed to establish a machine learning baseline for the purpose of forecasting crop yield on a wide scale. The fundamental principle of this workflow is to prioritize consistency, modularity, and reusability. In order to ensure accuracy, the authors prioritized the development of interpretable predictors or features pertaining to crop growth and development, as well as the implementation of machine learning techniques that prevent the inadvertent disclosure of information. The authors generated the features through the utilization of crop simulation outputs, as well as weather, remote sensing, and soil data obtained from the MCYFS database. The authors placed significant emphasis on a modular and reusable process that can effectively accommodate various crops and countries through minor configuration adjustments. The workflow has the capability to execute replicable experiments, such as forecasts made at the beginning or conclusion of a season, by utilizing standardized input data in order to achieve findings that can be reproduced. The findings provide a foundation for future enhancements. In the context of our case studies, we made projections regarding agricultural production at a regional scale for five specific crops, namely soft wheat, spring barley, sunflower, sugar beetroot and potatoes. These projections were conducted for three nations, namely the Netherlands (NL), Germany (DE) and France (FR). We conducted a performance comparison between a basic technique lacking predictive ability, which involved predicting either a linear yield trend or the average of the training set, Paudel, D., Boogaard, H., de Wit, A., Janssen, S., Osinga, S., Pylianidis, C., & Athanasiadis, I. N. (2021).

The study aimed to forecast the agricultural output of several crop varieties cultivated in India. This script employs basic criteria such as State, district, season, and area to facilitate the prediction of crop yield for a specified year. This study employed advanced regression approaches, including Kernel Ridge, Lasso, and Enet algorithms, to forecast yield. Additionally, the concept of Stacking Regression was utilized to enhance the algorithms and improve the accuracy of the predictions, Nishant, P. S., Venkat, P. S., Avinash, B. L., & Jabber, B. (2020, June).

Support Vector Machine

The support vector machine (SVM) is a very effective and adaptable technique in supervised machine learning, commonly employed for applications involving classification and regression. The utilization of this approach proves to be particularly efficient when handling intricate datasets characterized by non-linear decision boundaries. The Support Vector Machine (SVM) algorithm is designed to identify an optimal hyperplane that effectively divides distinct classes of data points while simultaneously maximizing the margin between them, Tang, L., Tian, Y., & Pardalos, P. M. (2019).

Support Vector Machines (SVMs) are a commonly employed machine learning algorithm. The aforementioned model is a widely used linear classifier that exhibits applicability in various domains such as Agriculture, face identification, and image classification [22]. The training sample set was assumed to be, Gao, Z., Fang, S. C., Gao, X., Luo, J., & Medhin, N. (2021):

$\{(x_i, y_j), i = 1,2, \ldots, l\}$

If there is a classification hyperplane as $\omega x + b = 0$, let $\omega x_1 + b \geq 1, y_j = 1,\ \omega x_1 + b \leq -1, y_j = -1, i = 1,2, \ldots, l$, where ω and x represented inner product, then it indicates that the sample is linearly separable and can be written as $y_i(\omega x_1 + b) \geq 1, i = 1,2, \ldots, l$ and the

classification interval is $\frac{2}{\|\omega\|}$. It can be converted to the

solution of $F(a) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i, \alpha_j, y_i, y_j(x_i x_j)$

when $\sum_{i=1}^{n} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1,2, \ldots, n$ using Lagrange method, where α indicates the Lagrange multiplier.

For non-linear problems, they can be turned into linear problems. After transformation through the kernel function $K(x_i, x_j) F(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i x_j)$ can be obtained, and the classification function will be $f(x) = sgn(\omega x + b) = sgn\{\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\}$.

Proposed Svm Based Multiclass Classification Methodology

Support vector machines (SVMs) are commonly employed for addressing binary classification tasks. However, it is worth noting that many real-world scenarios involve challenges that require multi-classification solutions. When confronted with multi-classification problems, SVM can either transform them into binary classification problems for analysis or adjust the objective function. However, the second approach is only suitable for small-scale classification problems. Currently, the predominant approach is the first way, which may be further categorised into one-to-many and one-to-one.

One-to-many classification SVM

The One-to-Many classification problem refers to a variant of the SVM classification algorithm, wherein the objective is to differentiate a single class from numerous other classes. This approach is alternatively referred to as a "one-versus-rest" or "one-versus-all" strategy. In this approach, every class is sequentially considered as the positive class, while the remaining classes are regarded as the negative class. Let's say you have "C" classes (C > 2), labeled as classes 1, 2, ..., C. You will create C different SVM classifiers, each focusing on distinguishing one class from the others.

For class i:

- Positive class: Class i
- Negative classes: All other classes (1, 2, ..., i-1, i+1, ..., C)

For each class i, you need to solve an SVM optimization problem to find the hyperplane that separates the positive class from the rest. The equations are as follows: Your training data consists of feature vectors (x) and their corresponding class labels (y). The class labels are modified: $y_i = +1$ for instances belonging to class i, and $y_i = -1$ for instances belonging to other classes. For class i, you need to find the optimal hyperplane parameters (w_i and b_i) that maximize the margin between the positive and negative classes.

min (1/2) $||w_i||$^2

y_i (w_i * x + b_i) ≥ 1 for all training instances

Once the SVM model is trained for class i, the decision function can be used to classify new instances.

If $w_i * x_{new} + b_i >= 0$, classify as class i.

Else, classify as other classes.

After training C binary classifiers, you will have C decision functions. To classify a new instance, apply all C decision functions and assign the instance to the class corresponding to the decision function with the highest value.

One-to-One Multi classification SVM

In the context of multiclass classification using SVM, a one-on-one (one-to-one) strategy involves the creation of distinct binary classifiers for every possible pair of classes. This technique transforms the multiclass problem into a sequence of binary classification tasks.

Let's say you have «C» classes (C > 2), labeled as classes 1, 2, ..., C. You will create C * (C - 1) / 2 different SVM classifiers, each focusing on distinguishing one class from another class. For class i and class j (i ≠ j):

- Positive class: Class i
- Negative class: Class j

For each pair of classes i and j, you need to solve an SVM optimization problem to find the hyperplane that separates the instances of class i from the instances of class j.

The training data consists of feature vectors (x) and their corresponding class labels (y). Modify the class labels: y_i = +1 for instances belonging to class i, y_j = -1 for instances belonging to class j, and y_k= 0 for all other classes k ≠ i, k ≠ j.

For classes i and j, you need to find the optimal hyperplane parameters ($w_{ij}$and b_{ij}) that maximize the margin between the positive class i and the negative class j.

min (1/2) $||^{w_{ij}}||$^2

y_i(w_{ij}* x + b_{ij}) ≥ 1 for instances of class i

y_j(w_{ij}* x + b_{ij}) ≤ -1 for instances of class j

0 for instances of all other classes k ≠ i, k ≠ j

Once the SVM model is trained for classes i and j, the decision function can be used to classify new instances.

If $w_{ij} * x_{new} + b_{ij}$> 0, classify as class i.

If $w_{ij} * x_{new} + b_{ij}$ < 0, classify as class j.

If both are zero, you can make a decision based on a voting strategy or another method. After training C * (C - 1) / 2 binary classifiers, you can use their decision functions to classify a new instance. You can use voting strategies to decide the final class based on the outputs of these classifiers.

Proposed Logistic Regression-based SVM multiclass Method

In this proposed LR-SVM method, Logistic Regression aims to find the coefficients that best separate the classes in a linear fashion. Multiclass logistic regression is a classification method used to predict the probability of an instance belonging to one of multiple classes. It's an extension of the binary logistic regression to handle multiple classes.

Let's assume that «C» classes are labeled as 1, 2, ..., C. For each class «c», the probability that an instance «x» belongs to class «c» is given by the Softmax function:

$$P(y = c|x) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}}$$

$P(y = c|x)$ represents the conditional probability of y being equal to c given the input x. z_c is the linear combination of feature values and coefficients for class «c». $\sum_{k=1}^{C} e^{z_k}$ is the sum of the exponential of linear combinations *z* for all classes.

The linear combination z_c is calculated as:

$$z_c = \beta_{0,c} + \beta_{1,c}x_1 + \beta_{2,c}x_2 + \cdots + \beta_{p,c}x_p$$

Where: $\beta_{0,c}, \beta_{1,c}, \beta_{2,c}$ are the coefficients for class «c». $x_1, x_2, \ldots, x_p$ are the feature values of the instance.

For a new instance x_{new}: Calculate the class probabilities using the trained Logistic Regression model. The Multiclass Logistic Regression model is trained by minimizing the negative log-likelihood (cross-entropy loss) of the observed classes. This involves finding the coefficients $\beta_{0,c}, \beta_{1,c}, \beta_{2,c} \cdots \beta_{p,c}$ that maximize the likelihood of the observed data. $x_1, x_2, \ldots, x_p$ are the feature values of the instance. In this equation, «C» represents the number of classes in your multiclass classification problem. The Softmax function ensures that the predicted probabilities sum up to 1 for each instance, enabling you to identify the most probable class.

When you apply this equation to each class, you'll obtain a vector of probabilities for each instance, where each element represents the probability of the instance belonging to the corresponding class. The class with the highest probability is the predicted class for that instance.

For each pair of classes (i, j), train a binary SVM classifier using the feature matrix: Positive class: Class I, and Negative class: Class j. Use SVMs with an RBF (Radial Basis Function) kernel for each binary SVM classifier. It is a common approach to capture complex relationships in classification tasks. For each binary SVM classifier in a one-to-one (one-vs-one) multiclass setting, you would apply the RBF kernel. Here's the equation for the decision function of an SVM with an RBF kernel:

$$f(x) = sign\left(\sum_{i=1}^{n_{support}} \alpha_i \,.\, y_i \,.\, K(x, x_i) + b\right)$$

Where:

- $f(x)$ is the decision function value for input instance x.
- $n_{support}$ is the number of support vectors.
- α_i is the Lagrange multiplier for support vector i.
- y_i is the class label (+1 or -1) of support vector i.
- $K(x, x_i)$ is the RBF kernel function evaluated for instance x and support vector i.
- b is the bias term.

The RBF kernel function $K(x, x_i)$ is given by:

$$K(x, x_i) = \exp(-\gamma . \|x - x_i\|^2)$$

Where: γ is the kernel parameter, controlling the shape of the kernel function. $\|x - x_i\|^2$ is the squared Euclidean distance between instance x and support vector i.

The «sign» function returns +1 if the expression inside the parentheses is positive, and -1 if it's negative. The final decision function value determines the predicted class label for the instance «x».

In a one-to-one multiclass SVM approach, you would have multiple binary SVM classifiers, each trained to distinguish between a specific pair of classes. Each binary SVM classifier uses the RBF kernel to create complex decision boundaries in the feature space.

Pass x_{new} through each binary SVM classifier. For each binary SVM classifier, calculate the decision function value. Apply a decision mechanism (e.g., voting) to determine the final predicted class for x_{new}.

Result And Discussion

Performance Metrics

Table 1 depicts the performance metrics used in this research work.

Description of the Dataset

The Indian crop yield prediction and estimation dataset are taken from Kaggle repository. The dataset is composed of 7 features. Among the 7 features, state_name features have 33 distinct values, district_name have 646 distinct values, crop_year have 19 distinct years, crop features have 124 crops types and season features have 6 seasons, https://www.kaggle.com/datasets/abhinand05/crop-production-in-india.

Table 1: Performance metrics

Metrics	*Equation*
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
True Positive Rate (TPR) (Sensitivity or Recall)	$\frac{TP}{TP + FN}$
False positive rate	$\frac{FP}{FP + TN}$
Precision	$\frac{TP}{FP + TP}$
True negative rate (Specificity)	1- False Positive Rate
Miss rate	1- True Positive Rate
False discovery rate	1-Precision

Table 2: Description of Indian Crop Yield Estimation Dataset

S. No.	*Feature Name*	*Description*
1	State_Name	Depicts the state name of the crop obtained (Total State Count: 33)
2	District_Name	Depicts the district name of the crops obtained (Total District Count: 646)
3	Crop_Year	Gives the crop cultivation year (Number of Years: 19)
4	Season	Describes the various seasons that the crop has been cultivated (Total number of Seasons: 6)
5	Crop	Describes the type of crops has been cultivated (Total Number of crop type: 124)
6	Area	Describes the area in sq.feet where the crops has been cultivated
7	Production	Describes the production obtained by the crop

In this dataset, only Tamilnadu State and its 31 districts are considered in this research to evaluate the multiclass classification model for predicting the major crops like rice, jowar, ragi, bajra, maize, and pulses. For training the model, crops cultivated year of 1997 to 2013 and only three seasons (Kharif, Rabi and Whole Year) are considered since the above-mentioned crops are cultivated during this season. Table 2 depicts the description of Indian Crop Yield Estimation Dataset.

In this research work, feature encoding is done with label encoding for the categorical features in the dataset. After the pre-processing step of Label Encoding, the dataset considered in this research work has one state name (Tamilnadu), 31 districts, 17 years of crop cultivation, 3 seasons of crop cultivation, area and production. So, in total, 54 are obtained after the Feature Encoding.

In the feature selection step, the proposed gain ratio differential evolution feature selection (GRDEFS) method [] is used. The performance of the proposed logistic regression SVM multiclass (LR-SVM-MC) Method is evaluated with the existing classification techniques like Support Vector Machine (SVM), Logistic Regression Classification (LR) Method and Random Forest (RF) Classification Method using the proposed and existing feature selection methods processed datasets.

Table 3 depicts the number of features obtained by the original dataset, proposed GRDEFS, gain ratio (GR), and differential evolution (DE) based feature selections processed datasets.

From Table 3, it is clear that the proposed GRDEFS method gives less number of features than the existing feature selection methods.

Table 4 depicts the classification accuracy (in %) obtained by the Proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

In Table 4, the classification accuracy (expressed in percentage) achieved by various classification methods using feature selection techniques is presented. The methods compared are the Proposed LR-SVM-MC, SVM, LR, and RF.

For the original dataset, the Proposed LR-SVM-MC achieved a classification accuracy of 53.76%, while SVM, LR, and RF achieved lower accuracies of 48.23, 45.67, and 40.32%, respectively.

Upon applying the GR (Genetic Algorithm Ranking) feature selection technique, significant improvements in classification accuracy were observed across all classification methods. The Proposed LR-SVM-MC exhibited the highest accuracy of 79.43%, followed by SVM at 67.49%, LR at 66.17%, and RF at 63.52%.

When the differential evolution (DE) feature selection technique was employed, improvements in accuracy were again seen. The proposed LR-SVM-MC achieved an accuracy of 60.42%, while SVM, LR, and RF achieved accuracies of 58.39, 57.42, and 54.71%, respectively.

The proposed genetic algorithm and differential evolution feature selection (GRDEFS) technique led to the highest accuracy values among all experiments. The Proposed LR-SVM-MC achieved an impressive accuracy of 95.66%, followed by SVM with 83.67%, LR with 89.45%, and RF with 79.22%.

Overall, the results highlight the effectiveness of the proposed LR-SVM-MC and feature selection techniques,

Table 3: Number of features obtained by the proposed and existing feature selection methods

Feature selection techniques	*Number of features obtained*
Original dataset	54
GR	37
DE	35
Proposed GRDEFS	33

Table 4: Classification accuracy (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*Classification accuracy (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	53.76	48.23	45.67	40.32
GR	79.43	67.49	66.17	63.52
DE	71.42	58.39	57.42	54.71
Proposed GRDEFS	95.66	83.67	89.45	79.22

Table 5: Recall (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*Recall (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	49.81	45.85	42.26	40.85
GR	73.46	61.30	60.62	57.22
DE	74.39	52.53	51.84	48.81
Proposed GRDEFS	95.32	80.48	79.73	75.21

Table 6: False positive rate (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*False positive rate (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	65.51	68.78	70.35	72.44
GR	34.81	46.22	54.64	59.21
DE	34.59	41.15	52.73	55.87
Proposed GRDEFS	12.58	20.43	22.58	35.63

particularly the combined GRDEFS approach, in significantly enhancing the classification accuracy of the various classification methods.

Table 5 depicts the recall (in %) obtained by the Proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

In Table 5, the recall values (in %) obtained from various classification methods using feature selection techniques are presented. The compared methods are the Proposed LR-SVM-MC, SVM, LR, and RF.

For the original dataset, the Proposed LR-SVM-MC achieved a recall value of 49.81%, while SVM, LR, and RF achieved lower recall values of 45.85, 42.26, and 40.85%, respectively.

Applying the GR feature selection technique resulted in improved recall values across all classification methods. The Proposed LR-SVM-MC achieved the highest recall of 73.46%, followed by SVM with 61.30%, LR with 60.62%, and RF with 57.22%.

When the DE feature selection technique was utilized, recall values were again positively impacted. The Proposed LR-SVM-MC achieved a recall of 74.39%, while SVM, LR, and RF had recalls of 52.53, 51.84, and 48.81%, respectively.

The Proposed GRDEFS technique yielded the highest recall values in all experiments. The Proposed LR-SVM-MC achieved a substantial recall of 95.32%, followed by SVM with 80.48%, LR with 79.73%, and RF with 75.21%.

These results emphasize the effectiveness of the Proposed LR-SVM-MC model, along with the feature selection techniques employed, particularly the combined GRDEFS approach. These techniques significantly enhanced the recall values of the various classification methods, demonstrating their potential for improving the identification of relevant instances in the dataset.

Table 6 gives the false positive rate (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

In Table 6, the false positive rates (expressed in percentage) obtained from various classification methods using feature selection techniques are presented. The methods compared are the proposed LR-SVM-MC, SVM, LR, and RF.

For the original dataset, the proposed LR-SVM-MC achieved a false positive rate of 65.51%, while SVM, LR, and RF achieved higher false positive rates of 68.78, 70.35, and 72.44%, respectively.

Applying the GR feature selection technique resulted in reduced false positive rates across all classification methods. The proposed LR-SVM-MC achieved the lowest false positive rate of 34.81%, followed by SVM with 46.22%, LR with 54.64%, and RF with 59.21%.

When the DE feature selection technique was used, false positive rates were further lowered. The Proposed LR-SVM-MC achieved a false positive rate of 34.59%, while SVM, LR, and RF had false positive rates of 41.15, 52.73, and 55.87%, respectively.

The proposed GRDEFS technique resulted in the lowest false positive rates in all experiments. The Proposed LR-SVM-MC achieved a remarkable false positive rate of 12.58%, followed by SVM with 20.43%, LR with 22.58%, and RF with 35.63%.

These findings highlight the effectiveness of the proposed LR-SVM-MC model and the feature selection techniques employed, particularly the combined GRDEFS approach, in significantly reducing false positive rates across the various classification methods.

Table 7 gives the precision (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

Table 7: Precision (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*Precision (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	57.85	50.53	48.77	45.81
GR	88.8	81.73	79.26	69.31
DE	83.68	79.47	71.13	67.41
Proposed GRDEFS	95.72	85.42	82.57	78.52

Table 8: Specificity (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*Specificity (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	34.49	31.22	29.65	27.56
GR	65.19	53.78	45.36	40.79
DE	65.41	58.85	47.27	44.13
Proposed GRDEFS	87.42	79.57	77.42	64.37

In Table 7, the precision values (in %) obtained from various classification methods using feature selection techniques are presented. The compared methods are the Proposed LR-SVM-MC, SVM, LR, and RF.

For the original dataset, the Proposed LR-SVM-MC achieved a precision value of 57.85%, while SVM, LR, and RF achieved lower precision values of 50.53, 48.77, and 45.81%, respectively.

Applying the GR feature selection technique led to increased precision values across all classification methods. The Proposed LR-SVM-MC achieved the highest precision of 88.8%, followed by SVM with 81.73%, LR with 79.26%, and RF with 69.31%.

When the DE feature selection technique was utilized, precision values were further enhanced. The Proposed LR-SVM-MC achieved a precision of 83.68%, while SVM, LR, and RF had precisions of 79.47, 71.13, and 67.41%, respectively.

The Proposed GRDEFS technique yielded the highest precision values in all experiments. The proposed LR-SVM-MC achieved an exceptional precision of 95.72%, followed by SVM with 85.42%, LR with 82.57%, and RF with 78.52%.

These results underscore the effectiveness of the proposed LR-SVM-MC model and the feature selection techniques employed particularly the combined GRDEFS approach. These techniques significantly improved the precision values of the various classification methods, highlighting their ability to correctly classify positive instances and minimize the rate of false positives.

Table 8 gives the specificity (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

In Table 8, the specificity values (in %) obtained from various classification methods using feature selection techniques are presented. The compared methods are the Proposed LR-SVM-MC, SVM, LR, and RF.

For the original dataset, the Proposed LR-SVM-MC achieved a specificity value of 34.49%, while SVM, LR, and RF achieved slightly higher specificity values of 31.22, 29.65, and 27.56%, respectively.

Applying the GR feature selection technique resulted in increased specificity values across all classification methods. The Proposed LR-SVM-MC achieved the highest specificity of 65.19%, followed by SVM with 53.78%, LR with 45.36%, and RF with 40.79%.

When the DE feature selection technique was employed, specificity values were further improved. The Proposed LR-SVM-MC achieved a specificity of 65.41%, while SVM, LR, and RF had specificities of 58.85, 47.27, and 44.13%, respectively.

The Proposed GRDEFS technique yielded the highest specificity values in all experiments. The Proposed LR-SVM-MC achieved a notable specificity of 87.42%, followed by SVM with 79.57%, LR with 77.42%, and RF with 64.37%.

These results underscore the effectiveness of the Proposed LR-SVM-MC model and the feature selection techniques employed particularly the combined GRDEFS approach. These techniques significantly enhanced the specificity values of the various classification methods, highlighting their ability to correctly classify negative instances and reduce the rate of false positives.

Table 9 depicts the miss rate (in %) obtained by the Proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

Table 9 presents the miss rate (in %) obtained by various classification methods, including proposed LR-SVM-MC, SVM, logistic regression (LR), and random forest (RF), when

Table 9: Miss rate (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*Miss rate (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	50.19	54.15	57.74	59.15
GR	26.54	38.7	39.38	42.78
DE	25.61	47.47	48.16	51.19
Proposed GRDEFS	4.68	19.52	20.27	24.79

Table 10: False discovery rate (in %) obtained by the proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets

Feature selection techniques	*False discovery rate (in %) by classification methods*			
	Proposed LR-SVM-MC	*SVM*	*LR*	*RF*
Original dataset	42.15	49.47	51.23	54.19
GR	11.2	18.27	20.74	30.69
DE	16.32	20.53	28.87	32.59
Proposed GRDEFS	4.28	14.58	17.43	21.48

applied to feature selection processed datasets using different feature selection techniques.

Without any feature selection, all classification methods had relatively high miss rates ranging from 50.19 to 59.15%. This indicates that the original dataset had a considerable degree of classification error.

Applying the GR feature selection technique led to a significant reduction in the miss rate for all classification methods. The miss rates dropped to a range of 26.54 to 42.78%, indicating that feature selection improved classification accuracy.

The DE feature selection technique also resulted in improved performance, with miss rates ranging from 25.61 to 51.19%. Similar to GR, DE helped reduce classification errors for all methods.

The Proposed GRDEFS feature selection technique produced the lowest miss rates across all classification methods, ranging from 4.68 to 24.79%. This suggests that the combination of the Proposed GRDEFS technique and the Proposed LR-SVM-MC method was particularly effective in reducing classification errors.

In summary, the data highlights the importance of feature selection in enhancing classification accuracy. Both GR and DE feature selection techniques led to substantial reductions in miss rates compared to the original dataset. The Proposed GRDEFS technique, in conjunction with proposed LR-SVM-MC, performed exceptionally well in minimizing classification errors, underscoring its effectiveness in improving classification performance. This analysis emphasizes the significance of feature selection in optimizing machine learning models when dealing with complex and high-dimensional datasets.

Table 10 gives the false discovery rate (in %) obtained by the Proposed LR-SVM-MC, SVM and RF classification methods using feature selection processed datasets.

Table 10 presents the false discovery rate (in %) obtained by various classification methods, including Proposed LR-SVM-MC, SVM, logistic regression (LR), and random forest (RF), when applied to feature selection processed datasets using different feature selection techniques.

Without any feature selection, all classification methods had relatively high false discovery rates ranging from 42.15 to 54.19%. This indicates that the original dataset had a substantial number of false positive errors.

Applying the GR feature selection technique led to a significant reduction in the false discovery rate for all classification methods. The False Discovery Rates dropped to a range of 11.2 to 30.69%, indicating that feature selection improved the ability to control false positive errors.

The DE feature selection technique also resulted in improved performance, with false discovery rates ranging from 16.32 to 32.59%. Similar to GR, DE helped reduce false positive errors for all methods.

The proposed GRDEFS feature selection technique produced the lowest false discovery rates across all classification methods, ranging from 4.28 to 21.48%. This suggests that the combination of the proposed GRDEFS technique and the proposed LR-SVM-MC method was particularly effective in minimizing false positive errors.

In summary, the data highlights the importance of feature selection in controlling false positive errors in classification. Both GR and DE feature selection techniques led to significant reductions in false discovery rates compared to the original dataset. The proposed GRDEFS

technique, when combined with the proposed LR-SVM-MC, demonstrated exceptional performance in minimizing false positive errors, underlining its effectiveness in improving the precision of classification models.

Conclusion

In this study, we explored the potential of combining support vector machine (SVM) with logistic regression (LR) as a classification method for multiclass prediction of crops. Our aim was to harness the strengths of both SVM and LR to develop a robust and accurate model for crop classification. Firstly, the combination of SVM and LR demonstrated remarkable performance in handling the complexities of multiclass crop prediction. SVM's ability to create optimal decision boundaries in high-dimensional space, coupled with LR's probabilistic modeling, allowed for a comprehensive understanding of the interclass relationships. In conclusion, our study highlights the efficacy of the SVM-LR classification method for accurate multiclass crop prediction.

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