Original Article

RESEARCH ON CROP CLASSIFICATION METHODS BASED ON MACHINE LEARNING USING WAVELET TRANSFORMATIONS

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ABSTRACT

Due to the growing demand for precise and efficient agricultural monitoring and management systems, interest in crop classification using machine learning has significantly increased in recent years. Conventional machine learning algorithms, however, have limitations when dealing with high-dimensional data. Training time is a crucial factor in developing crop classification models, as it directly impacts the model's efficacy and efficiency. Large volumes of data are often needed to train crop classification models properly, making the training procedure laborious and computationally demanding. In this paper, crop classification model training time is reduced by utilizing wavelet decomposition in combination with traditional machine learning techniques such as SVM, Naive Bayes, RF, and others. The performance of different algorithms before and after utilizing wavelet decomposition was evaluated in order to find the way that is the most efficient while using this methodology. Additionally, the significance of quality loss when applying wavelet coefficients was determined. The results of this paper show that applying wavelet transformation coefficients in combination with classification techniques can achieve accuracy levels that are comparable to those achieved by training on the original images. For example, using the Random Forest model in combination with Daubechies transformation coefficients can achieve an accuracy of 0,89 while significantly reducing training time from 11,15 to 3,49 seconds with Haar transformation providing almost identical results. The paper demonstrates the value of using wavelet transforms for crop classification and highlights the significance of accounting for training time when developing accurate and practical crop classification models that may be useful in developing decision support tools for agricultural applications, where it is crucial to make prompt decisions based on current data.

Key words: Crop classification, machine learning, support vector machine, random forest, wavelet transformation.

INTRODUCTION

Crop classification using machine learning have become a popular topic in recent years due to the increasing demand for accurate and efficient crop monitoring and management systems. Numerous studies have been conducted on crop classification using machine learning techniques such as support vector machines (SVM), artificial neural networks (ANN), decision trees (DT), and random forests (RF). However, traditional machine learning algorithms have limitations in dealing with high-dimensional data. Wavelet transformations have been proposed as a solution to this problem [1]. A wavelet transformation is a mathematical tool that can decompose complex signals into simpler components with different frequency bands. This technique has been applied in various fields, including image processing, signal analysis, and pattern recognition.

In this work, we apply wavelet decomposition to reduce the time spent by machine learning algorithms such as RF, SVM, Naïve Bayes, and others to train a classifier model. While developing crop classification models, training time is crucial because it has a direct impact on the model's efficacy and efficiency. Large volumes of data are frequently needed for crop classification models to be trained properly, and the training procedure can be laborious and computationally demanding. The capacity to swiftly iterate and modify the model may be hampered if the learning process is slow. In agricultural situations, where choices need to be made fast and correctly based on real-time data, this can be especially difficult. Also, when implementing a model in the field, time is essential. Crop classification models are frequently used to make in-the-moment choices, such as determining which fields need irrigation or pest control. The decision-making process can suffer if the model takes too long to analyze the data, which can lead to delays. As a result, time should be considered when crop classification models are being trained. This could involve employing hardware accelerators like GPUs or TPUs, optimizing the data processing pipelines and algorithms used for training, and picking the right hyperparameters to speed up training. We can create accurate and effective crop classification models by putting time first, making them more useful as decision support tools in agriculture.

Our goal is to conduct a comparative analysis of the performance of the most popular machine learning algorithms for classification before and after applying the wavelet decomposition and to choose which of the algorithms are the most efficient in terms of performance when used together with the wavelet transformation. In addition, we set the task of quality evaluation of the algorithms and determining how significant the quality loss is. The rest of the work is as follows. In section 2, we provide a literature review and statement of the problem. In section 3, we set the goals and objectives of the study, which we implement using the methodology described in section 4. In section 5, we present the results of the experiments. In Section 6, we formulate the conclusions obtained in this study and present a plan for future work.

MATERIALS AND METHODS

Literature review and problem statement

Several studies have explored the use of wavelet transformations in crop and weed discrimination and image classification in general including RGB and hyperspectral features. For instance, wavelet transform was used to discriminate between crop and weed in perspective agronomic images which showed that wavelets were well adapted for perspective images with the best results provided by Daubechies 25 and discrete approximation Meyer wavelets [1]. Another study proposed a hyperspectral image classification method based on two-dimensional Empirical Wavelet Transform (2D-EWT) feature extraction with the result of improved performance in terms of classification evaluation measures for hyperspectral image classification tasks [2]. The wavelet transform combined with a traditional machine learning algorithm can be used for a variety of classification problems, for example, the system of tuna fish classification was proposed to achieve an accuracy of 94.58% using a cubic support vector machine (SVM) classifier combined with complex wavelet-based deep architecture [3].

Wavelet optimization to eliminate interference that occurs because of external noise and internal multiple compositions, was used in [4] to assess the chlorophyll content in corn leaves. The results obtained by the authors made it possible to use wavelet optimization for accurate diagnosis of the state of corn growth. A new machine-learning algorithm to estimate a potato's shape and size based on a support vector machine was proposed in [5]. Wavelet moment and other geometric characteristics were extracted for marking the potato's characteristics. Various combinations of data fusion techniques at pixel, feature, and decision levels for crop classification were used in [6] on Sentinel-1 and optical data for the Yadgir district of Karnataka, India. For pixel-level data fusion, techniques such as principal component analysis, multiplicative transformation, and wavelet with IHS (intensity-hue-saturation) were used [6].

In [7], a detailed review of crop recognition methods and their application to the open dataset under the name Agriculture crop images [8] is presented. The authors compare various neural network architectures such as Inception V3, VGG16, VGG19, ResNet50, ResNet152 and demonstrate that Inception V3 is the most performing among them. It is worth mentioning that the recognition accuracy of a particular crop depends on the applied architecture. For example, the Inception V3 architecture often mistakes maize for rice whilst having no problem in a reverse situation. While ResNet50 faces a similar problem but with rice and sugarcane.

The difference of our work is that the deep learning algorithms which are resource intensive in terms of time and processing power spent on training are not applied. Our goal is to research how wavelet transformations can be used to reduce required time and resources without a significant loss of classification quality. Despite the promising results of using wavelet transformations in image classification and crop classification specifically, there is still a need for further research to investigate the effectiveness and explore the performance of different machine learning algorithms when combined with wavelet transformations for crop classification.

The aim and objectives of the study

The aim of this study is to investigate the use of different wavelet transformation methods combined with machine learning algorithms for crop classification using image data. The specific objectives of the study are:

- To compare the performance of different wavelet transformation methods (such as Haar and Daubechies) in reducing the dimensionality of features from image data for crop classification.
- To compare the performance of different machine learning algorithms (such as Support Vector Machines, Logistic Regression, Decision Tree, Random Forest, and Naïve Bayes) in classifying crops based on the features reduced by wavelet transformations.
- To evaluate the performance of the proposed approach of transforming data and compare it with machine learning algorithms that train on original data.

The findings of this study can contribute to the development of accurate and efficient crop monitoring and management systems, which can improve crop yield and quality by automation of the irrigation process and spraying while reducing the environmental impact of agriculture.

Data description

The dataset [8] used in this study is available in open source, and it consists of a collection of images of various crops that are commonly grown in agricultural practices. The dataset contains a total of 804 images, with each image representing a crop. The images are in JPEG format and have a resolution of 224x224 pixels. The images are organized into folders based on the type of crop they represent, with 5 different crop types represented in the dataset. The crop types in the dataset are as follows: maize, wheat, jute, rice, and sugarcane (Fig.1).For each crop type, there are around 160 images available. The images were taken from different angles and various lighting conditions. The dataset is split into subsets with the following proportions: 80% of images for the train-

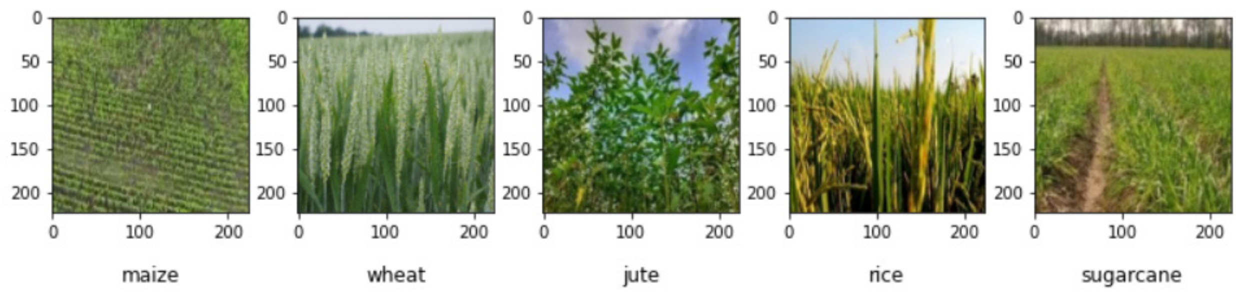

Figure 1 - Images from the dataset representing 5 different crop types.

ing process and 20% for testing. Each image in the dataset is normalized to avoid numerical issues and for the sake of faster convergence during training.

Wavelet transformation

Wavelet transformation is a mathematical technique used to analyze signals, images, and data. It decomposes a signal into different frequency components, which makes it easier to analyze and process. The Haar wavelet transformation is a simple and fast wavelet transform. It is a step function, which is a simple piecewise constant function that changes its value abruptly at certain points. The Haar wavelet transformation decomposes an image into four different components: approximation, horizontal detail, vertical detail, and diagonal detail. It works by first dividing the image into four different sub-images of the same size. The first sub-image is the approximation image, which represents the low-frequency components of the image. The other three sub-images represent the high-frequency components of the image, which are the horizontal, vertical, and diagonal details [9].

In case of 1D signal the simplest Haar transformation will divide the signal into the approximation which represents lower-frequency components:

$$a_i = \frac{S_{2i} + S_{2i+1}}{2} \quad (1)$$

and detail component which represents higher-frequency components:

$$b_i = \frac{S_{2i} - S_{2i+1}}{2} \quad (2)$$

To get the approximation coefficients from the image, the Haar wavelet transformation computes the average of the pixel values in each row and column of the image. This results in a new image that represents the low-frequency components of the original image. For the horizontal coefficients, the Haar wavelet transformation computes the difference between adjacent pixel values in each row of the image. That represents the high-frequency components of the image in the horizontal direction. When it comes to vertical coefficients, the Haar wavelet transformation computes the difference between adjacent pixel values in each column of the image. This results in a new image that represents the high-frequency components of the image in the vertical direction. Finally, to get the diagonal coefficients, the Haar wavelet transformation computes the difference between adjacent pixel values in both the horizontal and vertical directions [9].

The Daubechies wavelet is a more complex function than the Haar wavelet, but it has the advantage of providing a more accurate representation of the signal or image being analyzed. It is working with more than two coefficients depending on which type is used, in case of four points the filter looks like this:

$$a = c_1 x + c_2 y + c_3 z + c_4 t \quad (3)$$

The Daubechies wavelet transformation also decomposes an image into different components, which are the approximation, horizontal detail, vertical detail, and diagonal detail. However, it uses a different method to calculate these components than the Haar wavelet transformation. The Daubechies wavelet transformation works by first applying a series of filters to the image. These filters are designed to extract different frequency components from the image. The filters are applied repeatedly to the image, resulting in a series of sub-images at different resolutions [10].

As mentioned before, the wavelet transformation process involves applying a series of high-pass and low-pass filters to the image at different scales, producing a set of coefficients that represent the image in terms of its frequency content [10]. These coefficients can then be used as features for machine learning algorithms that can classify the crops based on their characteristics:

In this study, we will compare Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Naive Bayes.

Logistic Regression is a supervised machine learning algorithm that is used for binary classification tasks. However, it can also be extended to handle multiclass classification problems, where there are more than two categories such as crop type classification. The logistic regression algorithm works by modeling the probability of an input belonging to a certain class using a logistic function [11].

The Decision Tree algorithm works by recursively partitioning the input space into regions based on the values of the input features. At each node of the tree, the algorithm selects the feature that best separates the training data into different classes. The algorithm then continues to split the data until it reaches a stopping criterion, such as a maximum depth or a minimum number of samples required to make a split [12].

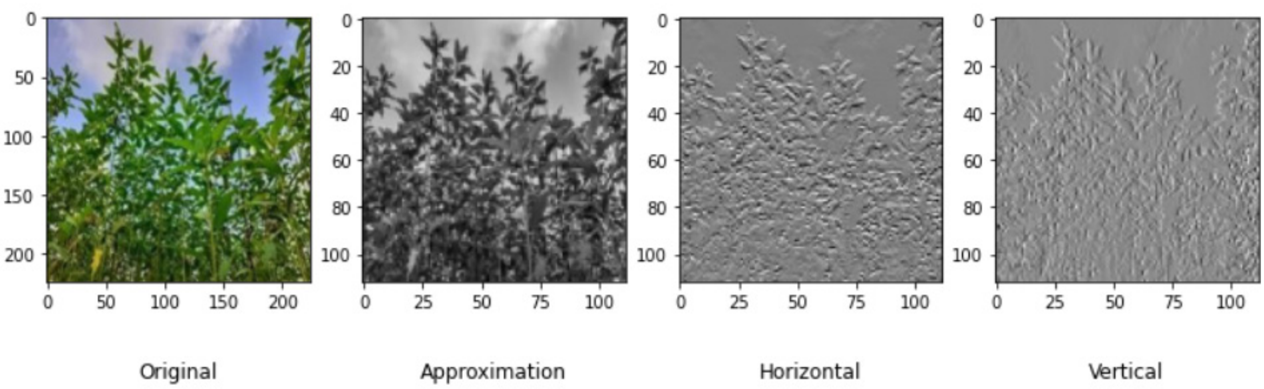

Figure 2 - Applying Haar wavelet transformation on an image from the dataset.

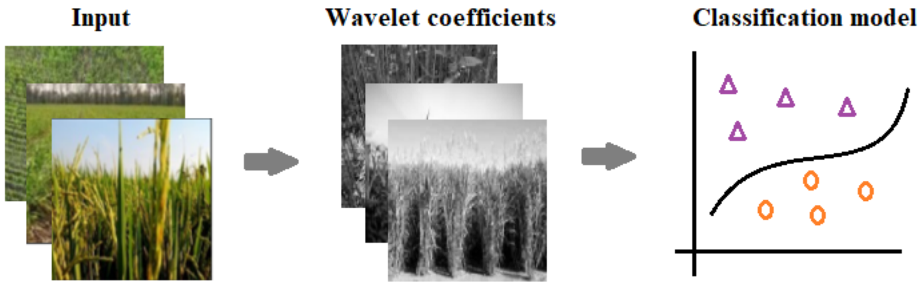

Figure 3 - Simplified crop classification process

Random Forest Classifier is an ensemble learning algorithm that combines multiple decision tree classifiers to improve the performance of the model. The random forest algorithm works by training multiple decision tree classifiers on different subsets of the training data and input features. During training, each tree is trained using a random subset of the training data and a random subset of the input features. The final prediction of the random forest classifier is then based on the predictions of all the individual decision trees, either by taking the majority vote or by weighing the votes based on the confidence of each tree [13].

The SVM algorithm works by finding a hyperplane that separates the training data into different classes with the largest possible margin. In the case of binary classification, the hyperplane separates the data into two classes, while in the case of multi-class classification, multiple hyperplanes are used to separate the data into multiple classes [14]. During training, the SVM algorithm learns the optimal hyperplane by maximizing the margin between the hyperplane and the training data. The margin is defined as the distance between the hyperplane and the closest training data points. The optimal hyperplane is the one that maximizes the margin while still correctly classifying all the training data.

Gaussian Naive Bayes (NB) is a probabilistic machine learning algorithm that is used for classification tasks. The Gaussian NB algorithm works by modeling the conditional probability of each class given the input features using Bayes' theorem [15].

Table 1 - Results on original images

Algorithm	Accuracy	training time (seconds)
Logistic Regression	0,85	87
Decision Tree	0,75	57,69
Random Forest	0,88	11,15
SVM	0,85	87,59
Gaussian NB	0,45	1,58

RESULTS AND DISCUSSION

As was mentioned before, classifiers had been trained using 80% of the dataset and evaluated their performance using the remaining 20%. The performance of the classifiers was evaluated based on the accuracy of the predictions:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

In addition, the training time of the classifiers was recorded. The table below shows the performance of classification on original normalized images:

From the results, we observe that the Random Forest classifier achieved the highest accuracy of 0.88, while Gaussian NB achieved the lowest accuracy of 0.45. Now we can estimate the results of these algorithms whilst combined with

Table 2 - Results on Haar wavelet coefficients

Algorithm	Wavelet coefficients	Accuracy	training time (seconds)
Logistic Regression	Approximation	0,85	10,29
Decision Tree	Approximation	0,77	6,22
Random Forest	Approximation	0,89	3,51
SVM	Approximation	0,78	6,1
Gaussian NB	Approximation	0,47	0,12
Logistic Regression	Horizontal	0,8	2,99
Decision Tree	Horizontal	0,72	5,3
Random Forest	Horizontal	0,77	4,31
SVM	Horizontal	0,75	4,83
Gaussian NB	Horizontal	0,55	0,11
Logistic Regression	Vertical	0,78	2,59
Decision Tree	Vertical	0,7	6,24
Random Forest	Vertical	0,73	4,17
SVM	Vertical	0,71	4,63
Gaussian NB	Vertical	0,5	0,1

Table 3 - Results on Daubechies wavelet coefficients

Algorithm	Wavelet coefficients	Accuracy	training time (seconds)
Logistic Regression	Approximation	0,85	11,08
Decision Tree	Approximation	0,77	5,81
Random Forest	Approximation	0,89	3,49
SVM	Approximation	0,78	8,95
Gaussian NB	Approximation	0,47	0,12
Logistic Regression	Horizontal	0,8	4,17
Decision Tree	Horizontal	0,72	5,02
Random Forest	Horizontal	0,77	3,21
SVM	Horizontal	0,75	5,29
Gaussian NB	Horizontal	0,55	0,09
Logistic Regression	Vertical	0,78	2,28
Decision Tree	Vertical	0,7	6,86
Random Forest	Vertical	0,73	3,53
SVM	Vertical	0,71	3,81
Gaussian NB	Vertical	0,5	0,1

Haar wavelet transformation:

As we can see, the results of combined approach do not lack accuracy compared to classification on original images while also being much faster in terms of training time of the algorithms. Now we will compare it with Daubechies wavelet transformation:

The performance of these algorithms combined with Haar and Daubechies transformations are almost identical both in terms of accuracy and training time. If we select the 5 best classifiers in terms of accuracy, we can clearly see the difference between training on original images and wavelet transformation coefficients (Fig.4).

The confusion matrices are used for the further comparison of models trained on original images and wavelet coefficients (Fig.5).

It shows that despite the similar performance of these models in terms of overall accuracy, the challenging labels for the models to classify are different. For example, the model trained on original data make mistakes on the images of rice and maize while the model trained on Haar coefficients have

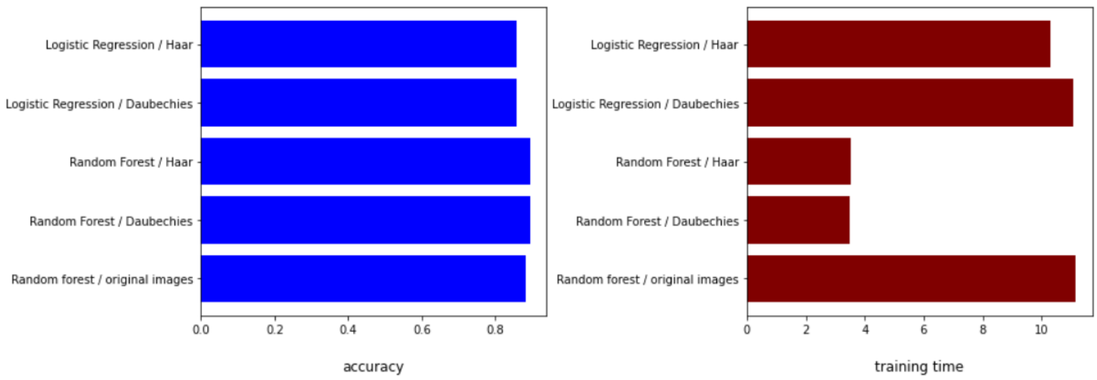

Figure 4 - Comparison of 5 best-performing classifiers

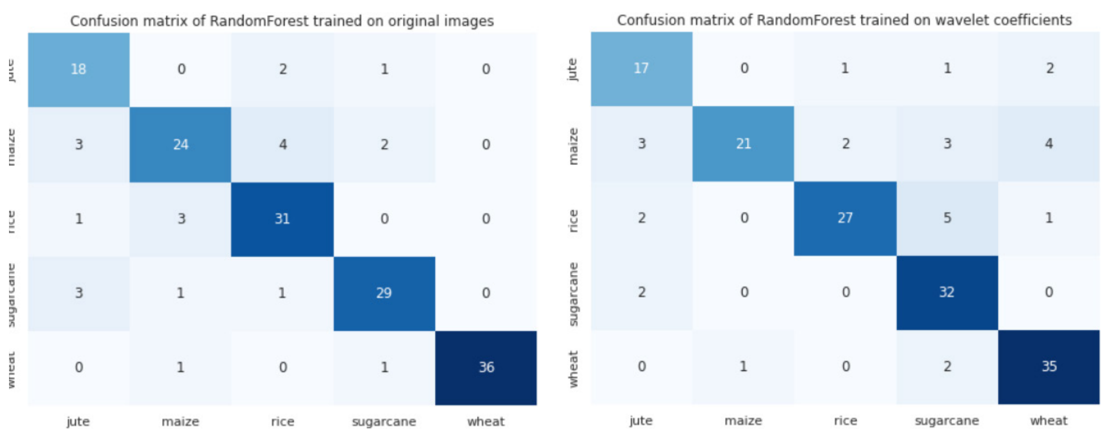

Figure 5 - Confusion matrix of the models where rows represent true labels and columns represent predicted labels

problems with differentiating sugarcane from rice.

CONCLUSION

We can see that the accuracy and training time of using wavelet transformation coefficients in combination with classification methods can be comparable to training on original images. This shows that feature extraction and reduction using wavelet transformation may be a useful technique in image processing applications. The outcomes also imply that the selection of the classification algorithm may affect accuracy more so than the selection of the feature extraction technique. It becomes clear, though, that training on the wavelet transforms coefficients yields superior results to training just on the original images when choosing the best classifiers. Thus, combining wavelet transformation with classification methods may enhance performance, especially in situations when accuracy, as well as training time, is important.

As a further step to expand the scope of the study, the evaluation of the results on the wider range of datasets and crop types can be considered as well as the investigation of the use of deep learning approaches, such as convolutional neural networks combined with different wavelet.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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ИССЛЕДОВАНИЕ МЕТОДОВ КЛАССИФИКАЦИИ КУЛЬТУР НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ С ИСПОЛЬЗОВАНИЕМ ВЕЙВЛЕТ-ПРЕОБРАЗОВАНИЙ

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АННОТАЦИЯ

В связи с растущим спросом на точные и эффективные системы сельскохозяйственного мониторинга и управления в последние годы значительно возрос интерес к классификации сельскохозяйственных культур с использованием машинного обучения. Однако традиционные алгоритмы машинного обучения имеют ограничения при работе с многомерными данными. Скорость обучения является решающим фактором при разработке моделей классификации сельскохозяйственных культур, поскольку оно напрямую влияет на эффективность и действенность модели. Для правильного обучения моделей классификации сельскохозяйственных культур часто требуются большие объемы данных, что делает процедуру обучения трудоемкой и требовательной к вычислительным ресурсам. В этой статье время обучения модели классификации сельскохозяйственных культур сокращается за счет использования вейвлет-преобразования в сочетании с традиционными методами машинного обучения, такими как SVM, Наивный байесовский классификатор, RF и другие. Производительность различных алгоритмов до и после использования вейвлет-преобразования была оценена, чтобы найти наиболее эффективный способ при использовании этой методологии. Дополнительно была определена значимость потери качества при применении вейвлет-коэффициентов. Результаты этой статьи показывают, что применение коэффициентов вейвлет-преобразования в сочетании с методами классификации может обеспечить уровни точности, сравнимые с теми, которые достигаются при обучении на исходных изображениях. Например, использование модели RF в сочетании с коэффициентами преобразования Добеши позволяет достичь точности 0,89 при значительном сокращении времени обучения с 11,15 до 3,49 секунд, а преобразование Хаара дает почти идентичные результаты. В документе демонстрируется ценность использования вейвлет-преобразований для классификации сельскохозяйственных культур и подчеркивается важность учета времени обучения при разработке точных и практичных моделей классификации сельскохозяйственных культур, которые могут быть полезны при разработке инструментов поддержки принятия решений для сельскохозяйственных приложений, где крайне важно принимать быстрые решения на основе текущих данных.

Ключевые слова: Классификация сельскохозяйственных культур, машинное обучение, метод опорных векторов, случайный лес, вейвлет-преобразование.

ВЕЙВЛЕТ ТРАНСФОРМАЦИЯ АРҚЫЛЫ МАШИНАЛЫҚ ОҚЫТУ НЕГІЗІНДЕ ДАҚЫЛДАРДЫ КЛАССИФИКАЦИЯЛАУ ӘДІСТЕРІН ЗЕРТТЕУ

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ТҮЙІН

Нақты және тиімді ауыл шаруашылығын бақылау және басқару жүйелеріне сұраныстың артуына байланысты соңғы жылдары машиналық оқытуды пайдалана отырып, дақылдарды жіктеуге қызығушылық айтарлықтай артты. Кәдімгі машиналық оқыту алгоритмдері жоғары өлшемді деректермен жұмыс істеу кезінде шектеулерге ие. Оқыту уақыты дақылдарды жіктеу үлгілерін әзірлеуде шешуші фактор болып табылады, өйткені ол модельдің тиімділігі мен тиімділігіне тікелей әсер етеді. Дақылдарды жіктеу үлгілерін дұрыс үйрету үшін жиі деректердің үлкен көлемі қажет, бұл оқыту процедурасын ауыр және есептеуді қажет етеді. Бұл мақалада SVM, Naive Bayes, RF және т.б. сияқты дәстүрлі машиналық оқыту әдістерімен үйлесімде вейвлет трансформация пайдалану арқылы дақылдарды жіктеу үлгісін оқыту уақыты қысқарады. Осы әдістемені пайдалану кезінде ең тиімді жолды табу үшін вейвлет трансформация пайдаланғанға дейін және одан кейінгі әртүрлі алгоритмдердің өнімділігі бағаланды. Сонымен қатар, вейвлет коэффициенттерді қолдану кезінде сапаның жоғалуының маңыздылығы анықталды. Бұл жұмыстың нәтижелері жіктеу әдістерімен үйлесімде вейвлет трансформация коэффициенттерін қолдану бастапқы кескіндерді оқыту арқылы қол жеткізілетін дәлдік деңгейлеріне жетуге болатынын көрсетеді. Мысалы, Random Forest моделін Daubechies түрлендіру коэффициенттерімен үйлестіре пайдалану 0,89 дәлдігіне қол жеткізуге болады, сонымен бірге бірдей нәтижелерді қамтамасыз ететін Haar түрлендіруімен жаттығу уақытын 11,15 секундтан 3,49 секундқа дейін айтарлықтай қысқартады. Бұл мақалада дақылдарды жіктеу үшін вейвлет трансформация пайдаланудың құндылығы көрсетіледі және ауылшаруашылық қосымшалары үшін шешімдерді қолдау құралдарын әзірлеуде пайдалы болуы мүмкін дақылдарды жіктеудің дәл және практикалық үлгілерін әзірлеу кезінде оқу уақытын есепке алудың маңыздылығы көрсетіледі.

Негізгі сөздер: Дақылдар классификациясы, машиналық оқыту, SVM, RF, вейвлет трансформациясы.