Harmonizing Cross View Image Transformation Through Local and Global Insights- A Review

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Abstract

Hyperspectral and multispectral information processing systems and technologies have demonstrated their value in enhancing agricultural productivity and practices by providing farmers and crop managers with valuable information on factors influencing crop condition and growth. These technologies play a crucial role in various agricultural applications, such as crop management, crop yield forecasting, crop disease detection, and monitoring soil, water, and land usage. To enhance the process of agriculture through effective crop management and assistance to farmer, using an advanced image transformation techniques the study delves into the exploration of techniques for harmonizing cross-view image transformation, with a focus on integrating both local and global insights. Further the study proposes the application of the 2D-DWT (Two-Dimensional Discrete Wavelet Transform) technique for image data preprocessing and the Extreme Learning Machine (ELM) algorithm for image classification in the context of hyperspectral images. Hyperspectral information sensing allows for the coverage of the electromagnetic spectrum in a single acquisition with several hundred spectral bands, resulting in a data cube containing significant spectral and spatial information ELM is particularly effective for classification problems because of its quick training time and capacity to operate with hidden nodes whose parameters are randomly assigned rather than modified iteratively. This comprehensive review aims to provide valuable insights and a critical analysis

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of the suggested method, shedding light on its potential contributions to the advancement of image transformation techniques for agricultural development.

Keywords: Extreme Learning Machine, electromagnetic spectrum, Hyperspectral, 2-Dimensional Discrete Wavelet Transform, Pixel information.

1. Introduction

A revolutionary era in agriculture has recently dawned thanks to the convergence of big data and machine learning, which has allowed farmers to use hyperspectral data for more accurate and sustainable crop management. Empower informed decision-making provide farmers and crop managers with valuable insights to make informed decisions about crop management, disease control, and resource allocation, thereby enhancing agricultural practices and productivity as well as enabling efficient data processing and classification. Implementing rapid and accurate data processing and image classification techniques, includes the use of the Extreme Learning Machine (ELM), to ensure precise categorization of agricultural regions. Hyperspectral data combined with machine learning techniques can monitor crop health, identify early disease symptoms, optimize irrigation, and precisely tailor fertilizer applications. This combination has the potential to increase yields, save resource consumption, and guarantee global food security. In the context of hyperspectral information, the synergy between big data and machine learning in agriculture aims to promote sustainability and resistance against climate change in addition to increasing productivity. This allows farmers to make data-driven decisions that minimize the effects of erratic weather events and maximize resource utilization. Additionally, early crop management intervention made possible by the use of hyperspectral data may lessen the need for chemical inputs and lessen their negative effects on the environment. Modern agricultural technology brings advantages to the economy in the form of higher crop yields, but it also helps to make food production more ecologically friendly and sustainable. We're on the verge of an agricultural revolution that might fundamentally alter how we farm and feed the globe as we continue to explore the fields of big data and machine learning using hyperspectral information.

2. Related Study

As suggested in this research [1], agricultural monitoring and management greatly benefit from large-scale crop mapping. Large-scale applications' requirements, however, are beyond the capabilities of conventional techniques. As a result, this study suggested a technique for large-scale crop mapping using images from many remote sensing sources. In particular, 1) the normalized difference vegetation index time-series from moderate resolution imaging spectroradiometer images and the synthetic aperture radar backscattering coefficient time-series from Sentinel-1 data, respectively, were subjected to harmonic analysis. This allowed for the extraction of harmonic-derived phenological features and harmonic-derived backscattering features, which were then combined with spectral features from Landsat-8 and Sentinel-2 images to create the final multisource feature set for crop classification; 2) the use of prior constraints of crop dominance and cropland distribution was employed to reduce misclassifications in large-scale crop mapping; and 3) the entire process was carried out on the Google Earth Engine online platform, which can lessen the computational burden brought on in the experimental study, we used the classification and regression tree classifier to assess three crops in Qinhai in 2018: wheat, rapeseed, and corn. The total accuracy is 84.25%, and the Jeffries–Matusita distances between crop samples are near to 2. Additionally, this study discovered a correlation between Qinghai's crop distribution and geography, climate, and production practices.

The authors in [2] suggested an approach for inspecting rice seeds is an essential activity for farmers and plant nurseries since it guarantees the quality of the seed used to develop seedlings. Traditionally, significant examples of rice seeds are manually screened by skilled inspectors to determine the species and grade the batch's cleanliness. Many methods use appearance-based characteristics retrieved from RGB images, while others use the spectral information obtained using Hyperspectral Imaging (HSI) devices in their effort to automate the screening process through machine vision. A limited number of species are used to benchmark the performance of new discrimination models in the majority of the research on this subject. Therefore, it's uncertain if the variance in model performance verifies the efficacy of suggested methods and features or if it may be merely ascribed to the dataset's intra- and inter-class differences. This research presents a novel approach that uses a mix of spatial and spectral information taken from high resolution RGB and hyperspectral images to automatically screen and categorize rice seed samples. An extensive 8,640 rice seed dataset taken from 90 different species was used in this method. The dataset is made accessible to the general public in order to support future thorough benchmarking and comparison of various currently in use and newly suggested methodologies. This massive dataset is used to test the suggested technique, and the experimental findings demonstrate how well the approach works to remove impure species by fusing spectral characteristics from hyperspectral data cubes with spatial features taken from high spatial resolution images.

In this system, [3] the authors have claim that the capability of multitemporal Earth observation is becoming more and more significant for crop monitoring. The necessity of understanding how to fully use the inherent phenological principles in dense multitemporal data is growing as satellite gathering of remote sensing images occurs more frequently. In this paper, a CNN-transformer method is suggested for crop classification. The suggested method significantly outperforms other conventional methods in terms of performance through the extraction of sequence correlation from multitemporal data, multiband multiresolution fusion, and category feature extraction. The cornerstone of global economic stability is FOOD security. In addition to being a necessary prerequisite for social development, agriculture plays a significant role in the economy by fostering social development. Monitoring the kinds of crops grown on agricultural land and managing crop type changes are becoming more and more crucial for the good growth of agriculture. We can now get more time-consuming remote sensing (RS) photographs thanks to the increasing number of earth observation satellites being used in recent years, which can help us increase the accuracy of crop classification. The method proves that deep learning has shown considerable success as a potent framework for feature extraction across a variety of domains. Deep learning is more versatile and easier to adapt to various domains and applications than classic machine learning algorithms, which necessitate intricate feature engineering. Deep learning can automatically learn strong feature representation. Deep learning also shows considerable promise in image processing problems related to remote sensing. Many deep learning methods, including CNN and super-resolution, were used and produced clear results in the Data Fusion Contest run by the IEEE Geoscience and Remote Sensing Society's Image Analysis and Data Fusion Technical Committee. suggested a unified spatiotemporal-spectral framework based on CNN to fill in the gaps in remote sensing images, and the suggested method is capable of resolving challenges involving the reconstruction of missing information.

As stated in this study, because of their combined temporal, geographical, and spectral resolutions, satellite image time series (SITS), including those from Sentinel-2 (S2) satellites, offer a wealth of information. S2's high revisit frequency and spatial resolution boost the likelihood of obtaining cloud-free images and make comprehensive information necessary for small object analysis available. Precision agriculture is interested in these features because temporally dense SITS can help understand crop behaviors. Historically, data on farming methods have been gathered across wide areas and concentrated on combined or mixed crops because there was insufficient trade-off between temporal and spatial resolutions. Either a daily basis with low spatial resolution or a weekly/monthly basis with high spatial resolution have been used to develop products. They are limited when fields exhibit a small average size, but significant for huge agricultural fields. S2 properties enable high temporal and spatial resolution products in this situation. Unfortunately, there is currently no automatic technique that can handle sporadically sampled data and effectively distinguish small fields from one another in an unsupervised manner. In order to account for S2 characteristics, this study proposes an approach appropriate for the analysis of small agricultural fields in S2 dense SITS. The technique combines spatiotemporal data, examines the spatiotemporal evolution of the data, and extracts pertinent spatiotemporal data. Experiments conducted on S2-SITS acquired over a region in Barrax, Spain, validated the efficacy of the suggested strategy. Following the separation of crop fields and the identification of their boundaries, field-level behavior analysis based on the calculation of phenological parameters from crop dynamics can be conducted [4].

According to research in [5], aflatoxin is a potent and highly carcinogenic chemical that is commonly present in peanuts, maize, and other agricultural goods. Using a grating module, SCOMS camera, and electric displacement platform, we initially constructed a hyperspectral imaging system to detect aflatoxin in peanuts. Using this system, we collected 146 hyperspectral pictures cubes of 73 peanut samples, both before and after they were affected with aflatoxin. Next, we suggested a modified pixel-spectral image strategy for the CNN approach. Through analysis of random selection data-sets and comparison with other identification models, we discovered that: (1) The pixel-level spectral-established reshape picture is sufficient for aflatoxin detection issues, with an overall recognition rate of above 95%. (2) The deep learning approach performs well and outperforms conventional identification models both at the pixel and kernel levels of identification. A kernel recognition rate of more than 90% can be rapidly included into the design of a sorting machine. Aflatoxin, a naturally occurring poisonous chemical created by mould and fungus and present in some foods, continues to pose a hazard to the world's population. Though it can be found in many different foods, the toxin is most frequently found in nuts, especially peanuts. Strict limitations have been imposed by the national standards of P. R. China and the United States, with 20 and 100 parts per billion (μg/kg) for food grade and feed grade, respectively. According to research, eating food contaminated with aflatoxin on a regular basis can raise your risk of dying from liver cancer by as much as 66 percent. It is thought to be 68 times more lethal than arsenic and is categorised as a group 1 carcinogenic agent. Generally speaking, aflatoxin grows in moist areas like warehouses that aren't kept below a specific humidity level. Once it starts to grow, it can spread fast, contaminating other foods and goods. It can be quite challenging to recognise because it has no colour and no taste. Moreover, it is heat-resistant, withstanding temperatures as high as 280 °C, so boiling or heating will not remove or destroy it. As a result, aflatoxin cannot be detected or eliminated using several conventional techniques, including HPLC. the area contaminated can be identified with aflatoxin by using the two hyperspectral images taken of the peanut kernel before and after it was contaminated. First, using an image banalization technique based on visible band images (e.g., 600 nm), the kernel regions were extracted. Next, using the experience the image band was adjusted to 430 nm, the difference between the pre- and post-contaminated images were computed for each pixel on the peanut region. In the binary image, pixels were labelled as polluted if the grey value ratio was larger than 1.2, and uncontaminated if not.

As has been suggested in [6] this system, the goal of modern earth observation (EO) systems is to monitor the earth's surface by producing enormous volumes of photographs. The Sentinel-2 constellation and other EO systems have high revisit times, which means that satellite image time series (SITS) are continuously produced. This enhances the monitoring of spatiotemporal occurrences. It is currently unclear in the world of remote sensing how to effectively assess SITS while taking both spectral and spatial information into account. To tackle the issue of SITS classification, The framework blends the spatial qualities extracted from SITS data with the available spectral and temporal information by means of mathematical morphology. on the trials on two research locations with different heterogeneous land covers show that spectral and spatial information combined is useful for SITS land cover classification. On a daily basis, the earth observation (EO) projects of today, supported by national or continental spatial missions, provide massive volumes of remote sensing data. One well-known instance of one of these programmes is the European Spatial Agency-funded Copernicus initiative (ESA). A constellation of two satellites with a spatial resolution of 10 and 20/60 m and a scheduled revisit duration of 5 days make up the Sentinel-2 (S2) mission in the Copernicus program. It provides optical information ranging from visible to near and shortwave infrared. The S2 mission's unparalleled spatial and temporal resolutions make it possible to produce dense satellite image time series (SITS). For a variety of land monitoring applications, including agricultural management, fire mapping, and vegetation growth duties, these data are increasingly significant sources of information.

In this work [7] the authors have proposed one of the calamities that seriously impairs crop productivity and causes irreparable harm is cold damage. High-throughput phenotyping can be used to identify crop types resistant to cold stress, hence preventing yield loss. Non-destructive spectral image analysis is now a popular and efficient method for high-throughput phenotyping, reflecting the composition and structure of plants as well as their growth and development processes and results. It also reflects their physiological and biochemical features. This study estimated the amount of cold damage to maize seedlings by using a convolutional neural network (CNN) model to extract spectral information in the visible, near-infrared, and infrared range. In this work, five different types of cold-treated maize seedlings were employed as research objects based on their hyperspectral pictures. The pictures' spectral range was 450–885 nm. For pre-processing spectral data, a Gaussian low-pass filter, the Savitzky-Golay smoothing technique, and the first-order derivative were employed. 3600 pixel samples from the chosen region of interest in each type of maize seedling were utilised for CNN modelling for each variety of maize. Following CNN modelling, the testing set for each variety consisted of 400 hyperspectral image pixel samples. Ultimately, by examining the classification accuracy and computational efficiency, a 10-layer knot CNN model was identified. The conventional approach to diagnosing cold damage mostly involves laborious and time-consuming fieldwork and temperature data interpretation. Remote sensing techniques have frequently been able to offer a thorough, quick, and comprehensive understanding of disasters. As a result, diagnostic techniques based on remote sensing are becoming more and more popular. These techniques have evolved into essentially three groups in recent years: hyperspectral imaging, vegetation index difference technique, and ground minimum temperature inversion. One technique that was developed from the cold damage disaster components is ground minimum temperature inversion. In addition to doing research on the regional mapping of cold damage in winter wheat in Argentina, Kerdiles constructed a linear regression association between the NOAA-AVHRR brightness temperature data and the lowest temperature data from meteorological stations. Juan put out a universal single window approach that works well for inverting the surface temperature of many different kinds of thermal infrared sensors.

The study aims to detect aflatoxin contamination in maize, a highly dangerous chemical linked to liver cancer. Using hyperspectral data at the pixel level, each with 600 hyperspectral bands categorized as 'clean' or 'dirty,' the study applies three feature extraction approaches. These include choosing certain hyperspectral bands from prior studies, using Principal Component Analysis (PCA) to minimize hyperspectral volume, and using feature selection methods. The Relieff feature selection approach yields the highest accuracy, 99.38% with the Random Forest (RF) classifier and 98.77% with the K-nearest neighbor (KNN) classifier. Surprisingly, employing all 600 bands without feature extraction leads to 100% accuracy. The study underlines the accuracy of feature extraction techniques, particularly Relieff, in detecting aflatoxin contamination. Furthermore, it suggests that if computational time allows, using the full set of 600 bands without feature extraction can provide exceptionally high accuracy in aflatoxin classification. Additionally, Fabiyi, et al [9] contributed to the field in 2020 with their study on "Varietal classification of rice seeds using RGB and hyperspectral images," employing cVAE-GAN, cLR-GAN, and BicycleGAN. The focus was on generating realistic images across multiple perspectives, with an emphasis on controlling model diversity and designing effective loss functions.

Finally, Tang, et al [10] in his research on "Image super resolution via simplified dense network with non-degenerate layers" explored improvements using the ImageNet dataset and ReLU nonlinearity. The study aimed at enhancing application performance in navigation, highlighting the network's resilience to degradation in static images.

These diverse studies showcase the innovative application of advanced technologies, including deep learning, hyperspectral imaging, and generative adversarial networks, in addressing agricultural and remote sensing challenges, while also shedding light on the inherent complexities and limitations associated with each approach. The Table.1 below summarize the complexities and limitations that were identified through the study.

Table 1. Comparative Study

Ref. No	Title	Year	Methodology	Merits	Demerits
[1]	"Large-scale crop mapping using Google Earth engine with multisource remote sensing images"	2020	Harmonic analysis, classifi cation and regression tree.	Crop yield predictio ns.	Data Preprocessing Complexity, Classification errors.
[2]	"Using RGB and hyperspectral images for variabilty classification of rice seeds"	2020	Hyperspectral Imaging (HSI), Linear Discriminant Analysis (LDA).	Precise identifica tion of rice varieties	Complexity of Hyperspectral Data, Overfitting.
[3]	"A hybrid CNN-transformer approach for multitemporal multisensor image crop classification"	2020	conditional generative adversarial networks, Cross-view Fork.	Facilitati ng data augment ation	Code and data will be shared.
[4]	"A deep learning based regression method on hyperspectral data for rapid prediction of cadmium residue in lettuce leaves".	2020	Super-resolution convolutional neural network (SRCNN)	High quality upscall-ing of low-resolutio n image	Image restoration problems
[5]	"Deep learning and hyperspectral imaging for pixel-level aflatoxin detection,"	2019	CNN-transformer, Support vector machine (SVM).	Crop classifica tion over time	Fuse the output feature sequences of different layers.

[6]	“Wide-area image geo localization with aerial reference imagery”	2023	Conditional generative adversarial networks, The pix2pix Baseline.	Detailed and contextu al images	High-resolution results are in demand but pre-trained networks are not available.
[7]	“A deep learning based regression method on hyperspectral data for rapid prediction of cadmium residue in lettuce leaves”	2020	Cross-View USA (CVUSA)dataset, Multi-scale model.	Urban planning, disaster manage ment	Many locations are not so distinctive
[8]	"Pixel-level aflatoxin detecting in maize based on feature selection and hyperspectral imaging."	2019	LAGGAN, CVUSA and Dayton datasets	Object detection, self-driving cars	Lack of High-Quality Data, Fine-Tuning and Hyperpar ameters
[9]	“Varietal classification of rice seeds using RGB and hyperspectral images”	2020	cVAE-GAN, cLR-GAN and BicycleGA N.	realistic images across multi perspecti ve	Model Diversity Control, Loss Function Design.
[10]	“Image super resolution via simplified dense network with non-degenerate layers”	2021	ImageNet dataset, ReLU Nonlinearity	Improvin g applicati on in navigatio n	network’s performance degrades far less obvious in static images.

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3. Limitations of Existing System

- Hyperspectral and multispectral sensors can be very expensive, both to purchase and to operate. This can make them inaccessible to many farmers, especially in developing countries.
- Hyperspectral and multispectral datasets can be very large, which can make them computationally challenging to process and analyze.
- This requires specialized hardware and software, which can also be expensive.
- The Hyperspectral and multispectral data can be complex and difficult to interpret.

4. Proposed Work

In order to improve agricultural practices and productivity, the suggested system makes use of hyperspectral and multispectral information processing technologies. In order to provide farmers and crop managers with valuable insights for a variety of agricultural applications, such as crop management, yield forecasting, disease detection, and land and resource monitoring, this system uses hyperspectral data acquisition, which captures a wide range of spectral bands in a single acquisition. The method combines the effective Extreme Learning Machine (ELM) algorithm for image classification with the 2D-DWT algorithm for image preprocessing to handle the complicated hyperspectral data.

4.1 Module Description

4.1.1 Dataset Description

Hyperspectral and multispectral data gathering from diverse sensors or imaging equipment is part of this module. It creates a precise picture of the agricultural environment by capturing a broad variety of spectral bands across the electromagnetic spectrum. Data may include details about the health of the crops, the state of the soil, and other pertinent elements.

4.1.2 Data Preprocessing

The obtained hyperspectral data needs to be pre-processed in order to improve its quality and usefulness before analysis. To make sure the data is in an appropriate format for analysis, this module comprises activities like atmospheric correction, radiometric calibration, noise reduction, and data resampling.

4.1.3 System Flow

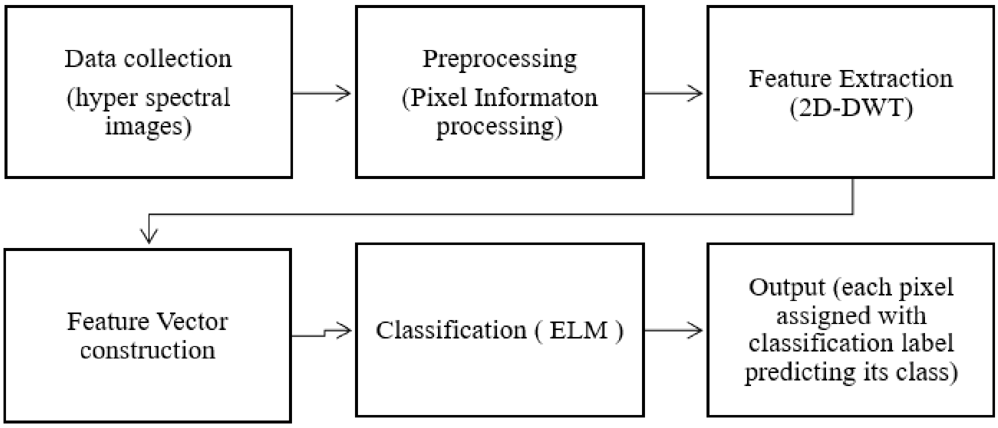

Figure 1. System Flow Diagram

4.1.4 Input Design

The input design for the proposed hyperspectral image classification system is as follows:

- **Input Image:** A hyperspectral image serves as the system's input. One kind of remote sensing image that has data on the spectral reflectance of the items in the scene is called a hyperspectral image. Typically, hyperspectral images are displayed as three-dimensional arrays, where the spectral wavelength is represented in the third dimension and the spatial coordinates of the pixels are represented in the first two.
- **Input Parameters:** The following are the system's input parameters:
  - Number of frequency bands: This option indicates how many frequency bands the 2D- DWT method will use to breakdown the hyperspectral image.
  - The 2D DWT decompose the images into different frequency components (coefficients) in both horizontal and vertical directions resulting in multi-resolution representation of the image.

- The 2D-DWT decomposition is followed by the construction of feature vectors to train the ELM. The feature vectors are constructed by concatenating the coefficients from different sub-bands or levels. This feature vector represents the image in the transformed domain.

- **Classification**: The suggested method uses the ELM to classify the images. The ELM is trained on the features vectors. The weights of the output layer in the ELM will be adjusted during training to map the input features to the desired output classes Once the ELM is trained, it can be used to predict the class labels of new images by passing their 2D DWT-based feature vectors through the trained network.

This approach leverages the ability of the 2D DWT to capture both spatial and frequency information in images. However, as the method could be made effective only by using an appropriate dataset, the proposed method in its future work aims to collect a large set of diverse datasets that include the health of the crops, the state of the soil, and other essential attributes that are related to agricultural crop growth management, followed by the evaluation of the system using metrics like accuracy, precision, recall, and F1 score.4.1.5 Output Design

Each pixel in the input image has a classification label assigned to it by the suggested hyperspectral image classification system. The class to which the pixel belongs is indicated by the categorization label.

4.2 Benefits of Proposed Work

- The proposed system has been shown to significantly improve the accuracy of hyperspectral image classification compared to other methods. This is because the proposed system uses a combination of the 2D-DWT algorithm to enhance feature representation and the ELM algorithm to improve the classification performance.

- It is also very efficient. The 2D-DWT algorithm is relatively efficient, and the ELM algorithm is very fast to train. This makes the proposed system a good choice for real-time hyperspectral image classification.

This is because the 2D-DWT algorithm is good at denoising images, and the ELM algorithm is very robust to overfitting. This makes the proposed system a good choice for classifying real-world hyperspectral images, which are often noisy and contain artifacts.

4.3 Future Work

The future work involves developing a comprehensive workflow, which includes collecting the dataset, preparing the dataset, implementing the model, training, and evaluation. Additionally, it encompasses deploying the model for real-world use.

5. Conclusion

The 2D-DWT and ELM algorithms are used in the suggested hyperspectral image classification system, a revolutionary approach that achieves high accuracy, efficiency, and robustness. The system has demonstrated superior performance on several real-world hyperspectral image datasets compared to other state-of-the-art techniques. The suggested method can be used to categorize hyperspectral images of various sizes and spectral resolutions and is also reasonably simple to put into practice. For a variety of hyperspectral image classification applications, including material identification, vegetation classification, and land cover classification, this makes it a good option. To sum up, the suggested hyperspectral image classification system is a novel and exciting method that might greatly enhance the precision, effectiveness, and resilience of hyperspectral image classification. Further the dataset collection, implementation, evaluation and the deployment of the proposed model will be carried out in the future work.

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