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Agricultural Land Image Classification

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Abstract:

In the last few years, Agricultural research has been developed faster from different computational technologies that last resources we can have the convenience of how agriculture can be grown. For the classification of lands, we have used land satellite images from which we have trained with images like Forests lands, Agriculture lands, Urban lands, and range performance of these classifiers are compared. There are only some studies with various training samples of some remote sensing images. Mostly the Sentinel-2 multispectral imager. Using sentinel-2 image data we have trained and compared the working of RF, KNN, and SVM classifiers for land. Along with the t algorithm, we have also compared deep learning highest like CNN. In Vietnam around the red river delta in the area of 30*30KM² land covers can be classified using 14 training sample sizes which include appropriate and inappropriate around 50 to till 1250 pixels. The high accuracy can be observed through all declassification from 90% to 95%. CNN produced the nation's overall dead-end training sample sizes. According to this, the next high accuracy produced after the CNN algorithm is SVM. Given the training sample sizes, this yielded the best accuracy with the least sensitivity. both machine learning and deep learning algorithms are used and compared. Comparing the deep learning algorithms produced high accuracy.

Introduction:

In this study, we assessed the effectiveness of various deep learning algorithms for identifying distinct types of agricultural land from Sentinel-1 remote sensing data. We explicitly accounted for the timely correction of the Sentinel-1 data, which was applied to the Camargue region. To accomplish this, we proposed two deep RNN approaches. According to our findings, traditional machine learning methods including KNN, RF, and SVM achieved good classification results using Sentinel-1 SAR time series data. We also compared traditional learning techniques with deep learning techniques and found that the latter significantly improved the accuracy of the project. Specifically, the CNN technique in modern learning techniques showed promise for improving the Sentinel-1 SAR time series data. By using deep learning techniques, we were able to classify the Sentinel-1 SAR image of agricultural land with

greater accuracy compared to traditional machine learning techniques. Overall, our findings suggest that deep learning approaches have the potential to enhance the management and analysis of Sentinel-1 remote sensing data for agricultural land image classification.

In this project, we are using deep learning algorithms that are mainly SVM (support vector machine) and CNN (convolutional neural network). These algorithms are used for classification and regression problems and are mainly used for image classification. We are comparing these algorithms. Both are getting high accuracy but SVM gets 72% accuracy and CNN gets 90% to 95% overall accuracy. The project aims to identify the agricultural land in different types of lands like forest land, urban land, agricultural land, and range lands.

LITERATURE SURVEY:

1. A survey of image classification methods and techniques for improving classification performance. *Int. J. Remote Sens.* 2007, 28, 823–870.

Authors: Lu, D.; Weng, Q.

Image analysis is a complicated process that may be altered by several factors. This study looks into existing picture categorization methods, challenges, and potential. The focus is on essential advanced classification methodologies and tactics for enhancing classification accuracy. Moreover, key issues influencing categorization performance are examined. The development of an adequate image processing procedure is necessary, according to the literature review, for the effective classification of remotely sensed data into a thematic map. The right utilization of various aspects of remotely sensed data, as well as the selection of an appropriate classification approach, are crucial for enhancing classification accuracy. Nonparametric classifiers including neural networks, decision tree classifiers, and knowledge-based classification are becoming more popular for multisource data categorization. However, further study is required to boost classification accuracy by locating and removing ambiguity in the image processing chain.

2. On-farm assessment of rice yield variability and productivity gaps between organic and conventional cropping systems under the Mediterranean climate. *Eur. J. Agron.* 2011, 35, 223–236.

Authors: Delmotte, S.; Tittonell, P.; Mouret, J.C.; Hammond, R.; Lopez-Ridaura, S.

When compared to traditional techniques, large production variability and

productivity disparities characterize organic rice growing. Variability may be accentuated in places with unpredictable

climates, such as the Mediterranean area of La Camargue in southern France. The study's goal was to determine the primary elements driving yield variability as well as farmer management practices utilized to sustain crop output while minimizing input consumption. Farmers' fields were monitored for yields, yield components, soil condition, weeds, and management approaches, resulting in a database with over 380 entries. These variables included continuous, discontinuous, and nominal values. They used classification and regression trees to define management strategies in conventional and organic systems, as well as to identify and categorize the key elements influencing rice production variability. The production gap between conventional and organic management ranged from around 1 t ha⁻¹ under favorable conditions to approximately 4 t ha⁻¹ under restricted settings. The following methods were used to achieve high yields under conventional and organic management: Conventional management compensated for a poor initial plant stand induced by early seeding with strong tillering rates given by N fertilizer, while weeds were managed with herbicides. Because of greater temperatures during emergence, late sowing provides for a higher initial plant density under organic management. If organic rice cultivation in the Mediterranean is to be developed further, technological approaches such as short-cycle cultivars suited to late planting in high latitudes should be adopted to aid such improvements. Other means of outcompeting and/or managing weeds without the use of herbicides, such as irrigation water management, crop

rotation, or the use of cover crops, must also be researched. These findings show that farmer innovations may pave the way

for the ecological intensification of existing agriculture.

3. Rice crop mapping and monitoring using ERS-1 data based on experiment and modelling results. IEEE Trans. Geosci. Remote Sens. 1997, 35, 41–56. Authors: Le Toan, T.; Ribbes, F.; Wang, L.F.; Flourey, N.; Ding, K.H.; Kong, J.A.; Fujita, M.; Kurosu, T.

Rice monitoring programs and research on methane emissions from flooded Rice fields need knowledge about rice-producing locations and rice growth characteristics. The purpose of this work is to evaluate the usage of ERS-1 SAR data for mapping rice-growing regions and retrieving rice parameters. The method begins with a synthesis of experimental results from two independent test regions, followed by the building of a theoretical model to understand the findings. The data were analysed using a theoretical model that is based on a realistic description of rice plants and takes into account the scatterers' backscattering amplification and clustering effects. Theoretical and experimental findings accord well. The significant temporal variability of rice field radar response is driven by wave-vegetation-water interaction, which increases from the transplanting to the reproductive stages. Based on the temporal fluctuation of the radar response between two acquisition dates, a technique for rice field mapping has been devised. SAR images were also inverted to calculate plant height and biomass. The results show promise for using ERS-1 and RADARSAT data to monitor rice.

EXISTING SYSTEM:

Multitemporal Sentinel-1 data across a region in the French Camargue are used for the analysis. From May 2017 to September 2017, the data was processed to build an intensity radar data stack. We improved this radar time series dataset by utilising temporal filtering to reduce noise

while maintaining as much fine detail as feasible. In this existing system previously, there are all SVM, KNN, and RNN algorithms for getting high accuracy. But the SVM algorithm gets only 74 % of accuracy.

Limitations:

- Less accuracy
- Not effective prediction

PROPOSED SYSTEM:

In this study, we used Sentinel-2 image data to evaluate and compare the performances of the CNN, and SVM classifiers for classifying land images. Six land use/cover categories were detected in a 30 X 30 km² region in Vietnam's Red River Delta using 14 different training large samples, including balanced and unbalanced samples, that ranged from fifty to 1250 pixels/class. The overall accuracy (OA) of the SVM algorithm classification result was high, ranging from 70 to 85%. CNN algorithm classification gives the highest OA, that range from 90% to 95%. we are comparing mainly two algorithms that are SVM and CNN, both algorithms perform better but the CNN algorithm gives high accuracy.

ADVANTAGES:

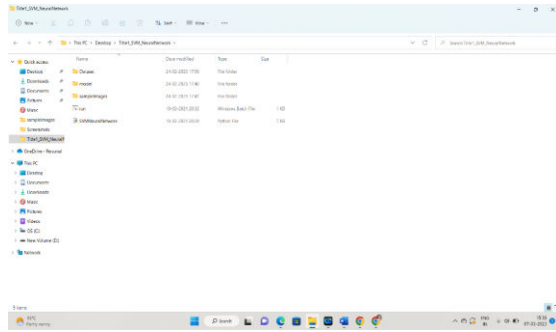
- Efficient prediction
- High accuracy

OUTPUT:

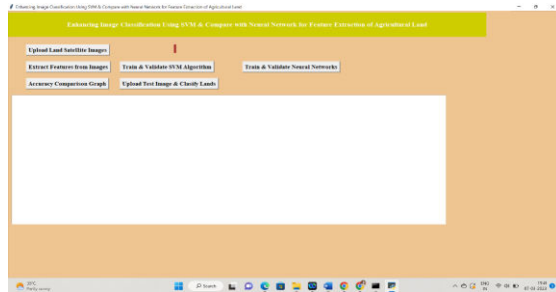
To implement this project, we have used LAND satellite images which contain images of FOREST, AGRICULTURE LAND, URBAN AREA, and Range LAND. The below screen shows dataset images and this image is saved inside the first module 'Dataset' folder in other modules you need to upload the X.txt.py file which contains this image only. To run this project, we are using some dataset images that images are collected from satellite images and this

dataset can be trained and validated to get accuracy.

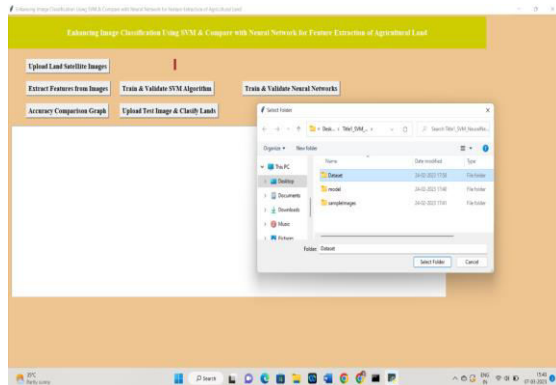
Execution process and output screenshots.



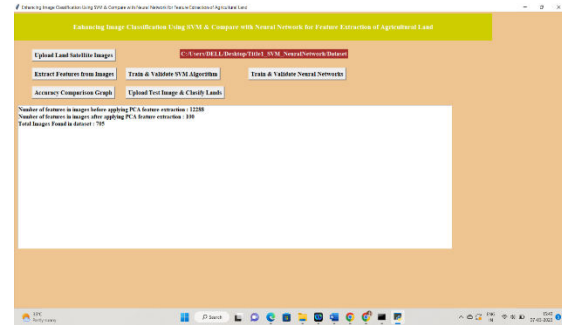
To run the project we need to click on the "run" file from the 'Title_SVM_NeuralNetwork' folder and get the below image.



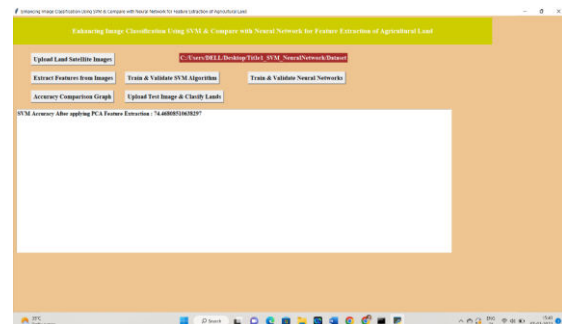
In the above image, we observe that the webpage contains different buttons. These buttons are used to get the results of the project. First, we need to select the first button and click the "upload satellite image" button.



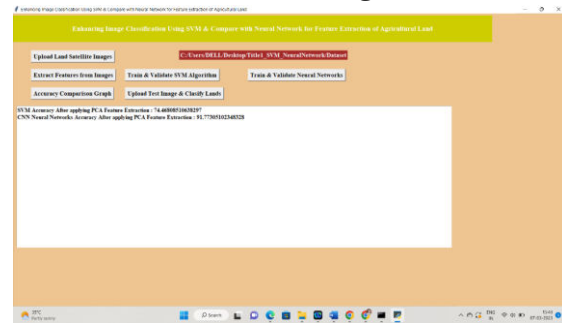
In above image explains we need to select the dataset folder and open it to get the below image.



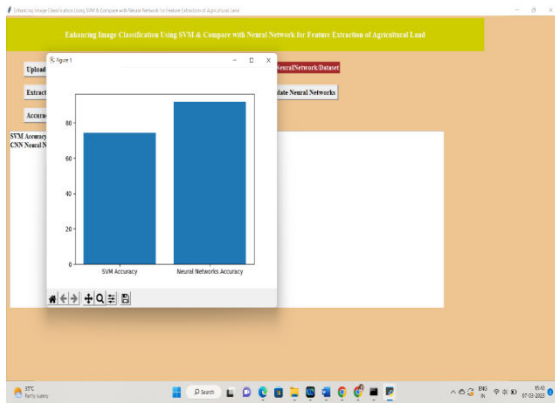
In the above image to get we need to click the "Extract features from Images". After that we get the number of features in images before applying PCA feature extraction is '12299'. And after applying PCA feature extraction is '100', and the total images found in the dataset is 705.



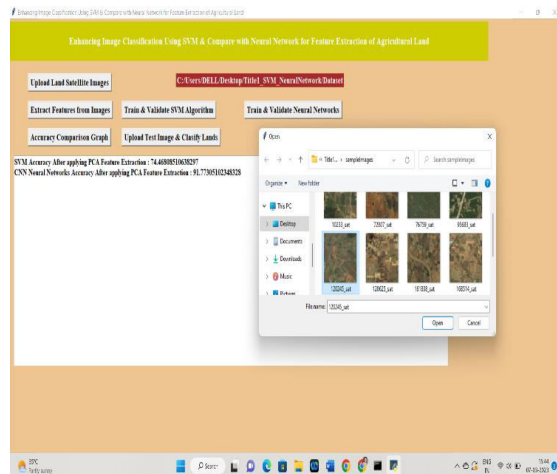
In above image shows the SVM algorithm accuracy is 74% and we need to click the "train and validate SVM Algorithm".



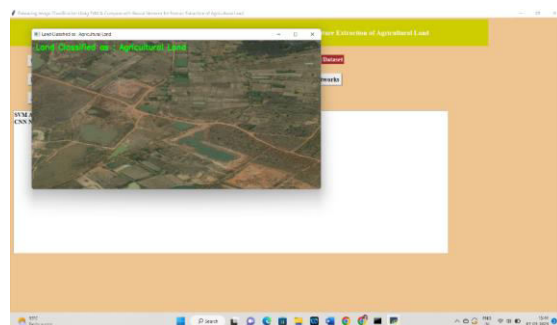
In above image shows CNN algorithm accuracy is 91% we need to click the "Train and validate neural network" button. Now we need to click the "Accuracy comparison" button.



In above image shows the graphs in which x- the axis indicates the algorithm names and the y-axis indicates the accuracy of those algorithms. Now we need to select the "Upload Test image and classify land" button. The results are shown below.



In above image shows the sample images folder and we need to select the on image and click the open button. We select the image like 120245_set.



The above image shows different types of land images which it identifies the agricultural land image

Conclusion:

the results of a study that evaluated the performance of two classifiers (CNN and SVM) and their sensitivity to training sample sizes. The study found that accuracy was high, ranging from 90% to 95% and that CNN had to get high accuracy when compared to SVM classifier. The SVM algorithm gives 75% accuracy and CNN gives 91% accuracy.

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