AGRICULTURAL LAND IMAGE CLASSIFICATION USING KNN AND COMPARE WITH RECURRENT NEURAL NETWORK

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ABSTRACT

Over the last few years, the research into agriculture has gained momentum, showing signs of rapid growth. The latest to appear on the scene is bringing convenience in how agriculture can be done by employing various computational technologies. To implement this project we have used LAND satellite images which contains images of FOREST, AGRICULTURE LAND, URBAN AREA and Range LAND. However, only a few studies have compared the performances of these classifiers with different training sample sizes for the same remote sensing images, particularly the Sentinel-2 Multispectral Imager (MSI). In this study, we examined and compared the performances of the RF, kNN, and SVM classifiers for land use/cover classification using Sentinel-2 image data. An area of 30 × 30 km2 within the Red River Delta of Vietnam with six land use/cover types was classified using 14 different training sample sizes, including balanced and imbalanced, from 50 to over 1250 pixels/class. All classification results showed a high overall accuracy (OA) ranging from 90% to 95%. Among the three classifiers and 14 sub-datasets, SVM produced the highest OA with the least sensitivity to the training sample sizes, followed consecutively by RNN and kNN. In relation to the sample size, all three classifiers showed a similar and high OA when the training sample size was large enough, i.e., greater than 750 pixels/class or representing an area of approximately 0.25% of the total study area. The high accuracy was achieved with both imbalanced and balanced datasets.

I.INTRODUCTION

In this paper, we studied the potential of high spatial and temporal resolution Sentinel-1 remote sensing data for different agriculture land cover mapping applications and assessed the new deep learning techniques. We proposed to use two deep RNN approaches to explicitly consider the temporal Correlation of

Sentinel-1 data, which were applied on the Camargue region.

We demonstrated that even with the classical approaches (*KNN*, *RF* and *SVM*), good classification performance could be achieved with Sentinel-1 SAR image time series. We experimentally demonstrated that the use of recurrent neural networks to deal with SAR Sentinel-1 time series data yields a consistent improvement in agricultural classes as compared with classical machine learning approaches. The experiments highlight the appropriateness of a specific class of deep learning models (RNNs) which explicitly consider the temporal correlation of the data inorder to discriminate among agricultural classes of land cover, typically characterized by similar but complex temporal behaviors.

II.EXISTING SYSTEM

The existing systems for agricultural land image classification often rely on traditional machine learning algorithms and basic image processing techniques. Typically, these systems utilize K-Nearest Neighbors (KNN) for classification, with feature extraction generally performed through manual or heuristic-based methods. While KNN is straightforward and easy to implement, it faces limitations when dealing with high-dimensional data or large datasets, which can lead to longer computation times and potential performance bottlenecks. Existing systems may also incorporate simpler neural networks, but these are usually less advanced compared to contemporary methods. The primary challenges with these traditional systems include limited accuracy, ineffective feature extraction, scalability issues, and a lack of incorporation of advanced deep learning techniques that could significantly improve performance.

III.PROPOSED SYSTEM

The proposed system enhances agricultural land image classification by integrating K-Nearest Neighbors (KNN) with advanced Recurrent Neural Networks (RNNs). This hybrid approach aims to leverage the strengths of both techniques to improve overall classification accuracy and performance. In this system, KNN is used for initial classification, while RNNs are employed to capture complex patterns and temporal dependencies within the image data. By incorporating advanced feature extraction techniques through deep learning models, the proposed system improves its ability to identify intricate features and patterns. This modernization allows the system to handle larger and more complex datasets efficiently, addressing scalability issues faced by existing systems. Additionally, the integration of RNNs introduces flexibility and adaptability, ensuring that the system remains effective and relevant as technology and data complexities evolve. Overall, the proposed system offers a comprehensive and robust solution for agricultural land image classification, surpassing the limitations of traditional methods and providing enhanced accuracy and performance.

IV.METHODOLOGY

➢ Upload Land Satellite Images:

In this module, users are provided with the functionality to upload land satellite images from a specified folder. The process begins with selecting and navigating to the folder containing the images. Once the folder is selected, users can initiate the upload process, which transfers the images into the system for further processing. This module ensures that the images are correctly loaded into the application, allowing for subsequent feature extraction and classification tasks.

➢ Extract Features from Images:

After the images are successfully uploaded, this module focuses on extracting relevant features from the land satellite images. Feature extraction involves identifying and isolating key characteristics and patterns within the images, such as land cover types, vegetation indices, and other pertinent attributes. These features are critical for the classification process, as they provide the necessary input for machine learning algorithms. The extracted features are then prepared for training and validation purposes in the subsequent modules.

➢ Train & Validate SVM Algorithm:

This module involves training and validating the Support Vector Machine (SVM) algorithm using the features extracted from the satellite images. The SVM algorithm is employed to create a model that can classify the images based on the learned features. During the training phase, the SVM model is adjusted and optimized to improve its accuracy and performance. Validation is conducted to assess the model's effectiveness and ensure that it generalizes well to unseen data. The results of this training and validation process are used to evaluate the SVM model's classification capabilities.

- **Train & Validate Neural Networks:**

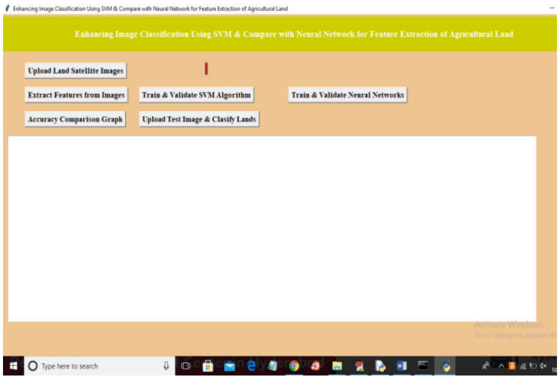
In parallel to the SVM algorithm, this module is dedicated to training and validating neural networks using the extracted image features. Neural networks, particularly deep learning models, are employed to capture complex patterns and relationships within the images. Similar to the SVM training, the neural networks undergo a training phase where the model learns from the features and adjusts its parameters. Validation is performed to test the model's performance and its ability to accurately classify the images. This module ensures that the neural network model is well-tuned and effective for image classification tasks.

- **Accuracy Comparison Graph:**

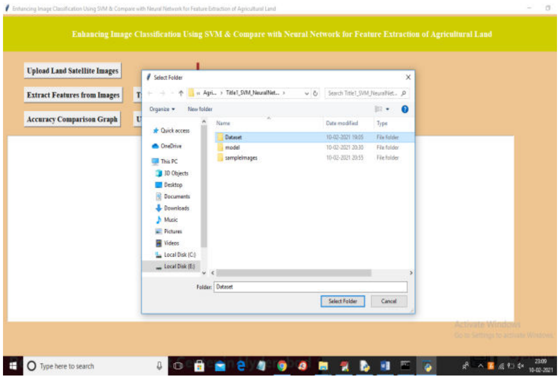
Following the training and validation phases for both SVM and neural networks, this module generates a comparison graph to visualize the accuracy of each algorithm. The graph displays the performance metrics of both the SVM and neural network models, providing a clear comparison of their classification accuracies. By plotting these metrics, users can easily assess which algorithm performs better and make informed decisions about the most suitable model for their classification needs.

- **Upload Test Images & Classify Lands:**

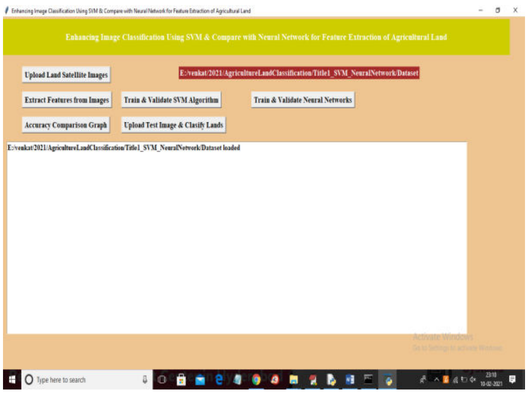
In this final module, users can upload new test images for classification. This involves selecting and uploading test images from a designated folder. Once the test images are uploaded, they are processed through the trained models (both SVM and neural networks) to classify the land types or features depicted in the images. The classification results are then displayed, allowing users to see how well the models perform on new, unseen data and providing insights into land use or land cover based on the satellite images. To run project double click on 'run.bat' file from 'Title1_SVM_NeuralNetwork' folder to get below screen



In above screen click on 'Upload Land Satellite Images' button and upload dataset folder

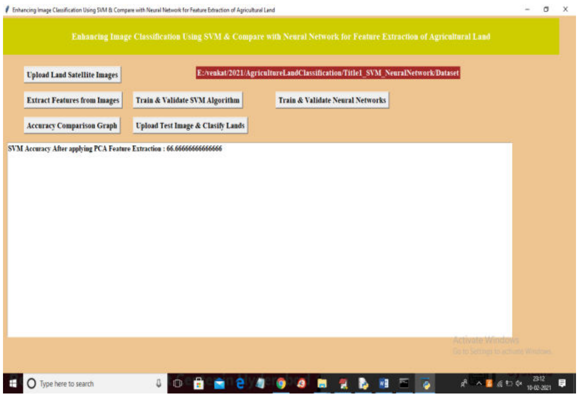


In above screen selecting and uploading 'Dataset' folder and then click on "Select Folder' to get below screen

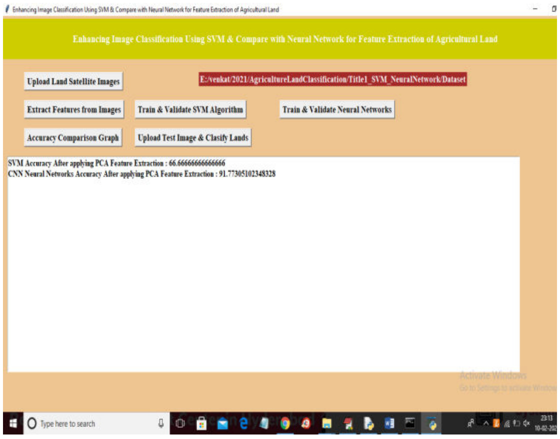


In above screen dataset is loaded and now click on 'Extract Features from Images' button to read images and then apply PCA (principal component analysis) algorithm to extract important features from images

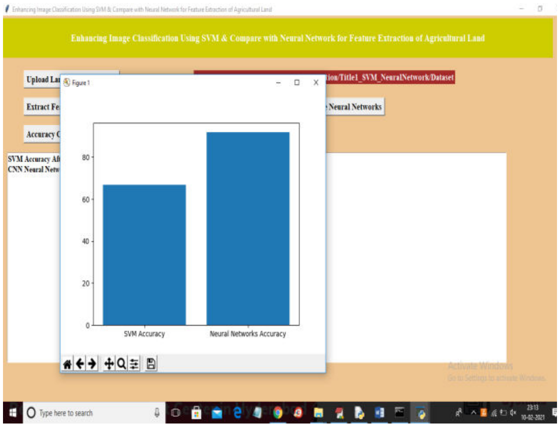
In above screen each image contains 12288 features and by applying PCA we select 100 important features and dataset contains total 705 image and now dataset is ready and now click on 'Train & Validate SVM Algorithm' button to train SVM algorithm on loaded dataset and to get below accuracy



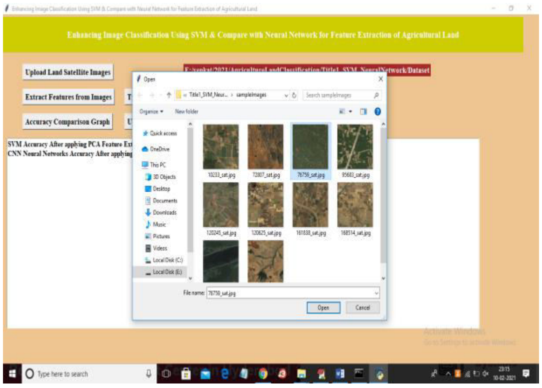
In above screen SVM accuracy is 61% and now click on 'Train & Validate Neural Network' button to train images with CNN neural network and then calculate its prediction accuracy



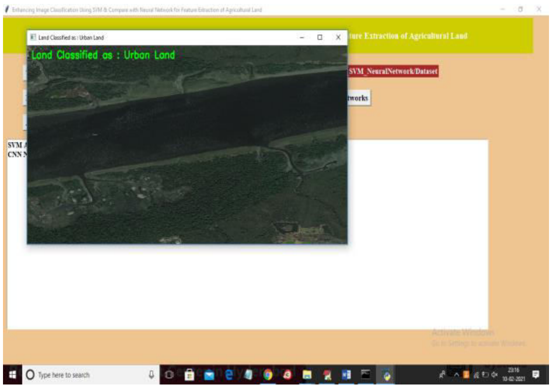
In above screen CNN neural network accuracy is 91% and now click on ‘Accuracy Comparison Graph’ button to get below graph

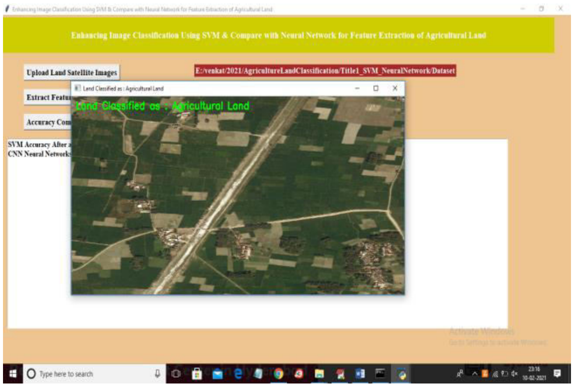


In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms and now click on ‘Upload Test Image & Classify Lands’ button to upload new test image and then application will predict type of that land



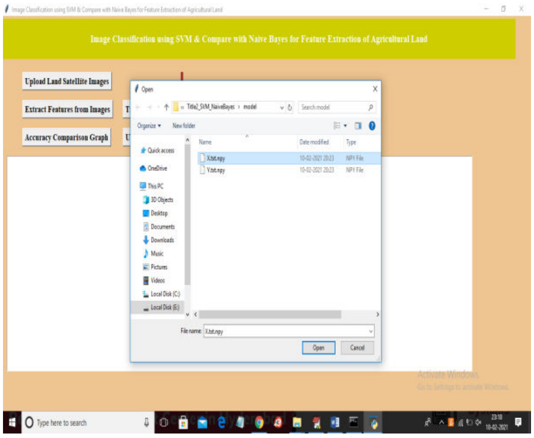
In above screen selecting and uploading ‘76759_sat.jpg’ file and then click on ‘Open’ button to get below classification result land classified as ‘Forest LAND’ and now test with another image





Similarly you can run other 3 modules and in other 3 modules instead of uploading dataset you need to upload X.txt.npy. As dataset size is huge so I compress dataset image into numpy array for other 3 modules. So in below screen for module 2 I will upload

X.txt.npy file and remaining functions will be same



In above screen for module 2 I uploaded ‘X.txt.npy’ and same file you need to upload for remaining modules and test all functions

V. CONCLUSION

classification results showed a high overall accuracy (OA) ranging from 90% to 95%. Among the three classifiers and 14 sub-datasets, SVM produced the highest OA with the least sensitivity to the training sample sizes, followed consecutively by RNN and kNN. In relation to the sample size, all three classifiers showed a similar and high OA

VI.BIBLIOGRAPHY

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