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

[1] Sirisha Palakursha, [2] Doppalapudi Pavan Kumar,[3] Mahaboob Subhani Dudekula, [4] Likki Manisree

[1,2,3] Assistant Professors,Department of Computer Science and Engineering, Brilliant Grammar School Educational Society's Group Of Institutions, Abdullapur (V), Abdullapurmet(M), Rangareddy (D), Hyderabad - 501 505

[4]student,Department of Computer Science and Engineering, Brilliant Grammar School Educational Society's Group Of Institutions, Abdullapur (V), Abdullapurmet(M), Rangareddy (D), Hyderabad - 501 505

ABSTRACT

Research into agriculture has been exhibiting indications of fast expansion over the last several years. The most recent entrant is making farming easier by using a variety of computational technology. We have used LAND satellite photos, which include coverage of FOREST, AGRICULTURE, URBAN, and RANGING LAND, to execute this project. While several classifiers have been developed for use with Sentinel-2 Multispectral Imager (MSI) and similar remote sensing pictures, very few research have examined their capabilities using various training sample sizes. In this work, we used Sentinel-2 picture data to classify land use and cover using RF, kNN, and SVM classifiers. We compared their results. A total of fourteen alternative training sample sizes, ranging from fifty pixels per class to more than twelve hundred, were used to categorise a thirty by thirty km2 region in the Red River Delta of Vietnam that had six distinct land use/cover classes. These sizes included balanced and unbalanced options. A high overall accuracy (OA) between 90% and 95% was shown by all categorisation findings. Using the training sample sizes as little a factor as possible, SVM generated the greatest OA across all three classifiers and fourteen sub-datasets. RNN and kNN trailed closely behind. With a sufficiently enough training sample size (i.e., more than 750 pixels/class or around 0.25 percent of the overall study area), all three classifiers showed a comparable and high OA. With both balanced and unbalanced datasets, the high accuracy was reached.

I.INTRODUCTION

In this research, we investigated the possibility of using Sentinel-1 remote

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sensing data, which have a high spatial and temporal resolution, to map various types of agricultural land cover.

examined new deep learning methods, and evaluated various applications. We suggested using two deep RNN methods to deliberate on the correlation between

The Camargue area was subjected to Sentinel-1 data.

We shown that Sentinel-1 SAR image time series could still be successfully classified using standard methods like KNN, RF, and SVM. We presented experimental evidence that recurrent neural networks, when applied to SAR Sentinel-1 time series data, consistently outperform traditional machine learning methods in agricultural classifications. The results show that a subset of RNNs—deep learning models that take time series correlation into account—are good at distinguishing between different types of agricultural land cover, which often exhibit comparable but complicated temporal behaviours.

II.EXISTING SYSTEM

Current agricultural land image categorisation systems often use out-of-date image processing methods and conventional machine learning algorithms. The feature extraction in these systems is usually done by hand or via heuristics, and for classification, they usually use K-Nearest Neighbours (KNN). While KNN is simple and quick to implement, it could have performance bottlenecks and lengthier calculation times when dealing with high-dimensional data or big datasets. Incorporating less complex neural networks into existing systems is possible, although they are often not as sophisticated as modern approaches. Traditional systems have problems with scalability, accuracy, and feature extraction, and they don't use new deep learning methods that may make a big difference in performance.

III.PROPOSED SYSTEM

The suggested method improves agricultural field picture categorisation by combining state-of-the-art Recurrent Neural Networks (RNNs) with K-Nearest Neighbours (KNN). The goal of this combined strategy is to boost classification performance and accuracy by capitalising on the advantages of both methods. Initially, the system uses KNN for classification, and then it uses RNNs to extract intricate patterns and relationships between images over time. The suggested system becomes better at recognising complex features and patterns by integrating deep learning models with sophisticated feature extraction methods. This update resolves the scalability problems that have plagued previous systems and makes it possible to effectively process bigger and more complicated datasets. As technology and data complexity continue to advance, the system will continue to be successful and relevant because to the flexibility and adaptability introduced by RNN integration. In conclusion, the suggested approach provides an all-encompassing and strong answer to the problem of agricultural field picture categorisation, outperforming and outperforming conventional techniques.

IV.METHODOLOGY

➢ Upload Land Satellite Images:

This module allows users to import land satellite photos from a folder of their choosing. Finding the folder that contains the photographs is the first step. Users may begin uploading their photographs into the system for processing after they've chosen a folder. Before feature extraction and classification can begin, this module verifies that the photos have been properly imported into the program.

➢ Extract Features from Images:

This module's main objective is to extract useful information from the land satellite photos after the uploading process is complete. Feature extraction is the process of sifting through photos in search of relevant qualities, such as land cover categories and vegetation indices. These characteristics are essential for categorisation because they provide machine learning algorithms with the data they need to do their jobs. The characteristics that were retrieved are then prepared for use in training and validation in the following stages.

➢ Train & Validate SVM Algorithm:

Using the characteristics retrieved from the satellite photos, this module trains and validates the Support Vector Machine (SVM) algorithm. To build a model that can use the learnt features for picture classification, the SVM method is used. The SVM model is fine-tuned and optimised during training to increase accuracy and performance. The goal of validation is to test how well the model works and if it can be applied to new data without any problems. The classification skills of the SVM model are assessed using the outcomes of this training and validation procedure.

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- **Train & Validate Neural Networks:**

This module's only purpose is to train and validate neural networks using the retrieved picture features in tandem with the SVM algorithm. We use neural networks, and more specifically deep learning models, to pick up on intricate visual correlations and patterns. In a training phase, the model learns from the characteristics and updates its parameters, much like SVM training. Neural networks follow a similar process. The purpose of validation is to check how well the model works and how well it can categorise the photos. This section checks whether the neural network model is optimised for picture categorisation.

- **Accuracy Comparison Graph:**

After the SVM and neural network training and validation processes are complete, this module creates a comparison graph to show how well the algorithms performed. In order to compare the two models' classification accuracies, the graph shows the performance metrics of the SVM and the neural network. Users may quickly determine which algorithm works better and choose the best model for their categorisation requirements by visualising these data.

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

This last section allows users to submit fresh test photos for categorisation. This requires going to a certain folder, picking out some test photographs, and then uploading them. Upon upload, the test photographs are run through trained models, which include both support vector machines and neural networks, in order to identify the various land types and attributes seen in the images. Users may see how the algorithms handle previously unknown data and get insights into land use or land cover from satellite photos by viewing the categorisation results. To launch the project, open the 'Title1_SVM_NeuralNetwork' folder and double-click the 'run.bat' file. The following screen will appear.

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

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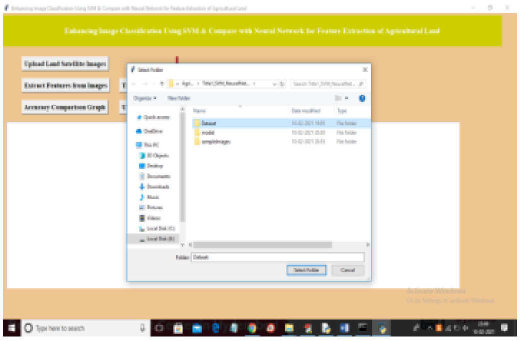

In above screen selecting and uploading 'Dataset' folder and then click on "Select Folder' to get below screen

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

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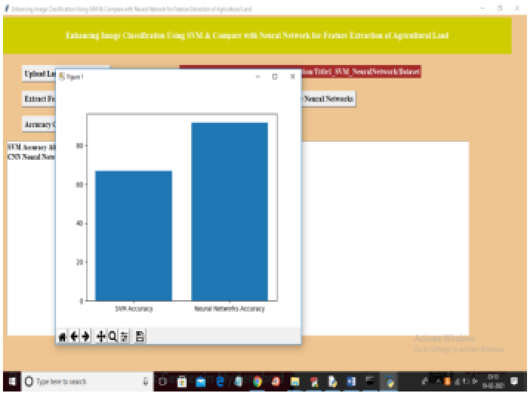
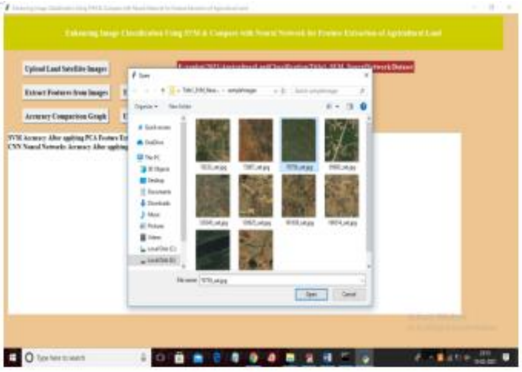
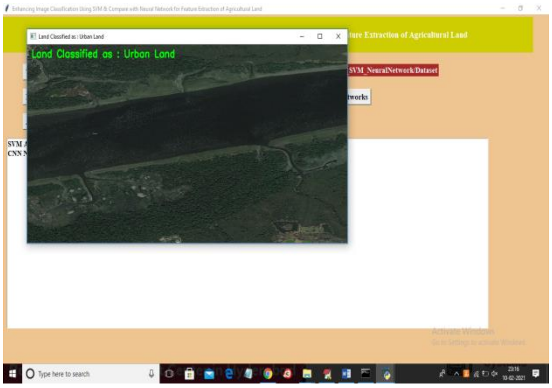
In above screen CNN neural network accuracy is 91% and now click on ‘Accuracy Comparison Graph’ button to get below graph



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



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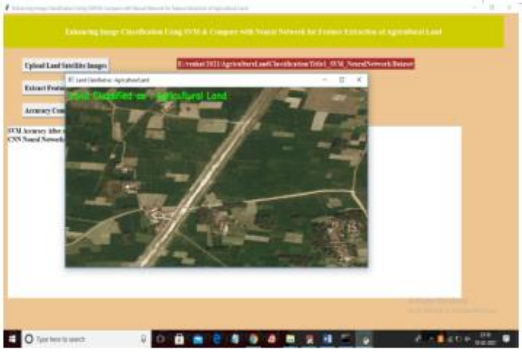
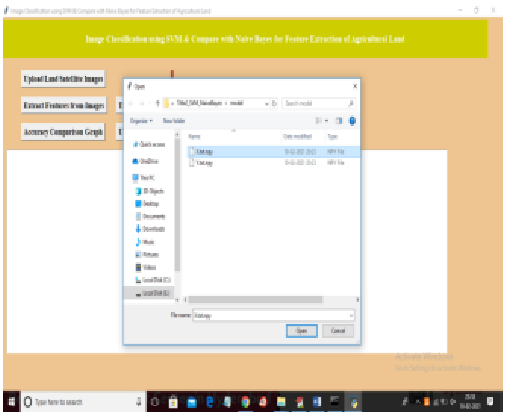


Similarly you can run other 3 modules and in other 3 modules instead of uploading dataset you need to upload X.txt.npy. As dataset size is huge so I compress dataset image into numpy array for other 3 modules. So in below screen for module 2 I will upload X.txt.npy file and remaining functions will be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

The results of the classification demonstrated an impressive overall accuracy (OA) ranging from 90% to 95%. Out of the three classifiers and fourteen sub-datasets, SVM demonstrated the most robust OA with respect to the training sample sizes, while RNN and kNN followed closely behind. All three classifiers exhibited comparable and high OA in relation to the sample size.

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