IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Neural Network Based Agricultural Land Image Classification

Mr. CH. Phanindra
Asst.Prof Electronics and Communication Department
Nalla Narasimha Reddy Group of Institutions Hyderabad
Ghatkesar,India

Narra Deepthi Reddy
Electronics and Communication Engineering
Nalla Narasimha Reddy Group of Institutions Hyderabad
Ghatkesar, India

Madineni Sai Kumar
Electronics and Communication Engineering
Nalla Narasimha Reddy Group of Institutions Hyderabad
Ghatkesar, India

Panuganti Swaroop Reddy
Electronics and Communication Engineering
Nalla Narasimha Reddy Group of Institutions Hyderabad
Ghatkesar, India

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.

INTRODUCTION

Agricultural land image classification is an important task in precision agriculture, and machine learning algorithms such as regression neural networks and K-nearest neighbors (KNN) are commonly used for this purpose. Regression neural networks are a type of artificial neural network that can be trained to predict continuous values, while KNN is a non-parametric algorithm that can be used for both classification and regression. In this paper, we will compare the performance of these two algorithms for feature extraction in agricultural land image classification.

A neural network is a computational model that is inspired by the structure and function of the human brain. It consists of a network of interconnected nodes, or neurons, that are organized into layers. The input layer receives data from the outside world, such as an image or text, and the output layer produces a prediction or classification based on that data. In between, there are one or more hidden layers that process the data and extract features. Each neuron in the network is connected to other neurons through weighted connections, which determine the strength and direction of the signal.

One of the main challenges of working with neural networks in Python is choosing the right architecture and hyperparameters for the network. This involves selecting the number of layers, the activation functions, and the learning rate.

LITERATURE SURVEY

Rice crop mapping and monitoring using ERS-1 data based on experiment and modeling results

Authors: T. Le Toan,F.Ribbes,Li-Fang Wang

Abstract: Information on rice growing areas and on rice growth conditions are necessary in rice monitoring programs and in studies on the emission of methane from flooded rice fields. The objective of this paper is to assess the use of ERS-1 SAR data to map rice growing areas and to retrieve rice parameters. The approach includes first a synthesis of experimental results at two different test areas followed by a development of a theoretical model to interpret the observations. The synthesis of experimental data at two test areas, a tropical site with short cycle rice (Semarang, Indonesia) and a temperate site with long cycle rice (Akita, Japan), has shown that flooded rice fields have characteristic increasing temporal radar responses. When the radar backscattering coefficients are expressed as a function of the rice biomass, the effect of cultural practices and climate (long cycle versus short cycle) is reduced. The observations have been interpreted by a theoretical model, which relies on a realistic description of rice plants and which considers the backscattering enhancement and clustering effects of the scatterers. Good agreement has been obtained between experimental data and theoretical results. The strong temporal variation of the radar response of rice fields is due to the wave-vegetation-water interaction, which increases from the transplanting stage to reproductive stage. By simulations using the validated model, the length of the rice cycle or the rice varieties have shown minor effects on the temporal curve. A method for rice fields mapping has been developed, based on the temporal variation of the radar response between two acquisition dates. Inversion of SAR images into plant height and plant biomass has also been performed. The results appear promising for the use of ERS-1 and RADARSAT data for rice monitoring.

A survey of image classification methods and techniques for improving classification performance

Authors: Lu, D.; Weng, Q. A

Abstract: Image classification is a complex process that may be affected by many factors. This paper examines current practices, problems, and prospects of image classification. The emphasis is placed on the summarization of major advanced classification approaches and the techniques used for improving classification accuracy. In addition, some important issues affecting classification performance are discussed. This literature review suggests that designing a suitable image-processing procedure is a prerequisite for a successful classification of remotely sensed data into a thematic map. Effective use of multiple features of remotely sensed data and the selection of a suitable classification method are especially significant for improving classification accuracy. Non-parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. Integration of remote sensing, geographical information systems (GIS), and expert system emerges as a new research frontier. More research, however, is needed to identify and reduce uncertainties in the image-processing chain to improve classification accuracy.

PROPOSED WORK

The proposed system of neural network-based agricultural land classification aims to leverage the power of artificial neural networks to accurately classify different types of agricultural land based on input features. Here is a theoretical overview of how such a system could work:

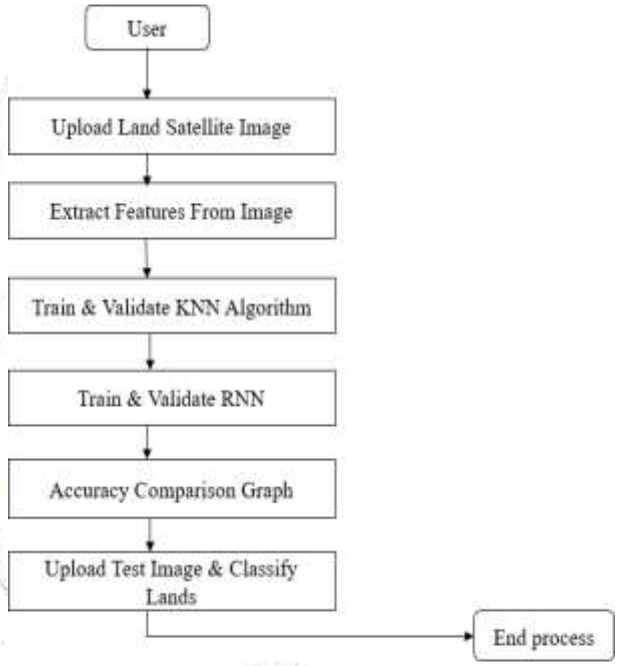
Data Collection: The system would require a comprehensive dataset consisting of various agricultural land samples. This dataset would ideally include information such as satellite imagery, soil composition, weather data, crop types, and any other relevant features that can help in classifying the land.

Preprocessing: Before feeding the data into the neural network, preprocessing steps would be performed to clean and normalize the data. This may involve removing outliers, handling missing values, and scaling the features to a common range.

Neural Network Architecture: The system would employ a neural network model specifically designed for classification tasks. Convolutional Neural Networks (CNNs) are commonly used for image-related tasks, so they could be suitable for processing satellite imagery. The network architecture may consist of multiple convolutional layers followed by pooling layers to extract important features. Additionally, fully connected layers could be added to the network to perform the final classification.

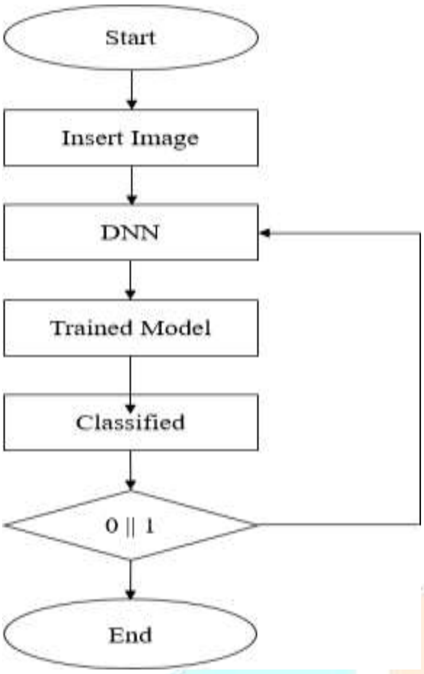
Training: The prepared dataset will be split into training and validation sets. The neural network model would be trained on the training set using techniques like backpropagation and gradient descent. The model's parameters (weights and biases) would be adjusted iteratively to minimize the classification error. The validation set would be used to monitor the model's performance and prevent overfitting.

Evaluation: Once the model is trained, it will be evaluated on a separate test set to assess its performance and generalization ability. Common evaluation metrics for classification tasks include accuracy, precision, recall, and F1-score.



The neural network model takes the input image data and extracts relevant features using convolutional layers, pooling layers, and activation functions. The extracted features are then passed through one or more fully connected layers, which perform the classification task by mapping the input features to a set of output classes. During training, the model learns to optimize the weights and biases of the neural network to minimize the error and improve the accuracy of the predictions. Once trained, the model can be used to classify new images of agricultural land into the appropriate categories.

The requirements of a proposed theory in neural network-based agricultural land image classification depend on the specific model and application. However, some general requirements include a large and diverse dataset of labeled images to train the model, a well-defined architecture that balances complexity and performance, and a suitable loss function and optimizer to minimize the error during training. Additionally, the model should be evaluated on a separate test set to measure its accuracy and generalization performance, and compared with other models and benchmarks to validate its effectiveness. Finally, the proposed theory should be able to handle different types of features and inputs, such as spectral, spatial, or temporal data, and be scalable and adaptable to different domains and scenarios.



RESULTS

To run our project click on the 'run.bat' file from the 'Title1_SVM_NeuralNetwork' folder to get the required screen, click on the 'Upload Land Satellite Images' button and upload the dataset folder, then select and upload the 'Dataset' folder and then click on "Select Folder".

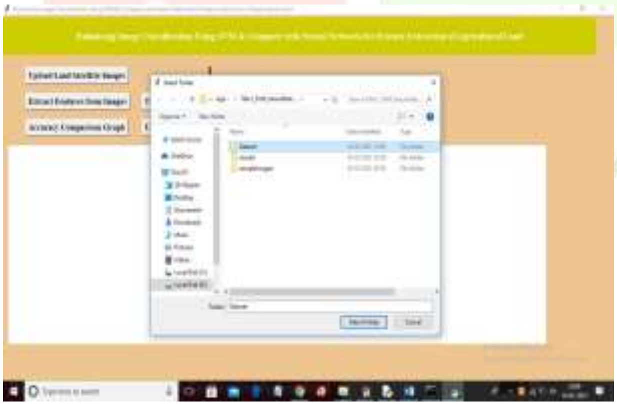


Fig 1 Selecting Dataset

The dataset is loaded and now click on the 'Extract Features from Images' button to read images and then apply the PCA (principal component analysis) algorithm to extract important features from images. Then the screen shows that each image contains 12288 features and by applying PCA we select 100 important features and dataset contains a total of 705 images and now the dataset is ready as shown below in fig 2 and then click on the 'Train & Validate SVM Algorithm' button to train the SVM algorithm and 'Train & Validate Neural Network' button to train images with CNN neural network on the loaded dataset.

Fig 2 Extracting Features from Images

In the above fig 2, we got an SVM accuracy is 61% and a CNN neural network accuracy is 91%. Then click on the 'Accuracy Comparison Graph' button to get the graph.

Fig 3 Comparison Graph

To upload the new test images, click on the 'Upload Test Image & Classify Lands' button, and then the application will predict the type of that land.

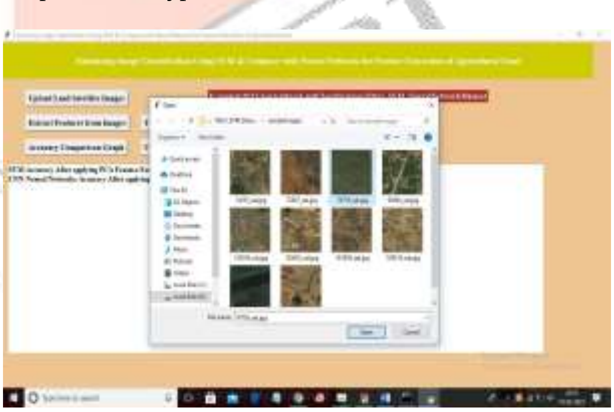


Fig 4 Uploading Test Images

From fig selecting and uploading the '76759_sat.jpg' file and then click on the 'Open' button to get the classification result as shown in fig 5.

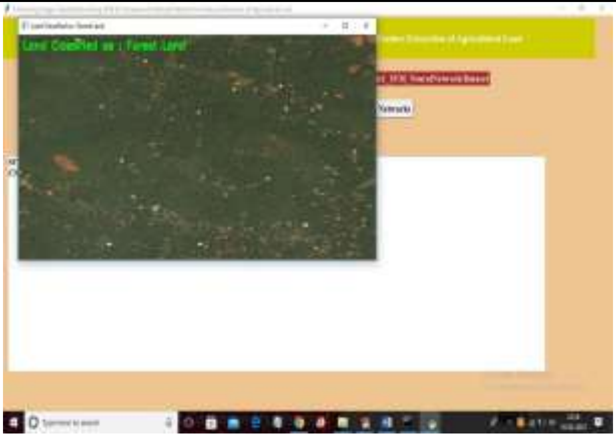


Fig 5 Final Output Screen

In the result from fig 5 the land is classified as 'FOREST LAND' and we can also upload other test images for the result.

CONCLUSION

In conclusion, neural network-based agricultural land image classification holds great potential for revolutionizing farming practices and land management. By leveraging the power of deep learning algorithms, it becomes possible to accurately classify different land cover types and monitor changes over time. This technology enables farmers, researchers, and stakeholders to make informed decisions and optimize resource allocation for improved agricultural productivity, sustainability, and environmental impact. As technology continues to evolve and more sophisticated algorithms are developed, neural network-based agricultural land image classification is expected to become an indispensable tool for precision agriculture, land use planning, and environmental monitoring. By harnessing the potential of AI and deep learning, we can pave the way for sustainable and efficient agricultural practices that meet the growing demand for food while minimizing the ecological footprint.

REFERENCES

[1] Buckley, C.; Carney, P. The potential to reduce the risk of diffuse pollution from agriculture while improving economic performance at farm level. Environ. Sci. Policy 2013, 25, 118–126.

[2] Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global consequences of land use. Science 2005, 309, 570–574.

[3]Polsot, A.; Speedy, A.; Kueneman, E. Good Agricultural Practices—A Working Concept. In Proceedings of the FAO Internal Workshop on Good Agricultural Practices, Rome, Italy, 27–29 October 2004; Volume 1, p. 41.

[4] Drusch, M.; Bello, U.D.; Carlier, S.; Colin, O.; Fernandez, V.; Gascon, F.; Hoersch, B.; Isola, C.; Laberinti, P.; Martimort, P.; et al. Sentinel-2 ESA Optical HighResolution Mission for GMES Operational Services. Remote Sens. Environ. 2012, 120, 25–36.

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

[6] Torres, R.; Snoeij, P.; Geudtner, D.; Bibby, D.; Davidson, M.; Attema, E.; Potin, P.; Rommen, B.; Floury, N.; Brown, M.; et al. GMES Sentinel-1 mission. Remote Sens. Environ. 2012, 120, 9–24.

[7] Mouret, J.C. Etude de l'AgrosystèmeRizicoleen Camargue dans ses Relations avec le Milieu et le Systeme Cultural: Aspects Particuliers de la Fertilite. Ph.D. Thesis, Université des Sciences et Techniques du Languedoc, Montpellier, France, 1988.

[8] Delmotte, S.; Tittonell, P.; Mouret, J.C.; Hammond, R.; Lopez-Ridaura, S. On farm assessment of rice yield variability and productivity gaps between organic and Neural Network Based Agriculture Land Image Classification DEPARTMENT OF ECE 34 NNRGESI conventional cropping systems under Mediterranean climate. Eur. J. Agron. 2011, 35, 223–236.

[9] Friedl, M.A.; Brodley, C.E. Decision tree classification of land cover from remotely sensed data. Remote Sens. Environ. 1997, 61, 399–409.

[10] Li, C.; Wang, J.; Wang, L.; Hu, L.; Gong, P. Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery. Remote Sens. 2014, 6, 964–983.

[11] Waske, B.; Braun, M. Classifier ensembles for land cover mapping using multitemporal SAR imagery. ISPRS J. Photogramm. Remote Sens. 2009, 64, 450– 457.

[12] Torres, R.; Snoeij, P.; Geudtner, D.; Bibby, D.; Davidson, M.; Attema, E.; Potin, P.; Rommen, B.; Floury, N.; Brown, M.; et al. GMES Sentinel-1 mission. Remote Sens. Environ. 2012, 120, 9–24.

[13] Mouret, J.C. Etude de l'AgrosystèmeRizicoleen Camargue dans ses Relations avec le Milieu et le Systeme Cultural: Aspects Particuliers de la Fertilite. Ph.D. Thesis, Université des Sciences et Techniques du Languedoc, Montpellier, France, 1988.

[14] Delmotte, S.; Tittonell, P.; Mouret, J.C.; Hammond, R.; Lopez-Ridaura, S. On farm assessment of rice yield variability and productivity gaps between organic and conventional cropping systems under Mediterranean climate. Eur. J. Agron. 2011, 35, 223–236.

[15] Friedl, M.A.; Brodley, C.E. Decision tree classification of land cover from remotely sensed data. Remote Sens. Environ. 1997, 61, 399–409.

[16] Li, C.; Wang, J.; Wang, L.; Hu, L.; Gong, P. Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery. Remote Sens. 2014, 6, 964–983.