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Article Title: Implementation of Deep Learning Technique for Accurate Land Cover Classification

Implementation of Deep Learning Technique for Accurate Land Cover Classification

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ABSTRACT

Detecting and modelling Land Cover are crucial for managing natural resources, assessing environmental impacts, and preserving ecological connectivity. Convolutional Neural Networks (CNNs) have become pivotal in advancing remote sensing applications, particularly in land cover classification. Therefore, this study introduces a CNN classifier for the prediction land cover efficiently. The preprocessing is carried out based on Principle Component Analysis (PCA), which reduces the dimensionality of the input data while retaining essential information. This step aims to enhance computational efficiency and improve the CNN's ability to extract relevant features during training. Following preprocessing, a comprehensive training phase involves optimizing the CNN architecture using a labelled dataset. This process allows the network to learn intricate spatial patterns and spectral characteristics crucial for accurate land cover classification. Evaluation of the trained model occurs in the testing phase, where performance metrics such as accuracy, precision, recall, and F1-score are computed using an independent validation dataset. Results obtained from the python software demonstrate that the CNN-PCA framework's capability to achieve high classification accuracy across diverse land cover types.

Keywords: Land Cover, Convolutional Neural Networks, Principle Component Analysis, Python software.

1 Introduction

Detecting and modelling Land Cover are essential tasks that underpin various aspects of natural resource management, environmental assessment, and ecological connectivity preservation [1-2]. Accurate detection allows to understand how land is being utilized and its impact on ecosystems, biodiversity, and climate. This knowledge is crucial for making informed decisions regarding sustainable development, conservation efforts, and disaster risk management [3-4]. Preprocessing is a necessary step in Land cover analysis to enhance the quality of input image and improve the effectiveness of subsequent classification tasks. It involves techniques such as image enhancement, noise reduction, geometric correction, and feature extraction [5-6]. Methods like histogram equalization or contrast stretching improve the visual quality of images by adjusting pixel intensities across the entire spectrum. This

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enhancement can reveal details in dark or bright regions, enhancing interpretability [7]. Techniques such as median filtering or Gaussian smoothing eliminate or mitigate noise, which distort image features and affect classification accuracy. Filtering operations help preserve relevant spatial and spectral information while reducing unwanted artifacts. Each preprocessing technique offers distinct advantages in preparing data for classification [8]. Image enhancement improves visual clarity, noise reduction enhances data integrity, geometric correction ensures spatial accuracy, and feature extraction emphasizes relevant information [9]. However, these methods can also introduce challenges. Enhanced images may become overly processed, noise reduction might over smooth subtle details, geometric correction could introduce registration errors, and feature extraction may overlook context-specific nuances [10].

Henceforth, the PCA is utilized to further enhance data quality and reduce dimensionality, thereby improving computational efficiency and aiding in feature selection for classification tasks. PCA transforms the original image bands into principal components that capture the maximum variance in the data while minimizing redundancy. This transformation simplifies subsequent classification processes by focusing on the most informative features, potentially enhancing classification accuracy and interpretability. Classification follows preprocessing and involves categorizing pixels or image segments into predefined land cover classes. This step allows us to map and quantify different land uses and covers across a landscape. Conventional classifiers include Support Vector Machines (SVMs), Random Forests, and Decision Trees [11-12]. SVMs excel in handling complex datasets and are effective for binary classification tasks. Random Forests offer robustness to noise and over fitting while Decision Trees provide interpretability of classification rules. However, SVMs can be computationally intensive, Random Forests may struggle with class imbalance, and Decision Trees may over fit noisy data [13-15]. In order to overcome the above said limitations, the proposed work employs the Deep Learning based CNN classifier is employed for effectual prediction accuracy. The objectives of the proposed work is expressed as follows,

- To accurately predict and monitor land cover dynamics, supporting sustainable development and environmental stewardship efforts globally.
- To dimensionality reduction by retaining only the most informative component with the aid of PCA based preprocessing.
- To accurately classify land cover types based on spectral information extracted from remote sensing imagery, the CNN model is developed.

2 Proposed Methodology

Accurate land cover classification plays a pivotal role in various fields such as environmental monitoring, urban planning, agriculture, and natural resource management. Traditional methods of land cover classification often rely on manually crafted features and lack the ability

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to effectively capture complex spatial patterns and spectral characteristics inherent in remote sensing data. Henceforth, the deep learning technique, particularly CNN is employed in this work, which is a powerful approach for automatic feature learning and extraction from high-dimensional data like satellite imagery.

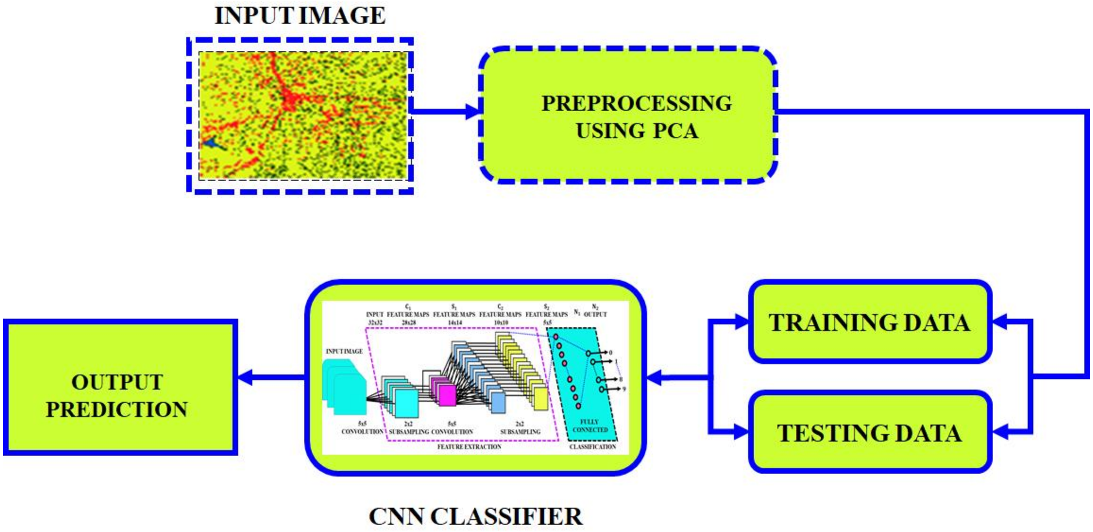

Figure 1: *Block diagram of the proposed work*

The block diagram represents the process of land cover prediction using PCA and CNN classifier. Initially, a hyper spectral image is provided as the input data, capturing detailed spectral information across various wavelengths. This input data undergoes preprocessing using PCA. PCA is a dimensionality reduction technique that extracts the most significant features from the data while removing noise, thereby making the data more manageable for further processing. Following the preprocessing step, the data is divided into training and testing datasets. The training data is used to train the CNN classifier, which is designed to learn and recognize different land cover types from the pre-processed features. The trained CNN classifier is then validated and tested using the testing data to evaluate its performance and accuracy in predicting land cover types. Overall, this process integrates PCA for effective data preprocessing and a CNN classifier for robust land cover prediction, ensuring accurate and efficient analysis of hyper spectral images.

2.1 Preprocessing Based PCA

PCA is a powerful technique used in various fields, including remote sensing and land cover prediction, to reduce the dimensionality of data while preserving important information. PCA is effective for preprocessing in land cover prediction as it reduces multi collinearity among spectral bands, identifies key components of variance, and facilitates improved modelling by focusing on the most informative features.

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Input image

Assume you have a dataset where each sample (or pixel) is represented by multiple features (e.g., spectral bands from satellite imagery).

Data Scaling

Normalize or standardize your data to ensure that each feature contributes equally to the analysis. PCA is sensitive to the scale of the input features, so it's crucial to scale them appropriately.
PCA starts with computing the covariance matrix of the cantered data. Let's denote the data matrix as XXX, where each row represents a sample and each column represents a feature.

$$Cov(X) = \frac{1}{n-1} X^T X \tag{1}$$

Perform eigenvalue decomposition of the covariance matrix to find its eigenvectors and eigenvalues.

$$Cov(X)v = \lambda v \tag{2}$$

Where λvan eigenvector and λ is is the corresponding eigenvalue.
Rank the eigenvectors based on their corresponding eigenvalues in descending order. The eigenvectors with the largest eigenvalues (principal components) capture the most variance in the data. Project the original data onto the new feature space defined by the selected principal components.

2.2 Classification Using CNN

CNNs are highly effective for land cover classification from satellite imagery due to their ability to automatically learn spatial hierarchies of features. The CNN architecture typically consists of convolutional layers that extract spatial features from input images, followed by pooling layers that down sample the feature maps to reduce dimensionality while retaining important spatial information. These layers are often interleaved with activation functions like ReLU to introduce non-linearity and improve model performance. For land cover prediction, the final layers of the CNN are fully connected, leading to a softmax layer that outputs class probabilities. Training a CNN involves feeding it with labelled satellite image patches, optimizing using back propagation and an appropriate loss function (e.g., categorical cross-entropy), and validating its performance on a separate test set. Fine-tuning with techniques like data augmentation and transfer learning can further enhance the CNN's ability to generalize across different geographic regions and varying environmental conditions, making it a robust tool for accurate land cover classification tasks.

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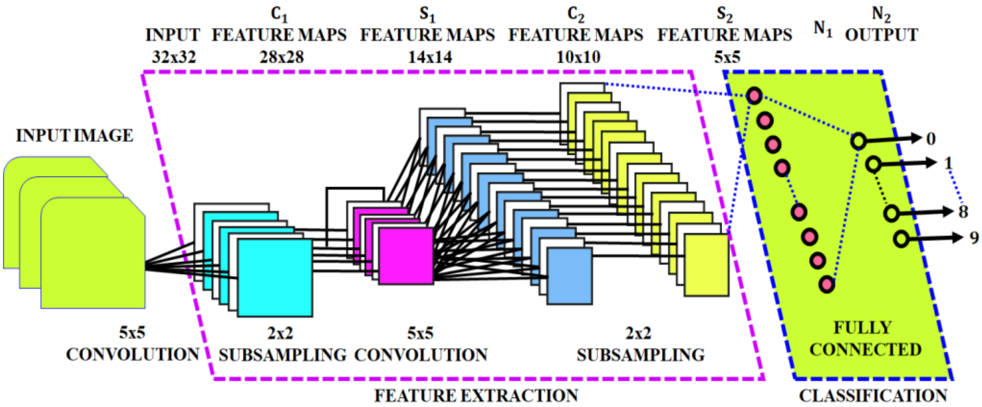

Figure 2: *Architecture of CNN classifier*

Equations (3) and (4) show how the 1D convolutional layer works.

$$x_k = b_k + \sum_{i=1}^{N}(s_k, w_{ik}) \quad (3)$$

$$y_k = f(x_k) \quad (4)$$

Equation (6) indicates the pooling layer's input, which is the convolutional layer's output. The output values of convolutional layer are included in region $\Re$, from which we take the maximum value. The output of the max-pooling layer is s_k.

$$f_{(x_k)} = max(0, x_k) \quad (5)$$

$$s_k = \max_{i \in \Re} y_k \quad (6)$$

Layer	Output Volume	Description
Input	M,1,80	
Conv1D-1	100,1,71	Number of filters:100,Kernal size:1×10,Activation:ReLu
Dropout	100,1,71	Gaussian dropout:0.3
Pool	100,1,35	Maxpooling1D:2× 2
Conv1D-2	50,1,36	Number of filters:50,Kernal size:1×10,Activation: ReLu
Dropout	50,1,26	Gaussian dropout:0.3
Pool	50,1,13	Maxpooling1D:2× 2
Dense_CNN	n	Fully connected n units,Activation:Softmax
MLP-1	100,1,80	Number of nodes:100, Activation: ReLu
Dropout	100,1,80	Gaussian dropout:0.3
MLP-1	50,1,80	Number of nodes:50, Activation: ReLu
Dropout	50,1,80	Gaussian dropout:0.3
Dense_DNN	n	Fully connected n units,Activation:Softmax
Softmax Average	n	Average:[Dense_CNN,Dense_CNN]Fully connected n units activation: Softmax

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3 Results and Discussion

Implementing PCA-based preprocessing in conjunction with deep learning techniques represents a powerful approach for accurate land cover classification from satellite imagery. PCA aids in reducing the dimensionality of high-dimensional spectral data while preserving important variance, thereby enhancing computational efficiency and reducing over fitting risks in subsequent deep learning models. The DL based CNN is employed to achieve robust and precise land cover classification outcomes essential for environmental monitoring. The proposed work is implemented in MATLAB/Simulink for validating the developed work.

Figure 3: *Input image*

The Input image shows a diverse landscape with a clear distinction between urban and rural land cover. The urban areas are densely built-up with significant infrastructure, while the rural areas are characterized by agricultural fields and open spaces. The mixed-use areas likely support a range of activities, contributing to the economic and social fabric of the region.

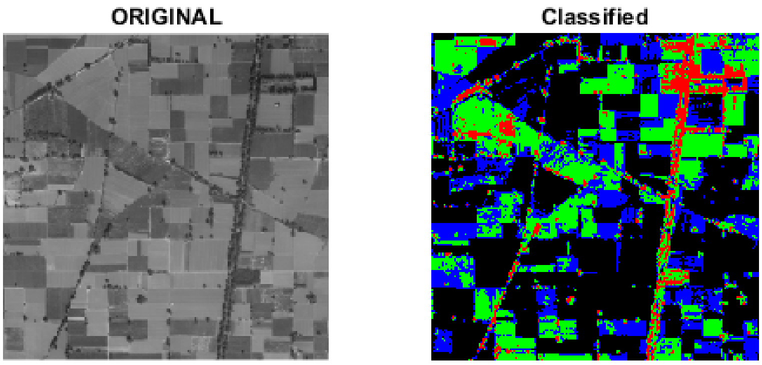

Figure 4: *Original and classified image*

The original grayscale image depicts agricultural fields with structured patterns, roads, and possible vegetation areas. The classified image provides a color-coded representation: green for vegetation or crops, blue for water bodies or wetlands, red for urban or built-up areas, and

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black for barren or non-vegetated land. This classification helps in distinguishing different land cover types efficiently.

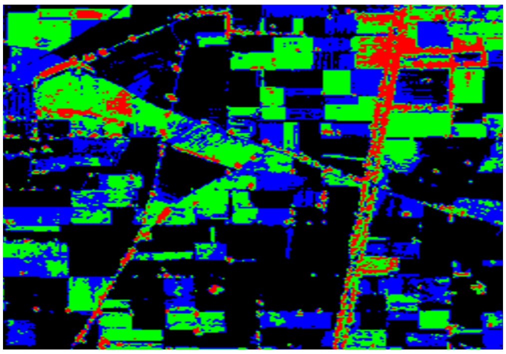

Figure 5: *Output image using CNN classifier*

The classified image, processed using a CNN classifier, provides a color-coded breakdown: green indicates vegetation or crops, blue denotes water bodies or wetlands, red marks urban or built-up areas, and black represents barren or non-vegetated land. This classification highlights various land cover types effectively, aiding in landscape analysis and planning**.**

Table 1: *Comparison of Accuracy*

Classifier techniques	Accuracy (%)
RF	90.51
SVM	91.21
ANN	92.34
Proposed CNN	94.34

The proposed CNN classifier is compared with the conventional ML classifiers for showing the importance of the developed work, from the table 1 it is evident that the CNN classifier attains high accuracy of 94.34% compared to the others.

4 Conclusion

The integration of PCA-based preprocessing with deep learning techniques offers a compelling strategy for enhancing the accuracy of land cover classification from satellite imagery. PCA based preprocessing effectively reduces the dimensionality of spectral data while retaining essential variance, thereby optimizing the input for subsequent deep learning models such as (CNNs. By focusing on the most informative components extracted by PCA, CNNs efficiently learn and recognize complex spatial patterns inherent in land cover types. This combined approach not only improves computational efficiency but also enhances the model's ability to generalize across diverse geographic regions and environmental conditions. The MATLAB is employed to validate the performance of the proposed system and the comparative analysis proved that the proposed CNN classifier has high accuracy of 94.34% compared to the

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conventional topologies. Ultimately, DL based CNN classifier represents a robust framework capable of delivering accurate and reliable land cover classification results, crucial for various applications in environmental science, urban planning, and resource management.

Reference

1. Tarun Kumar Thakur; Digvesh Kumar Patel; Arvind Bijalwan; Mammohan J. Dobriyal; Anirudh Kumar; Anita Thakur; Abhishek Bohra; Jahangeer A. Bhat, Year: 2020, "Land use land cover change detection through geospatial analysis in an Indian Biosphere Reserve", Trees, Forests and People, Vol: 2, pp. 100018.

2. Richard M Lucas; Sophia German; Graciela Metternicht; Rebecca K. Schmidt; Christopher J. Owers; Suzanne M. Prober; Anna E. Richards; Sally Tetreault-Campbell; Kristen J. Williams; et al, Year: 2022, "A globally relevant change taxonomy and evidence-based change framework for land monitoring", Global Change Biology, Vol: 28, no: 21, pp. 6293 – 6317.

3. Ryan Nedd; Katie Light; Marcia Owens; Neil James; Elijah Johnson; Aavudai Anandhi, Year: 2021, "A synthesis of land use/land cover studies: Definitions, classification systems, meta-studies, challenges and knowledge gaps on a global landscape", Land, Vol: 10, no: 9, pp. 994.

4. Khangwelo Desmond Musetsho; Munyaradzi Chitakira; Willem Nel, Year: 2021, "Mapping land-use/land-cover change in a critical biodiversity area of south africa", International Journal of Environmental Research and Public Health, Vol: 18, no: 19, pp. 10164.

5. Dyah R Panuju; David J. Paull; Amy L. Griffin, Year: 2020, "Change detection techniques based on multispectral images for investigating land cover dynamics", Remote Sensing, Vol: 12, no: 11, pp. 1781.

6. Qiqi Zhu; Xi Guo; Weihuan Deng; Sunan Shi; Qingfeng Guan; Yanfei Zhong; Liangpei Zhang; Deren Li, Year: 2022, "Land-use/land-cover change detection based on a Siamese global learning framework for high spatial resolution remote sensing imagery", ISPRS Journal of Photogrammetry and Remote Sensing, Vol: 184, pp. 63 – 78.

7. Ganesh B. Rajendran; Uma M. Kumarasamy; Chiara Zarro; Parameshachari B. Divakarachari; Silvia L. Ullo, Year: 2020, "Land-use and land-cover classification using a human group-based particle swarm optimization algorithm with an LSTM Classifier on hybrid pre-processing remote-sensing images", Remote Sensing, Vol: 12, no: 24, pp. 4135.

8. Ozlem Akar; Esra Tunc Gormus, Year: 2022, "Land use/land cover mapping from airborne hyperspectral images with machine learning algorithms and contextual information", Geocarto international, Vol: 37, no: 14, pp. 3963 – 3990.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 03(05), May 2024, pp. 35-43

9. Yawogan Jean Eudes Gbodjo; Olivier Montet; Dino Ienco; Raffaele Gaetano; Stephane Dupuy, Year: 2021, “Multisensor land cover classification with sparsely annotated data based on convolutional neural networks and self-distillation”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol: 14, pp. 11485 – 11499.

10. Saeid Amini; Mohsen Saber; Hamidreza Rabiei-Dastjerdi; Saeid Homayouni, Year: 2022, “Urban land use and land cover change analysis using random forest classification of landsat time series”, Remote Sensing, Vol: 14, no: 11, pp. 2654.

11. Sotiria Fragou; Kleomenis Kalogeropoulos; Nikolaos Stathopoulos; Panagiota Louka; Prashant K. Srivastava; Sotiris Karpouzas; Dionissios P. Kalivas; George P. Petropoulos, Year: 2020, “Quantifying land cover changes in a mediterranean environment using Landsat TM and support vector machines”, Forests, Vol: 11, no: 7, pp. 750.

12. Fang Zhang; Xiaojun Yang, Year: 2020, “Improving land cover classification in an urbanized coastal area by random forests: The role of variable selection”, Remote Sensing of Environment, Vol: 251, pp. 112105.

13. Vikas Kumar Rana; Tallavajhala Maruthi Venkata Suryanarayana, Year: 2020, “Performance evaluation of MLE, RF and SVM classification algorithms for watershed scale land use/land cover mapping using sentinel 2 bands”, Remote Sensing Applications: Society and Environment, Vol: 19, pp. 100351.

14. Thanh Noi Phan; Verena Kuch; Lukas W. Lehnert, Year: 2020, “Land cover classification using Google Earth Engine and random forest classifier—The role of image composition”, Remote Sensing, Vol: 12, no: 15, pp. 2411.

15. Abdulhakim Mohamed Abdi; Abdulhakim Mohamed, Year: 2020, “Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data”, GIScience & Remote Sensing, Vol: 57, no: 1, pp. 1 – 20.