Land Use Land Cover Classification using Deep Learning

Project Group 01

Anshumali Suri - Roll: 2106024
Ritwik Singh - Roll: 2106037
Anshu Gupta - Roll: 2106089

Under the Guidance of
Dr. M.T.U. Haider

Computer Science and Engineering Department
National Institute of Technology Patna

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Overview

Understanding Land Use Land Cover Classification

- Land use and land cover (LULC) classification categorizes Earth's surface into distinct classes like forest, water, crops, and more.
- It utilizes remote sensing and geospatial data to visually represent the Earth's surface.
- LULC classification aids in detecting changes in land cover over time, evaluating shifts in land use patterns, and assessing the impact of climate change.
- It provides valuable insights into how human activities and environmental factors influence the Earth's surface within specific regions.
- LULC classification facilitates data-driven decision-making for infrastructural development, such as determining optimal locations for roads, buildings, and plants.

Introduction Contd.

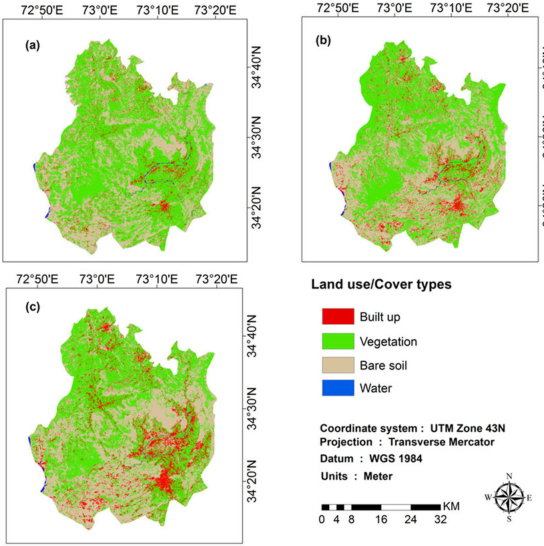


Figure: An example of LULC classification [5]

Introduction Contd.

Understanding Hyperspectral Images (HSI)

- A technique that captures and processes information across the electromagnetic spectrum, obtaining the spectrum for each pixel in an image
- It enables the identification of objects and materials by analyzing their unique spectral signatures.
- Spectral imaging utilizes multiple bands across the electromagnetic spectrum to gather information.
- It provides a two-dimensional image of the scene while simultaneously recording the spectral information of each pixel.

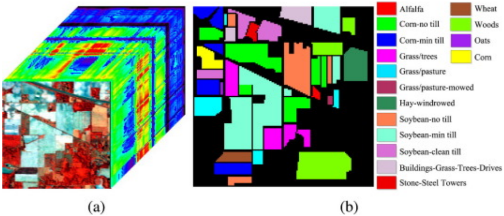


Figure: Indian Pines Dataset

Literature Survey

Table: Literature Review

Paper Title	Year of Publication	Dataset	Model	Accuracy
Evaluation of DCNN for LULC Classification and Crop Identification using Hyperspectral Remote Sensing Images [1]	2019	Indian Pines	DCNN	97.58%
A Framework for Evaluating LULC Classification using CNN [2]	2019	Indian Pines	CNN	96.78%
A Framework based on DNN for LULC and Rice Crop Classification without using Survey Data [3]	2023	Sentinel-2 Data	DNN	97.45%
Understanding deep learning in land use classification based on Sentinel-2 time series. [4]	2020	Sentinel-2 Data	2-BiLSTM	98.7%

Objective

- To design a simplified(shallow) CNN model capable of achieving accuracy levels comparable to the state-of-the-art approaches for efficient Land Use Land Cover(LULC) classification.

Challenges Identified

- The state of art models are way too complex and take many hours to some days for training.
- The Indian Pines dataset suffers from class imbalance which would result in wrong classification of under represented classes.
- HSI data poses inherent challenge of the inability to identify spatial features correctly because of the absence of a differentiating factor.
- The 200 bands of the Indian Pines dataset results in overfitting of the model ,so there is a need of reduction of bands.

Methodology

Indian Pines Dataset

- The Indian Pines dataset is a widely used hyperspectral remote sensing dataset in the field of Land Cover Classification.
- The Indian Pines dataset has a spatial resolution of approximately 20 meters per pixel, meaning each pixel in the image represents a 20-meter by 20-meter area on the ground.
- The Indian Pines dataset poses several challenges for classification algorithms, including class imbalance and high dimensionality due to the large number of spectral bands.
- This dataset consists of a single image that is of dimensions 145x145 with 200 spectral bands.

Methodology

Indian Pines Dataset Ground Truth: (1x145x145)

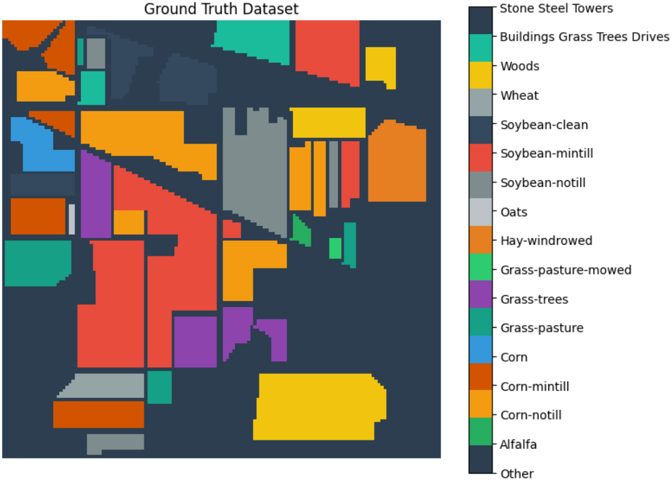


Figure: Ground Truth

Methodology

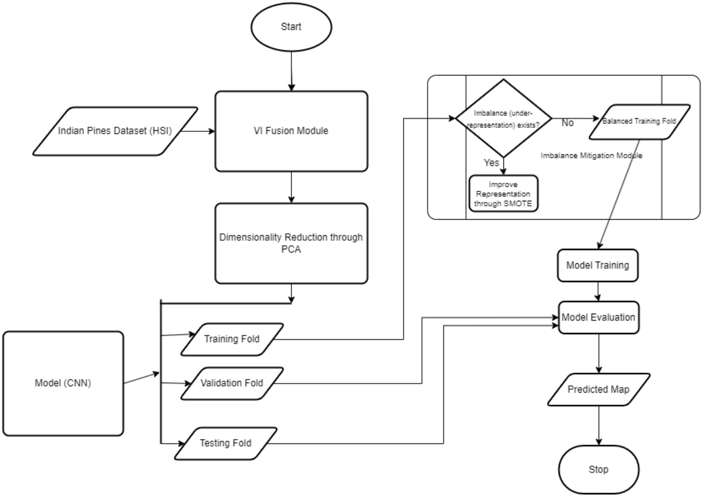


Figure: Flow Diagram

Methodology

Class Imbalance Mitigation Module

- Class imbalance can negatively impact the predictive performance of a classifier.
- CNN models may be biased toward majority classes and perform poorly on minority classes.
- HSI datasets are often class-imbalanced, making CNN-based HSI classification challenging.

Figure: Table-1. Indian Pines dataset classes and their frequencies

Sample Distribution		
#	Class	Samples
1	Corn-notill	286
2	Corn-min	166
3	Grass/Pasture	97
4	Grass/Trees	146
5	Hay-windrowed	96
6	Soybeans-notill	195
7	Soybeans-min	491
8	Soybean-clean	119
9	Woods	253
10	Alfalfa	10
11	Corn	48
12	Grass/pasture-mowed	6
13	Oats	4
14	Wheat	41
15	Bldg-Grass-Tree-Drives	78
16	Stone-steel towers	19
	Total	2055

Class Imbalance Mitigation Module

- Addressing class imbalance involves ensuring each class has approximately equal samples.
- Sampling techniques, such as undersampling and oversampling, are commonly used for this purpose.
- Oversampling techniques like SMOTE generate synthetic samples by interpolating between neighboring minority class samples.
- Oversampling methods retain valuable information from the original dataset and can avoid overfitting.
- For each train-fold in k-fold stratified cross-validation, we applied SMOTE to increase the minority ratio to at least 10%.
- We made sure not to put artificial samples in the test or validation folds.
- Thus we have utilized the oversampling technique, SMOTE to tackle class-imbalanced HSI classification.

Methodology

VI Integration Module Implementation

- Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index in remote sensing for Land Use and Land Cover (LULC) classification.
- NDVI is beneficial as it provides valuable information about the presence and health of vegetation, which is essential for distinguishing different land cover types.
- The formula for NDVI is calculated as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

- As per the dataset's calibration files, we identified the corresponding bands for NDVI calculation: Red - 29 and NIR - 44.
- Integrating NDVI into the classification process enhances the model's ability to differentiate land cover types, especially those related to vegetation.

NDVI Visualization for Indian Pines Dataset

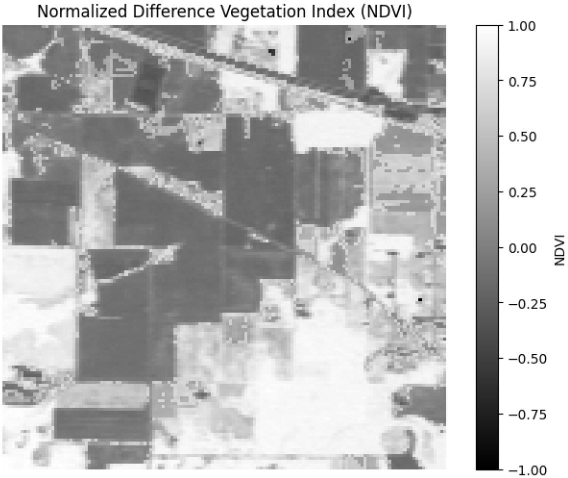


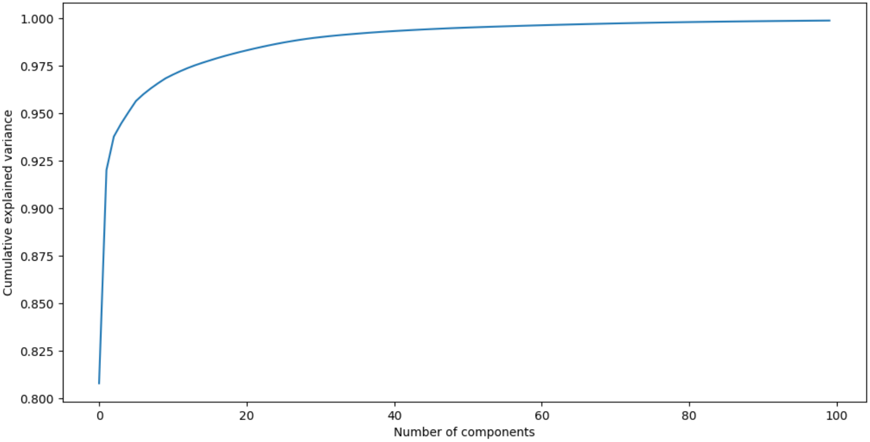
Figure: Normalized Difference Vegetation Index

Methodology

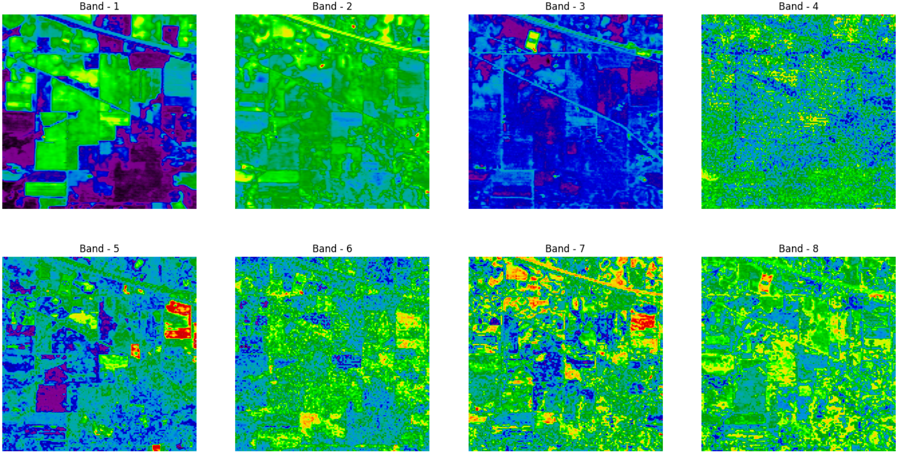
Dimensionality Reduction Module

- Hyperspectral imaging (HSI) datasets often contain a large number of spectral bands, leading to high-dimensional data.
- Managing and processing such high-dimensional data can be computationally intensive and may result in overfitting.
- PCA provides a solution by reducing the dimensionality of the data while preserving most of the relevant information.
- PCA reduces the number of spectral bands, simplifying the dataset and making it more manageable for analysis. In our case, the number of bands was reduced from 201 to 40.

Dimensionality Reduction Module



Dimensionality Reduction Module



Methodology

Data Preparation Steps

- The image is of size 145x145x40. This image cannot be passed as a single image because there are too many features in it that would require more complex CNN model for feature extraction.
- Patch Extraction: Initially, patches (5x5) centered around each pixel are extracted from the HSI Indian Pines dataset. Each patch captures a spatial neighborhood around a pixel, enabling the CNN to analyze local spectral information.
- Data Augmentation: Following patch extraction, data augmentation techniques are applied to enhance the dataset's diversity and robustness. Specifically, each patch is rotated by 45 degrees seven times, resulting in a total of eight rotated versions of each patch, thereby improving its ability to generalize and recognize patterns effectively.
- An edge padding operation is performed for edge pixels to ensure that patches extracted near the image boundary contain sufficient spatial context.
- After patch extraction, rotation, and edge padding, our input data becomes of the following shape: (168200, 5, 5, 40)

Methodology

Model Architecture

CNN Architecture			
Layer	**Type**	**Neurons & # Maps**	**Kernel**
0	Input	$P \times P \times N$	
1	Batch normalization	$P \times P \times N$	
2	Convolutional	$P \times P \times 32$	3×3
3	ReLU	$P \times P \times 32$	
4	Batch normalization	$P \times P \times 32$	
5	Max-Pooling	$\lceil P/2 \rceil \times \lceil P/2 \rceil \times 32$	2×2
6	Convolutional	$\lceil P/2 \rceil \times \lceil P/2 \rceil \times 64$	3×3
7	ReLU	$\lceil P/2 \rceil \times \lceil P/2 \rceil \times 64$	
8	Batch normalization	$\lceil P/2 \rceil \times \lceil P/2 \rceil \times 64$	
9	Max-Pooling	$\lceil P/4 \rceil \times \lceil P/4 \rceil \times 64$	2×2
10	Fully connected	1024 neurons	
11	Dropout	1024 neurons	
12	Softmax	C neurons	

Figure: CNN architecture

Training Methodology

- We utilized k-fold cross-validation for training the model, a robust technique for estimating model performance on unseen data.
- K-fold cross-validation partitions the dataset into k subsets (folds), trains the model on k-1 folds, and evaluates it on the remaining fold.
- This process is repeated k times, with each fold used once as the test set.
- We chose stratified k-fold cross-validation to ensure that each class is represented in equal proportions across folds, maintaining class balance.
- The model is trained for multiple repetitions to obtain stable and reliable performance estimates.
- We applied the SMOTE (Synthetic Minority Over-sampling Technique) algorithm to address class imbalance, particularly for minority classes.

Methodology

Model Hyperparameters

- Loss Function: Categorical Cross Entropy
- Optimizer: Stochastic Gradient Descent
- Initial Learning Rate: 0.01
- Decaying Learning Rate: Exponential
- Dropout Rate: 0.2
- Number of epochs: 10
- Batch Size: 16

Results

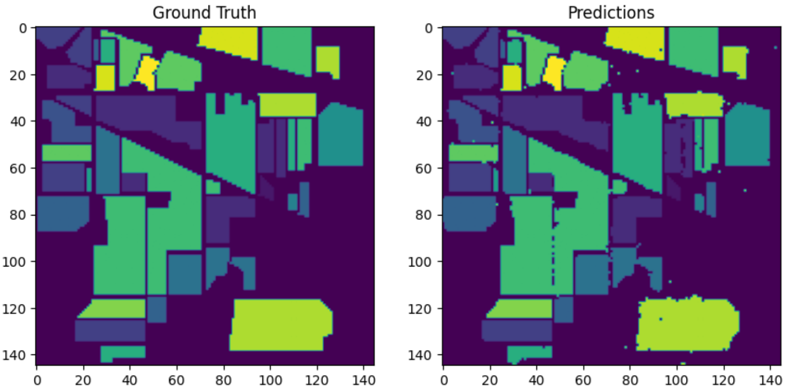
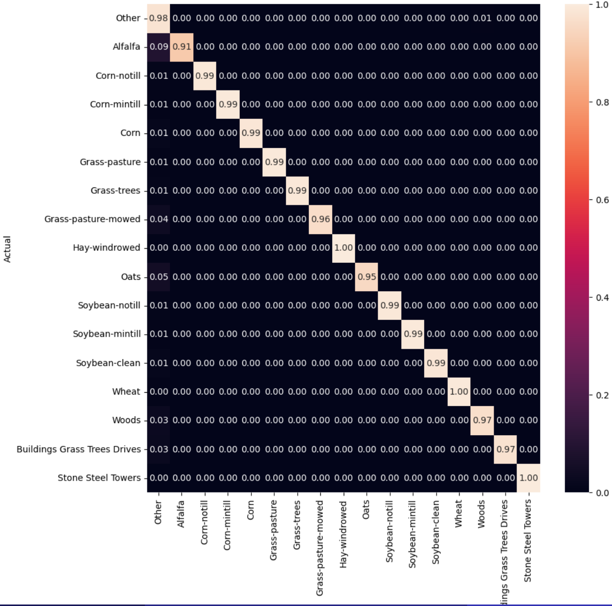


Figure: Overall Training Accuracy: 97.909%, Test Accuracy: 97.32%

Results



Actual
Other 0.98 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.00 0.00
Alfalfa 0.09 0.91 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Corn-notill 0.01 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Corn-mintill 0.01 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Corn 0.01 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Grass-pasture 0.01 0.00 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Grass-trees 0.01 0.00 0.00 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Grass-pasture-mowed 0.04 0.00 0.00 0.00 0.00 0.00 0.00 0.96 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Hay-windrowed 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Oats 0.05 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.95 0.00 0.00 0.00 0.00 0.00 0.00 0.00
Soybean-notill 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00 0.00
Soybean-mintill 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00 0.00
Soybean-clean 0.01 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.99 0.00 0.00 0.00 0.00
Wheat 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00
Woods 0.03 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.97 0.00 0.00
Buildings Grass Trees Drives 0.03 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.97 0.00
Stone Steel Towers 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00
Other
Alfalfa
Corn-notill
Corn-mintill
Corn
Grass-pasture
Grass-trees
Grass-pasture-mowed
Hay-windrowed
Oats
Soybean-notill
Soybean-mintill
Soybean-clean
Wheat
Woods
Stone Steel Towers
1.0
0.8
0.6
0.4
0.2
0.0

Conclusion

Conclusion

- Through our research project, we aimed to develop a simplified CNN model for LULC classification with HSI.
- We successfully integrated domain knowledge of Remote Sensing, particularly the use of Normalized Difference Vegetation Index (NDVI), to enhance the model's performance.
- By addressing class imbalance using SMOTE and implementing stratified k-fold cross-validation, we achieved robust and reliable model evaluation.
- The utilization of SMOTE ensured that each class had a minimum representation of 10%, improving the model's ability to generalize to under-represented classes.
- Our findings demonstrate the effectiveness of combining deep learning techniques with domain knowledge to tackle challenges in HSI classification.

References

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Thank You!