Letters in High Energy Physics
ISSN: 2632-2714 Volume 2024

Investigation of Land-Use and Land-Cover Classification with synergization of Resnet50, PCA, and Machine Learning Classifiers

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Abstract

This research developed a novel strategy for land-use classification that combines feature extraction through deep learning with dimensionality reduction and machine learning (ML) classifiers. The UCMerced LandUse (UCMLU) dataset with 21 classes is used in this work, using pre-trained ResNet50 to extract high-level spatial and contextual features from high-resolution aerial imagery. Then, Principal Component Analysis (PCA) is used to reduce dimensionality, to combat overfitting, and to enhance computation efficiency. Four prominent classifiers, Logistic Regression(LR), Random Forest(RF), Gradient Boosting(GBst), and Support Vector Machine (SVM), are then employed to classify the reduced feature representations. Before training and testing, stratified train-test splits are used to ensure a balanced representation of the classes while training and testing the models. This study evaluated the performance of classifiers with various performance metrics and ROC curves.
The results indicate that the SVM outperforms other models, giving the highest accuracy (81.67%), AUC-ROC (0.9928), thus demonstrating its robustness towards high-dimensional data. LR and RF yield almost equivalent results with strong overall performance, while GBst shows moderate effectiveness. The application of PCA would greatly contribute to an efficiency and generalization by the model. This hybrid approach exemplifies the possibilities of effectively exploiting deep learning features for accurate and efficient LULC classification.

Keywords: Resnet50, Land-Use and Land-cover Classification, PCA, SVM, RoC

1. Introduction

High-precision and timeous classification of land uses is vital for addressing global challenges like sustainable urban planning, environmental conservation, and general resource management [1, 2]. The rise of high-resolution remote sensing imagery has realized some very impressive possibilities for detailed analysis yet has introduced great limitations such as very high computational costs, constrained interpretability, and reliance on huge datasets with labels. These challenges warrant innovative and efficient yet interpretable classification frameworks in order to meet the modern day requirements of land-use analysis [3, 4].

Recent advancements in deep learning, especially convolutional neural networks (CNNs), have really revolutionized image classification tasks with very high precision [5, 6, 7]; however, they are not commonly used in real-world applications because they are compute-intensive and often possess a kind of "black box" nature, which inhibits interpretability. Accordingly, hybrid architectures, which incorporate the strong feature extraction capabilities of pretrained CNNs (like ResNet50) for the hybrid functionality and the clear interpretability and computation-efficient nature of the classical ML classifiers, should provide a system quite close to practical applicability. Nonetheless, research on such hybrid frameworks is not well investigated in details, particularly as pertains to land-use classification.

This study delves into the integration of a new hybrid architecture of ResNet50-feature extraction, PCA-dimensionally reduced data, and a suit of classical ML classifiers with regard to LULC classification; such a combination has not been vigorously construed in the literature. While PCA enhances computational efficiency and minimizes overfitting, leading to better model performance, the framework itself is carried out using the dataset that has all different kinds such as residential, agricultural, and industrial areas, making it the strongest testbed for checking the model.

The overall contribution of this research is by addressing the two critical areas of computational efficiency and interpretability for enabling better monitoring of deforestation, urban sprawl, and land degradation. As a result, there can be well-informed decisions regarding environmental conservation and resources management in utilizing the ground benefits of technology for land use classification.

Therefore, the following is a list of the main objectives of this study:

1. To design a hybrid LULC classification model that is cost-effective in computations while achieving accuracy.
2. Apply ResNet50 to extract features and perform preprocessing
3. Evaluate the performance of ML classifiers which are integrated by features from ResNet50 with various measures.

The scope of this investigation was to set up and validate a hybrid framework with respect to the most important categories of land use that fit the profile of urban and environmental contexts. Furthermore, it enhanced the interpretability of classical classifiers relative to complex deep learning models. Hence it provides insights into their features and decision-making processes.

The reminder of this paper is structured as follows: Section 2 presents associated works that spotlight the lapses in the current methodologies, while Section 3 captures the methods that include data preprocessing, feature extraction, and classification. The experimental results and findings and further implications of the work are discussed in Section 4 and Section 5 respectively. Finally, Section 6 concludes the study and indicates future research directions.

2. Related Work

Owing to the increasing availability of high-resolution images as well as the bidding for quicker analytical techniques, LULC classification has become an important area of study in the realm of remote sensing. This section expounds the notable advancements in feature extraction, dimensionality reduction, hybrid methods, and reviews of the pertinent literature identifying the existing gaps.

2.1 Feature Extraction Approaches

CNNs have become crucial in image hierarchical feature retention and have transformed how land use classification is done by shining light on feature extraction through deep learning. According to Alem and Kumar (2022) [8], transfer learning improved trained CNNs are the best for processing complicated attributes of remote sensing imagery, attaining high scores on the UCMLS data set. Huang et al. (2023) on the other hand, utilized ResNet-50 to Cluster rural areas, achieving an impressive 88.3% accuracy on the model while also surpassing the other methods in comparison [9].

The results of these studies, in unison, indicate how effective transfer learning and the utilization of pretrained CNNs aid in the tasks of image classification and land-use that relate to solving seasonal variations amongst other complex attributes of an image, aiding in complex tasks.

Still, they say there also exists a trade off between the accuracy and the amount of computation required. It provided the impetus for such techniques looking for more efficient ways of doing things.

2.2 Dimensionality Reduction Methods

It is important for the feature spaces often produced by deep learning models as high dimensional spaces to be combined with classical classifiers within hybrid frameworks. The study in [8] was focused on investigating how model performance can be enhanced by using a certain type of deep learning. Ma et al (2023) [10] on the other hand, designed the Feature Enhancement Network which aims to lessen the loss of vital information of the channel during the process of segmentation resulting in 2% gain in MIoU when compared to other models including that of the PSPNet. The findings described above provide evidence for the usefulness of different types of methods to aid in minimizing loss of some vital information while at the same time maximizing efficiency. While some of the findings quoted above may lead to particular dispositional expectations with respect to PCA it is less clear how they might be expected to interact with other forms such as autoencoders and t-SNE in hybrid deep learning/classical machine learning frameworks.

2.3 Classical Machine Learning Classifiers

SVMs, RFs, and GBst Machines as traditional ML classifiers have shown great efficiency and interpretability attributes especially when the feature spaces are limited. Patel et al. (2023) validated the use of transfer learning alongside the structures of VGG16, ResNet and DenseNet with minimal amount of labeled samples for hyperspectral crop classification by achieving 99% on benchmark datasets [11]. Hamza et al. (2023) also highlighted the enhanced performance of conventional classifiers through feature fusion and Bayesian optimization on the same dataset as investigated in this research and were able to achieve an accuracy of 96.3% [12].

Such research provides insight into ideals of hybrid structures favoring the use of classical classifiers and deeper learning features together. Nevertheless comparison in terms of efficiency using other metric and datasets has not been addressed.

2.4 Hybrid Frameworks

The integration of deep architectures with traditional ML classifiers is also getting popular due to the promise of efficiency without compromising on accuracy. Aljebreen et al, (2024) presented a module designed using the concepts of Dense EfficientNet as Well as multi scale convolutional autoencoders, outperforming baseline models on several benchmark datasets [13].

By the same token, Papoutsis et al. (2023) developed deep learning models that were benchmarked to 62 and presented compound scaling for light-weighted Wide Residual Networks which proved to be scalable for wide land use land cover classification tasks [14, 16].

These efforts indicate that hybrid frameworks might be a viable approach in dealing with issues like noise interference and scalability. On the other hand, the use of such methods on UCMLU dataset with very high intra class differences and very few training samples still to be done, requires further investigation.

As a whole, the studies reviewed above support deep learning and hybrid frameworks as useful methods in the classification of land use. They also indicate that there is scope for the integration of feature extraction and dimension reduction followed by some classical classifier that can achieve adequate accuracy, computation time and understanding of the model. But such researches have not been fully exploited especially in evaluating the different dimensionality reduction techniques and tuning the hybrid frameworks over difficult datasets.

2.5 Research Gaps

A comparison of PCA with other modern procedures such as autoencoders and t-SNE but in hybrid frameworks has not been done in deeply systematic way.

There is a dearth of research that explores the possibilities that arise from TrueForge optimization and its inclusion into hybrid systems flooding the field such as the work done by Hamza et al,2023 for improving the feature selection and the classification accuracies [12].

1. It is pertinent to note that despite the popularity of UCMLU dataset, it is still plagued by problems such as very high intra training sample class variance and very few samples for use in training. This calls for relevant custom built hybrid architectures which can properly assist in solving these issues.

2.6 Contributions of this Study

A ResNet50 based feature extraction is then followed by PCA based dimensionality reduction and is then coupled with various ML classifiers such as SVM, RF, LR and GBM, this study addresses the gap by coming forward with the hybrid framework.

The key contributions of study include:

- Explaining how best can PCA be exploited in order to improve the cost of computation while maintaining, if not improving, the classification accuracy.
- Comparing the performances of the classical classifiers against one another based on several metrics.
- Discussing the outcome of the framework in relation to its usability is expected to unveil more information especially on its usability in classifying diverse land-use categories.

This information then opens new avenues for urban planners, environmental experts, and resource managers, enhancing the methodologies on land-use classification in terms of scalability and interpretability.

3. Methodology

The proposed hybrid approach has been framed using an amalgamation of several factors like pre processing steps performed, feature extraction techniques employed, dimensionality reduction methods and classification framework.

3.1 Dataset Overview

UCMLU dataset is the combination of 100 images directed towards a specific classification model. It consists of 2,100 JPEG images, each measuring 256×256 pixels, distributed across 21 land-use categories such as residential, agricultural, industrial, forest, and water bodies. Moreover, this dataset offers a balanced class distribution, which is crucial for unbiased model evaluation [15, 17].

3.1 Data Preprocessing

Resizing, feature extraction, data augmentation and normalization are the several steps taken to ensure a holistic approach when embedding the input data. First, models are trained on a certain input that removes any bias towards uneven data distributions. Following this, the pre trained RestNet-50 model requirements of 224 * 224 pixel images are validated to ensure a degree of control.

Overfitting was avoided and the robustness of the model was improved through the integration of data augmentation methods to the training images. Some of the methods employed were basic methods like horizontal flipping which allowed for rotation changes, and random rotations (up to a ten degree shift) for more real changes in the image capturing angle. Furthermore, the AutoAugment policy, which was put to use by the torchvision library, allowed for an optimized policy of sub-policies to be used retailing cropping, shearing and color jittering. Initial tasks suggested a better performance to the model with a range of techniques due to this dynamic augmentation being employed.

Sample images in each stage of preprocessing are shown in Fig.1 (a)-(d).

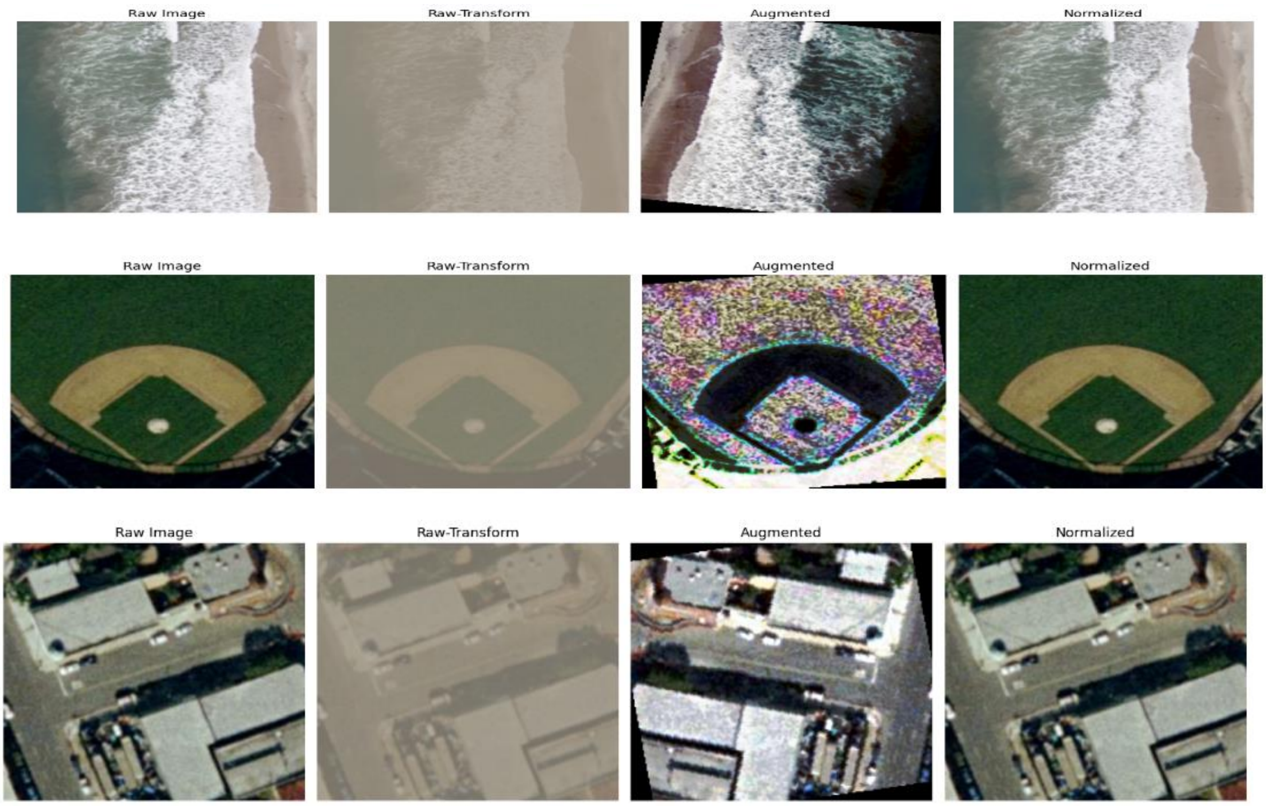

Figure 1: Sample images during different preprocessing stages

To optimize the input data, the image net statistics were employed to normalize the pixel vales of the images which included mean to be 0.485, 0.456 and 0.406 along with the standard deviation to be 0.229, 0.224 and 0.225. The pixel normalization ensured consistent scales while allowing for features with larger ranges to dominate the learning process. Moreover, the final fully connected layer (fc) of the ResNet-50 model was removed. This was done so that the focus could lie on the layer for extractive convolution, which are more relevant for the classification that was to follow. The land use classification models were enhanced in performance through these methods as they were able to optimize the quality, diversity and generalization potential.

3.2 Feature Extraction

Feature extraction through the ResNet50 model which is a CNN specialized in classification tasks which performs remarkably well is demonstrated here. It has been determined that this model is very efficient and proficient in extracting representations from complex land use images because it can solve the vanishing gradient problem and extract features at multiple levels. The ResNet50 version has 50 layers with clear development blocks which allow for much greater training capability as the vanishing gradient problem is resolved. Every image in the dataset is transformed into a feature vector by the GAP layer, located right before the end of the network model. There is no need to store complex spatial information but linear images since the architecture does not require details in order to perform effectively.

In the feature extraction process, the pretrained ResNet50 model, which was trained using ImageNet dataset was implemented as a way to take the advantage of the pre-trained hierarchical representations. The last classifying layers were discarded and the data obtained from the GAP layer, which are 2048-dimensional feature vectors, were collected. These vectors summarize the high level semantics of every image, and serve as an input for the next task, the classification task. Architecture of Resnet50 used for feature extraction process is illustrated in Figure 2.

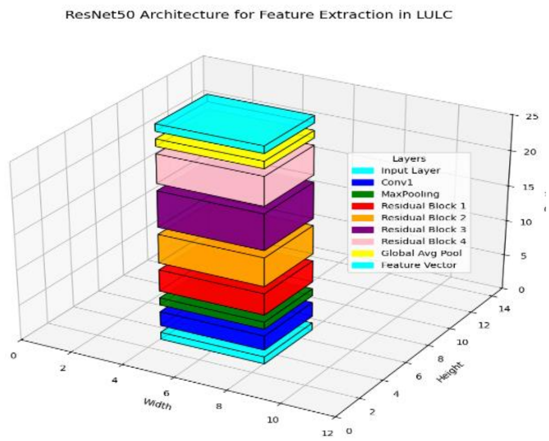

Figure 2: Resnet50 Architecture for Feature Extraction

3.3 Dimensionality Reduction

To resolve the computational difficulties that result from the use of high-dimensional feature vectors, PCA was used as a technique for dimensionality reduction. It does so by performing rotation of the feature vectors to a different coordinate system, where the new axes are directed along the maximum variance directions. By eliminating components that are not required, the computational efficiency and model performance is enhanced when the principal components are kept whereby essential information was not lost because of the decrease in dimensionality. Moreover, it assists in eliminating features and noise irrelevant to the output by emphasizing the important variance thus preventing over fitting.

For implementation, the first 95 percent of the cumulative variance was taken to guarantee that a majority of the relevant data was kept. The original 2048-dimensional feature vectors were projected down to a range of 300-500 principal components depending on the differing class variance distribution. eFocusing on areas of high variance allowed PCA to achieve a good balance between computational load and resource preservation thereby improving the classification feature space. The complete process flow followed in this study is depicted in Figure 3.

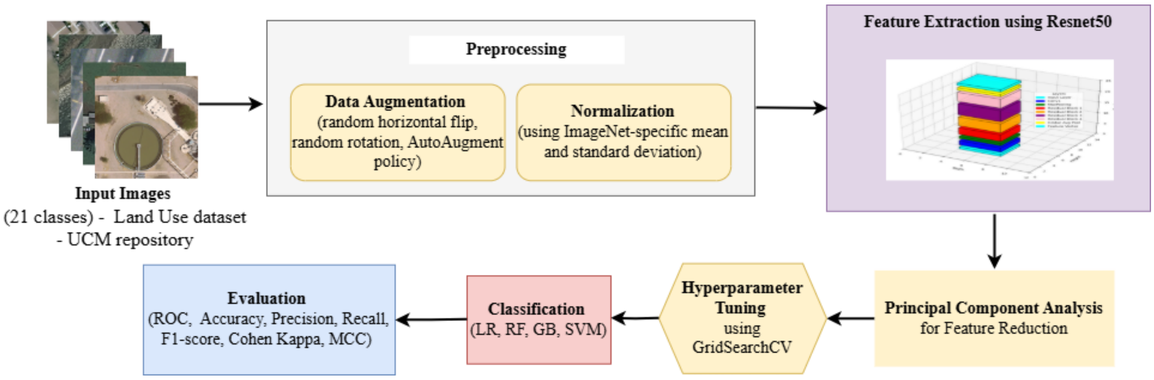

Figure 3: Process Flow in LULC classification

3.4 Classification

The corresponding feature vectors after dimensionality reduction were classified using other traditional ML models (SVM, RF, LR, GBst). For SVMs, the kernel that was selected, the Radial Basis Function (RBF), is able to model complex non-linear relationships owing to its flexibility. In order to discover the optimal bias-variance trade-off, hyperparameters grids – generalizations of the C parameter (regularization) and gamma (kernel coefficient) were searched, was carried out. Another tool, the RF, the ensemble method which is averaging a number of decision trees, was employed as well because of the ability of handling non-linear relationships and generalization. To enhance model performance and mitigate overfitting, parameters such as the maximum tree depth and the number of trees were carefully optimized, while L2 regularization was introduced to penalize large weights and thus increase generalisation.

A 5-fold in cross validation model evaluation was used to prevent overfitting. Hyperparameter tuning of the classifiers was performed through a grid search to determine the best set of parameters for each classifier. The models were assessed on a number of parameters to provide an understanding of their performance from many perspectives. It does so by determining the overall correctness of the prediction, class imbalance and the models' ability to differentiate between land-use classes. Key parameters set for each model investigated in out study are shown in Table.1.

Model	Classifier	Key Parameters
LR	LogisticRegression	max_iter=1000
RF	RFClassifier	n_estimators=100, random_state=42
GBst	**GBst**Classifier	n_estimators=100, random_state=42
SVM	SVC	kernel="rbf", probability=True, random_state=42

Table.1 : Parameter tuning for LCLU classification

4 Experimental Results

The evaluation of the hybrid LULC classification with multiple classifiers was assessed with a variety of performance metrics and the results are depicted in Figure. 4. These metrics were intended to facilitate a detailed evaluation of the models' features and capabilities. Predictive accuracy gives a measure of how much predictions are right but precision and recall are more concerned with a model's true positive identification capabilities. he F1-score serves as a harmonic mean of precision and recall, making it particularly useful for imbalanced datasets. AUC-ROC assesses the capability of the classifiers to discriminate the classes while Cohen's Kappa and MCC incorporate the level of agreement between predictions and observation outcomes. SVM was the most effective model with accuracy of 81.67%, AUC-ROC of 0.993 and an F1-score of 0.819 demonstrated best results in terms of both Cohen's Kappa and MCC. LR and RF had similar levels of performance while GBst delivered lower recall and F1-score. Class imbalance sensitivity offers an explanation. Average Classifiers' performance are shown in the heatmap in Figure 5. ROC Curve Comparison of Classifiers is shown in Figure 6. In order to enable a better understanding of the relative efficiencies of the classifiers a performance comparison in 21 classes in terms of AUC-ROC curve has been compiled in Figure 7. The ROC curves make it apparent that SVM has maximum discriminant power, followed by LR, RF and GBst.

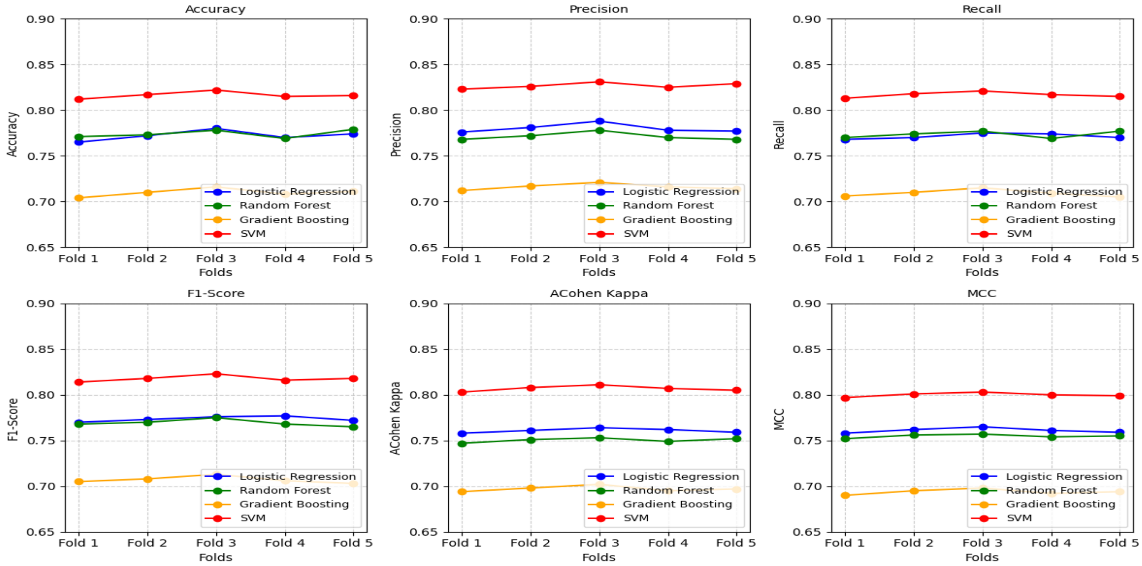

Figure 4: Classifier performance in Five folds during LULC

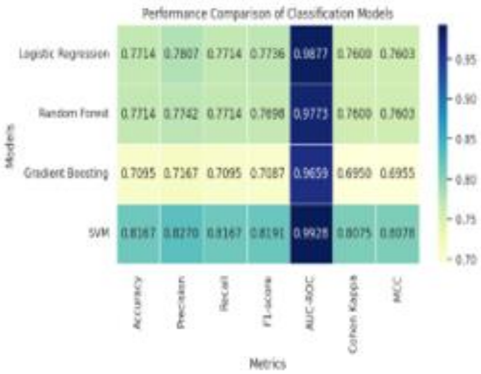

Figure 5: Average performance of Classifiers i

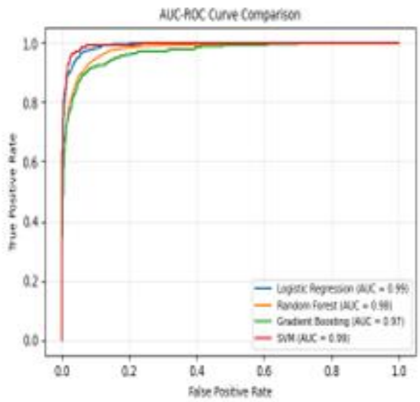

Figure 6: ROC Curve Comparison of Classifiers

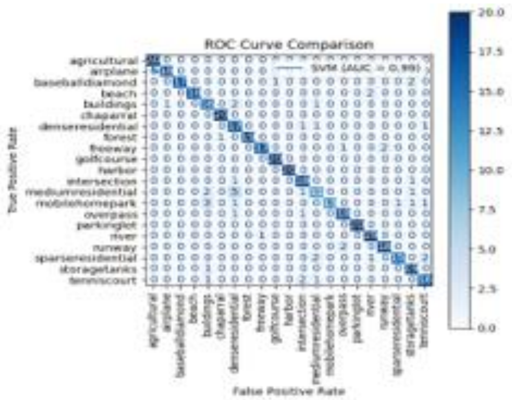

Figure 7. ROC Curve comparison of SVM

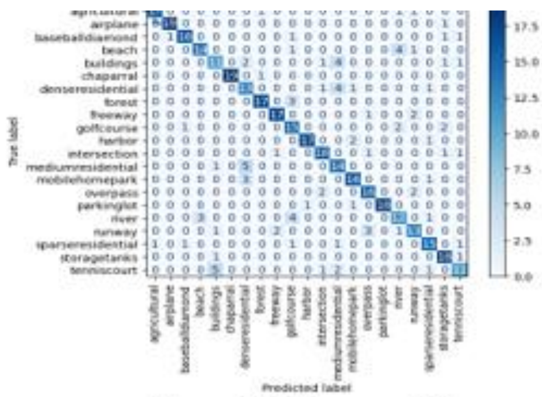

Figure 8. Performance of LR

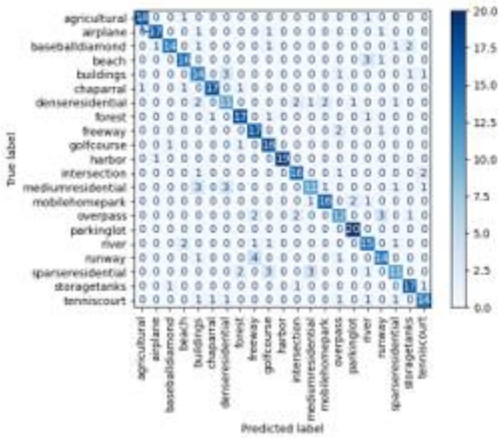

Figure 9. Performance of RF

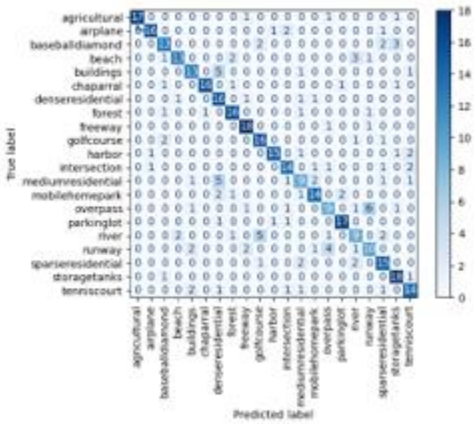

Figure 10. Performance of GBst

Figure 8, 9 and 10 show confusion matrices for LR, RF and GBst in terms of land use/cover mapping by means of 21 different classes. The diagonal entries are the number of the properly classified samples in each class, while the off-diagonal ones are the ones with mistakes. The radar reflectance is used to indicate the frequency of predictions, the darker the hue the higher the number of predictions. Most of the predictions that the model makes are near the diagonal line, this proves the model's high accuracy, but, some similar classes have been misclassified.

4.1. Insights and Key Findings

- The high performance of the SVM indicates that this type of model is quite effective when dealing with high dimensional data, in conjunction with the particular usefulness of the RBF kernel's mapping to non-linear space.
- Using PCA also contributed significantly in increasing the training efficiency and in reducing the risk of overfitting by constraining the feature space.
- Consideration of ensemble learning approaches and classifiers based on neural networks could provide classification performance enhancements in the future.

SVM classifier achieved the best performance with an accuracy of 81.67 % and AUC-ROC of 0.9928. The ability of a SVM to work with a high-dimensional space but especially with the RBF kernel has been important in the accurate modeling of non-linear dependencies in the space of the factors.

The elevated Cohen's Kappa (0.8075) and MCC (0.8078) values also support SVM strategy's reliability indicating that land use classification can be correctly done for even imbalanced or noisy data.

4.2 Performance Comparison

Both LR and RF performed parallel attaining accuracy score of 77.14 percent. Although LR is simple to model with a degree of interpretability RF performed somewhat marginally better in precision scoring of 0.7742 and 0.7807 recall and F1s scores were quite even for the pair of models.

SVM still has an overall upper hand, while according to SVM, RF achieved accuracy in retaining structural complexity due to its ensemble nature. The GBst model was the weakest in relation to the metrics such as recall score of 0.7095, F1 score of 0.7087, but then again had a 70.95 percent accuracy. This is potentially due to sensitivity to hyperparameter tuning and the dataset.

4.3 Impact of Dimensionality Reduction

The use of PCA for the reduction of dimensionality was crucial for the improvement of the model's performance as it facilitated computation by enforcing speed. The noise and irrelevant information were minimized by ensuring that only the most considerable features were retained by PCA by holding 95% of the variance.

As a result, the PCA was useful in avoiding feature overfitting because of the sheer multidimensionality of the feature vectors which have been sourced from ResNet50.

5: Conclusion and Future Research Directions

This study aims to analyze a novel methodology by combining feature extraction using ResNet50 with traditional machine-learning classifiers (SVM, RF, LR, and GBST) for land-cover classification. The results of the models demonstrate effectiveness of this method, with SVM showing highest accuracy of 81.67% and AUC-ROC of 0.9928.

The use of PCA was successful in reducing data dimensions without loss of important information which boosted the model by increasing its efficiency and getting rid of noise. These results prove that the efficacy of utilization of ResNet50 with PCA for feature extraction followed by traditional machine learning classifiers.

This hybrid paradigm has great potential of increasing the effectiveness and accuracy in LULC mapping with resultant benefits for a range of activities including urban planning, environmental surveillance, disaster management and other geospatial activities.

6.2 Future Research Directions

Although the study has successfully built a framework for land-use classification, there are several areas of consideration that could be explored further. These considerations would enable the developed method to be more accurate by expanding its ability to operate in more complex environments and with more extensive datasets.

Investigate the full set of deep learning unending networks like ResNet-101 CNN, DenseNet, and EfficientNet as additional options to learn only the blurred images instead of the pre-trained ones.

Implement transfer learning technique on the pre-trained models of machine learning that were previously fit on given land cover datasets in order to allow the models to better adapt to specific local features.

Apply multi-modal data fusion approaches in conjunction with the use of GANs to aid in the problem of class imbalance in the model.

Employ ensemble learning (e.g. stacking, bagging, and boosting) to examine stacked deep learning models that are integrated with classical machine learning classifiers for enhanced performance.

Apply Bayesian optimization and various other advanced computational algorithms (e.g., Genetic Algorithms, Particle Swarm Optimization) for efficient hyperparameters tuning.

Finally, work scopes will be to assess scalability via utilization of larger and diverse datasets, develop real-time classification systems, and nifty applications might encompass the real-time monitoring of land-use change.

References

1. G. Cheng, Z. Li, J. Han, X. Yao, and L. Guo, ‘‘Exploring hierarchical convolutional features for hyperspectral image classification,’’ IEEE Trans. Geosci. Remote Sens., vol. 56, no. 11, pp. 6712–6722, Nov. 2018.
2. M. Mahdianpari, B. Salehi, M. Rezaee, F. Mohammadimanesh, and Y. Zhang, ‘‘Very deep convolutional neural networks for complex land cover mapping using multispectral remote sensing imagery,’’ Remote Sens., vol. 10, no. 7, p. 1119, 2018.
3. S. Li, W. Song, L. Fang, Y. Chen, P. Ghamisi, and J. Benediktsson, ‘‘Deep learning for hyperspectral image classification: An overview,’’ IEEE Trans. Geosci. Remote Sens., vol. 57, no. 9, pp. 6690–6709, Sep. 2019.
4. M. A. Shafaey, M. A. Salem, H. M. Ebied, M. N. Al-Berry, and M. F. Tolba, ‘‘Deep learning for satellite image classification,’’ in Proc. Int. Conf. Adv. Intell. Syst. Inform., vol. 845, 2019, pp. 383–391.
5. G. J. Scott, M. R. England, W. A. Starms, R. A. Marcum, and C. H. Davis, ‘‘Training deep convolutional neural networks for land–cover classification of high-resolution imagery,’’ IEEE Geosci. Remote Sens. Lett., vol. 14, no. 4, pp. 549–553, Apr. 2017.
6. B. Hamida, A. Benoit, P. Lambert, and C. B. Amar, ‘‘3-D deep learning approach for remote sensing image classification,’’ IEEE Trans. Geosci. Remote Sens., vol. 56, no. 8, pp. 4420–4434, Aug. 2018.
7. Deng, Y. Xue, X. Liu, C. Li, and D. Tao, ‘‘Active transfer learning network: A unified deep joint spectral–spatial feature learning model for hyperspectral image classification,’’ IEEE Trans. Geosci. Remote Sens., vol. 57, no. 3, pp. 1741–1754, Mar. 2019.
8. Alem, A., & Kumar, S. (2022). Deep Learning Models Performance Evaluations for Remote Sensed Image Classification. IEEE Access, 10, DOI:10.1109/ACCESS.2022.3215264.
9. Huang, Q., Xia, H., & Zhang, Z. (2023). Clustering Analysis of Integrated Rural Land for

Three Industries Using Deep Learning and Artificial Intelligence. IEEE Access, 11, 110530-110543, DOI: 10.1109/ACCESS.2023.3321894

10. Z. Ma, M. Xia, H. Lin, M. Qian, and Y. Zhang, "FENet: Feature enhancement network for land cover classification," International Journal of Remote Sensing, vol. 44, pp. 1702-1725, 2023, https://doi.org/10.1080/01431161.2023.2190471
11. Patel, U., Pathan, M., Kathiria, P. et al. Crop type classification with hyperspectral images using deep learning : a transfer learning approach. Model. Earth Syst. Environ. 9, 1977–1987 (2023). https://doi.org/10.1007/s40808-022-01608-y
12. Hamza et al., "An Integrated Parallel Inner Deep Learning Models Information Fusion With Bayesian Optimization for Land Scene Classification in Satellite Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 9888-9903, 2023, doi: 10.1109/JSTARS.2023.3324494.
13. M. Aljebreen, H. A. Mengash, M. Alamgeer, S. S. Alotaibi, A. S. Salama and M. A. Hamza, "Land Use and Land Cover Classification Using River Formation Dynamics Algorithm With Deep Learning on Remote Sensing Images," in IEEE Access, vol. 12, pp. 11147-11156, 2024, doi: 10.1109/ACCESS.2023.3349285
14. Papoutsis, N. I. Bountos, A. Zavras, D. Michail, and C. Tryfonopoulos, "Benchmarking and scaling of deep learning models for land cover image classification," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 195, pp. 250-268, 2023. https://doi.org/10.1016/j.isprsjprs.2022.11.012
15. Yi Yang and Shawn Newsam, "Bag-Of-Visual-Words and Spatial Extensions for Land-Use Classification," ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS), 2010.
16. Jayanthi, S., Geraldine, J.M. (2019). Development and Investigation of Data Stream Classifier Using Lagrangian Interpolation Method. In: Saini, H., Sayal, R., Govardhan, A., Buyya, R. (eds) Innovations in Computer Science and Engineering. Lecture Notes in Networks and Systems, vol 74. Springer, Singapore. https://doi.org/10.1007/978-981-13-7082-3_38
17. Dataset: http://weegee.vision.ucmerced.edu/datasets/landuse.html