Classification of Landsat 8 Images Using Convolutional Neural Network Based on Minimum Noise Fraction Transform

Saif Kamil Shnain[1], Nahlah M. A. M. Najm[2], Nada Adnan Taher[3]
Al-Rafidain University College
Baghdad, Iraq
saif.kamil@ruc.edu.iq[1], nahla.moiuddin@ruc.edu.iq[2], nada.taher@ruc.edu.iq[3]

Alaa Salim Abdalrazzaq
Al-Noor University College
Nineveh, Iraq
alaa.salim@alnoor.edu.iq

Brzhanov Rashit
Caspian University of Technology and Engineering named after Sh. Yessenov
Aktau, Republic of Kazakhstan
вrzhanov@mail.ru

Valerii Lishchyna
Lutsk National Technical University
Lutsk, Ukraine
v.lishchyna@lutsk-ntu.com.ua

***Abstract*—The use of remote sensing methods has transformed environmental management and regional planning by allowing the identification of items or phenomena on the Earth's surface. However, noise in picture data remains a chronic difficulty in this discipline, compromising spatial resolution and object detection accuracy.**

The purpose of this study is to improve the classification accuracy of Landsat 8 pictures by developing a Convolutional Neural Network (CNN) based on the Minimum Noise Fraction (MNF) transform. The goal is to evaluate MNF's efficacy in compressing and organizing multispectral images, hence reducing the influence of noise on picture categorization.

The MNF transform is used to Landsat 8 image data to remove noisy bands before adopting CNN as a supervised classification approach. The current study takes use of CNN's inherent benefits in dealing with high-dimensional data, learning complicated representations, and automatically extracting key features from pictures, while simultaneously evaluating MNF's efficiency in increasing image quality.

The findings show that using MNF as a preprocessing step produces images with improved quality and organization. Subsequent classification using CNN obtained an astounding accuracy of 97.41%, with a great representation of the study region and varied land use categories, highlighting the synergy between MNF and CNN in improving classification performance.

The article suggests that combining MNF transform with CNN enhances classification accuracy of Landsat 8 pictures, with positive implications for developments in environmental monitoring, land use mapping, and remote sensing technologies.

I. Introduction

Remote sensing (RS) is a quick, affordable, and effective tool for Earth monitoring [1]. Making current, genuine land cover maps has gotten easier with the maturation of RS algorithms, making it possible assess and manage alterations in ecosystem and land use that result in variations in land cover [2].

Since the early 1990s, “Artificial neural networks (ANNs)”, have been utilized with positive findings to evaluate RS photographs [3]. As the remote sensing community has used ANNs more frequently, more studies are being reported by Luis Andrés Guillen, Timothy A. Warner, and Aaron E. Maxwell [4], [5]. Numerous publications have noted that ANNs have significant advantages over traditional techniques. In summary, the widely established capacity of neural techniques to understand complicated patterns is largely responsible for the quick uptake of these approaches in remote sensing, including any nonlinear complicated relationships between the dependent and explicative variables [6]. The ANN approach's ability to execute supervised categorization is another benefit utilizing less training data compared to the optimum likelihood since a category's rules of recognition because a category's criteria of recognition require less training data than the maximum probability.

CNN, Recurrent neural networks (RNN), and Recurrent-CNN (R-CNN) are examples of Deep learning (DL) approaches that have lately been extensively employed to classify remotely sensed data [7-9]. The most popular deep learning techniques for classification of satellite images are CNN-based methods. Despite CNN's enhanced performance, it still needs to be trained with a variety of hyperparameters in order to obtain the desired classification accuracy [10]. Considering that the choice and value of a hyperparameter have an impact on the accuracy of any classification algorithm, Deep learning (DL) using CNN is a potent, recently developed method for classifying images that employs many layers remote sensing photos were found to significantly enhance classification accuracy when high-level features were extracted from the raw input data [11-14]. The multi-structure CNN feature cascade method's overall classification accuracy for the University of California Merced land use dataset achieved 97.55 percent, suggesting an improvement between 2 and 5%. After fine-tuning, the accuracy increased by between 3 and 5% [15], [16].

For classifying land cover using RS datasets, DL classifiers such as CNN, deep belief network, deep autoencoder, and RNN have been extensively reported [17-20]. CNN classifier is analogously more reliable efficient at bring out the spatial characteristics among different DL classifiers. The data from distant sensing has a local link and a weight-sharing framework. CNN architectures were created by Chen et al. [21]. The proposed method used a number of convolutional and pooling layers to derive nonlinear, selective, and consistent deep attributes from hyperspectral images for extracting the spatial-spectral information from satellite imagery. These characteristics are helpful for target recognition and image classification. The gathered data demonstrates that the intended sparse restriction models deliver outcomes that are competitive with those of cutting-edge methods. A (3D)-CNN model for spatial and spectral categorization of hyperspectral image was put out by Li, Zhang, and Shen [22], the experimental Observations indicate that the postulated 3D CNN-based hyperspectral classification technique had highest accuracy across all datasets, while local 3D patterns that can be collected could enhance pattern recognition performance. An effective 3D CNN model-based kernel technique for classification was put forth by Ji et al. [23], research demonstrates that the 3D CNN performs better than other conventional techniques when it comes to defining the dynamics of crop growth. Guo et al. [24], [25] extracted spectral and multiscale spatial characteristics to create a CNN model for hyperspectral classification, While Feng et al. [26]suggested a CNN architecture that used complimentary spatial and spectral data to classify land cover. CNN and active learning were suggested by Cao et al. [20] the suggested technique performs better while using much less labeled samples.

A) The Aim of the Article

The study's objective is to investigate a novel methodology for precise land cover categorization via remote sensing data. The use of Landsat 8 satellite imagery is a significant asset in the monitoring of Earth's surface. However, conventional classification techniques often need help with this data's intricate nature and noise.

The authors of this article provide a unique approach that integrates CNNs with the Minimum Noise Fraction Transform (MNF) to improve the precision of land cover categorization. The MNF technique mitigates noise and enhances the discriminative content in Landsat 8 images. Concurrently, Convolutional Neural Networks, renowned for their efficacy in image recognition assignments, are utilized for classification.

This article aims to enhance the accuracy and dependability of land cover classification by integrating several methodologies. This improvement is significant since land cover classification finds extensive use in environmental monitoring, urban planning, and agriculture. The study introduces a potentially fruitful approach to furthering the capabilities of remote sensing and deepening our comprehension of the ever-changing landscapes of the Earth.

B) Problem Statement

The article discusses a noteworthy issue within remote sensing and image processing. The use of Landsat 8 satellite imagery offers significant insights into the observation of Earth's surface. However, the extraction of relevant data from these pictures presents challenges owing to the presence of several sources of noise and fluctuation.

This study aims to enhance the precision of land cover categorization in pictures obtained from Landsat 8. Conventional approaches need help effectively reducing noise and extracting features, resulting in less-than-ideal outcomes. The paper presents an innovative methodology that uses CNNs in conjunction with MNFT to improve the classification procedure.

The main focus is to provide a rigorous technique capable of effectively managing the varied and intricate characteristics of Landsat 8 data. This methodology must guarantee precise land cover categorization, facilitating its use in urban planning, environmental monitoring, and disaster management. The primary objective of this paper is to provide a valuable contribution to the progress of remote sensing methods and their practical implementations across many domains.

II. Literature Review

The insistence for one distinct skill set known as Deep Learning, has increased significantly over past several years in the IT industry. DL employs algorithms that draw inspiration from how the human brain or neural networks work to train computers to perform actions that come naturally to people. The ANN, Auto encoders, RNN, and Reinforcement Learning are just a few examples of the several types of models that can be used in DL. CNN is tremendously beneficial because it reduces manual input by automatically identifying the traits [27]. CNNs, a kind of deep neural network, are widely employed for the analysis of visual images because they are capable of recognizing and categorizing certain characteristics of pictures [28].

CNN uses the term "convolution" to refer to procedure involves multiplication of two functions to create a third function that describes how morphology of two functions interacts [4].

Two images that can be described as matrices are multiplied to extract features from image.

One of the key benefits of using CNNs for the classification of Landsat 8 images based on MNFT is their ability to automatically learn and extract relevant features from the input data. CNNs can effectively identify intricate patterns and spatial dependencies within the images, making them highly suited for image analysis tasks. By leveraging their hierarchical architecture, CNNs can capture low-level features such as edges and textures, and progressively learn more complex and abstract features for accurate classification. This allows the model to adapt and generalize well to various types of landscapes and environmental conditions, enhancing the classification accuracy of Landsat 8 images. Moreover, CNNs can efficiently process large datasets, enabling faster analysis and interpretation of the vast amounts of data obtained from Landsat 8 satellites. Their ability to handle high-dimensional data and learn complex representations makes CNNs a powerful tool for improving land cover classification, thus contributing to better land monitoring and environmental management efforts [29].

CNN is composed of an input, output, and numerous hidden layers, which are fundamental building blocks of architecture. In contrast to a traditional neural network, the hidden layers composed of convolution, pooling, normalizing, and fully connected layer. In order to abstractly filter input volumes,

CNN employs many Convolutions layers. CNN architecture is comprised entirely of three major elements [30]:

- Convolutional tool uses a process called feature extraction to detach and identify the diverse facets of the image for study.
- The feature-based network consists of a large number of convolutional or pooling layers.
- Using the convolutional output, a fully connected layer predicts the image's class using the information acquired in earlier processes [31].

The reduction of the number of features in a dataset is the target of this CNN classification algorithm. There are several CNN layers, as seen in the CNN architectural diagram (Fig. 1) [32].

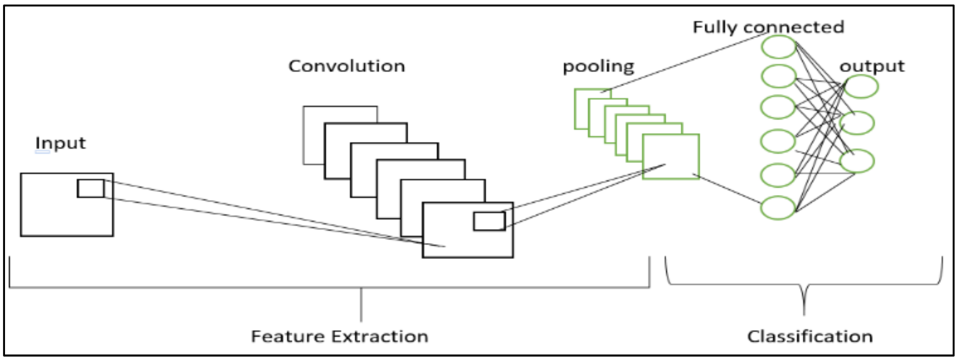

Fig.1. CNN Architecture Diagram

III. Methodology

Convolutional Neural Networks for image classification, several key components play crucial roles in the architecture. These components, along with their functionalities, contribute to the success of CNNs in extracting and learning meaningful features from input images. Three fundamental types of layers in a CNN are the convolutional layer, pooling layer, and fully connected (FC) layer [26]. The convolutional layer is responsible for extracting different characteristics from the input images through the computational convolution with specific-sized filters. This process generates feature maps that describe the image's corners and edges in detail, allowing subsequent layers to learn more features from the input [33], [34].

The pooling layer comes after the convolutional layer and aims to reduce the size of the convolved feature map. By summarizing the characteristics of the convolutional layer, the pooling layer reduces the number of connections between layers and helps generalize the features, enabling independent recognition. The FC layer, also known as the dense layer, is responsible for connecting the neurons between layers. It is typically inserted before the output layer and receives the flattened input image from the preceding layers. The FC layer performs mathematical operations to classify the input data into different categories, reducing human involvement in the process [35].

To address overfitting in the training dataset, CNNs utilize the dropout layer. This layer randomly removes a percentage of neurons from the neural network during training, reducing the model's size and preventing overfitting. The dropout rate, such as 0.3, determines the proportion of nodes removed.

Activation functions are another essential component of CNNs, responsible for defining the network's output. They determine which information should be propagated forward and which should not. For multi-class classification in a CNN model, sigmoid and SoftMax functions are commonly used. The sigmoid function is utilized for binary classification, while the SoftMax function is employed for multi-class classification. The sigmoid function is defined by Equation (1), where "a" represents the slope parameter. On the other hand, the SoftMax function is represented by Equation (2), with "Z" denoting the values from the neurons of the output layer.

$$\emptyset(s) = \frac{1}{1 + e^{(-as)}} \tag{1}$$

$$(zi) = \frac{e^{(zi)}}{\sum_j e^{(zj)}} \tag{2}$$

The various components of CNNs work together to create powerful image classification models. The convolutional layer extracts meaningful features, the pooling layer reduces data dimensionality, and the FC layer performs classification tasks. The dropout layer prevents overfitting, and the activation functions determine the final output of the network. With this architecture, CNNs demonstrate remarkable capabilities in image classification tasks, making them a popular and effective choice for various image analysis applications [28].

Minimum Noise Fraction transformation is a more effective method of compressing and arranging multispectral (and eventually hyperspectral) data according to the quality of their images [36]. The MNF transform is frequently used as a dimension-reduction approach in remote sensing and image processing sectors, because of the aforementioned feature.

Multispectral datasets contain bands with varying amounts of noise; it may be desirable to filter out or eliminate the bands that produce the greatest noise. MNF is used to identify the innate dimension of data, separate out noise from the data, and lower the computing demands for further processing [37].

MNF uses linear transformations to optimize signal-to-noise ratio (SNR) or, alternatively, to gradually lower the noise percentage. By decorrelating the bands and highlighting the data that is most pertinent to the application at hand. No matter what type of sensor or imaging device was used to capture the data, MNF may be applied to any multispectral images.

In order to apply MNF to a multispectral image, the image

data must first be transformed into a two-dimensional array, where each column corresponds to an image band and each row corresponds to an image pixel[8], [38], [39].

The mean of each band is then subtracted from all pixels in that band to center the array.

The centered data's covariance matrix is then constructed. Following the computation of the covariance matrix's eigenvectors and eigenvalues, eigenvectors are arranged in decreasing order of associated eigenvalues.

After averaging eigenvectors corresponding to lowest eigenvalues, noise eigenvectors are calculated. The noise-adjusted eigenvectors are then calculated by deducting the noise eigenvectors from the original eigenvectors.

Projecting the center image data into the area bounded by the noise-adjusted eigenvectors yields the MNF-transformed image. The information that is most pertinent to the application at hand is highlighted, and the bands are decorated [40].

The type of data used in this research is Landsat 8 images of bands 1–7 of path 168 raw 37, with the scene focused on Baghdad airport, Iraq, and the data acquired on July 27, 2019. Fig. 2 shows the image of Landsat 8 of study area.

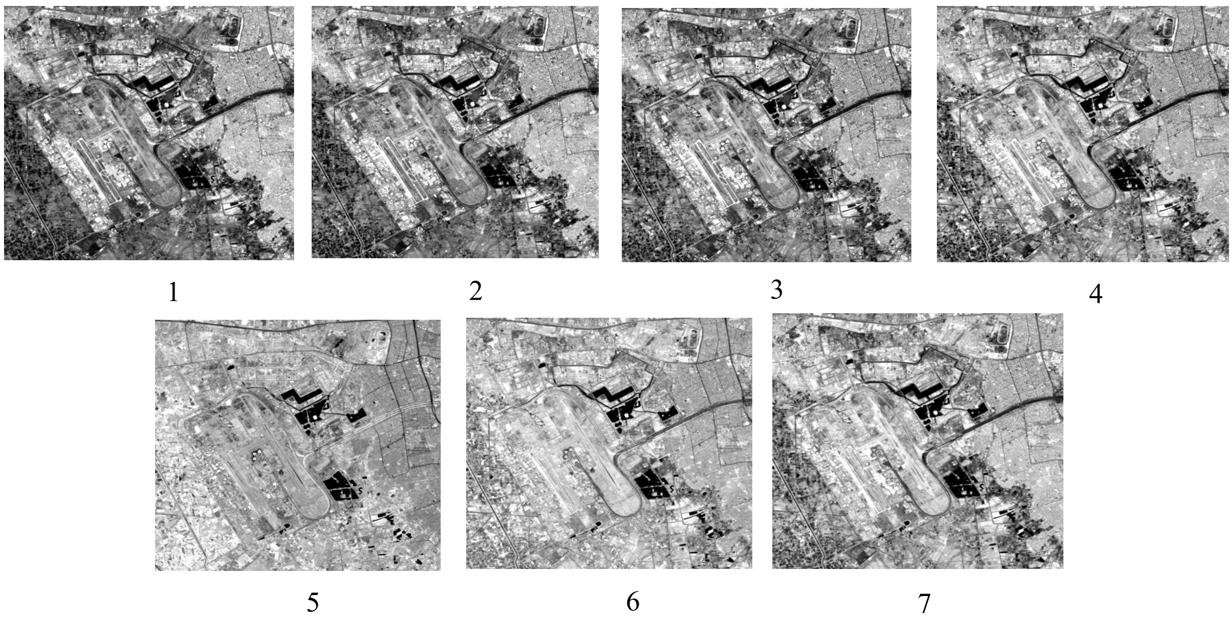

Fig. 2. Landsat 8 Images of Study Area

The methodology of research is demonstrated in Fig. 3 below.

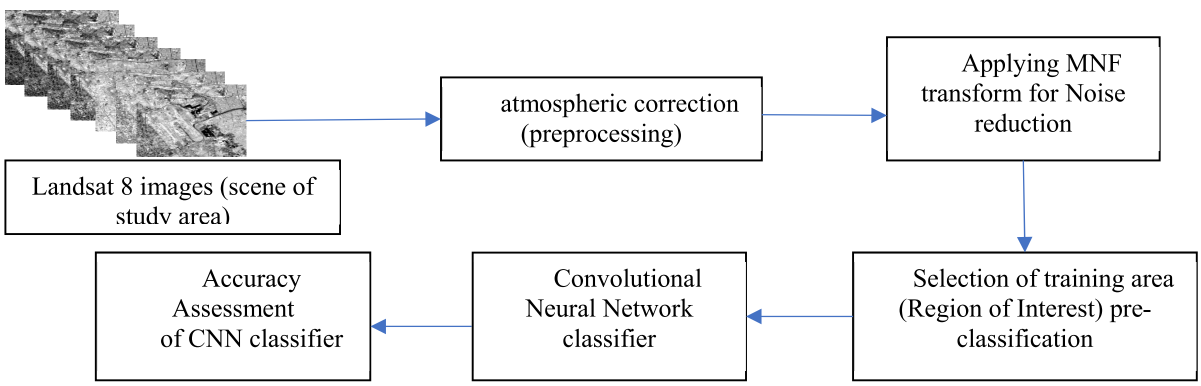

Fig. 3. Methodology Procedure

Fig. 3 depicts the research strategy for this study. Included are the input multispectral satellite images for the study area, the preprocessing method represented by calibration and atmospheric correction, the application of the MNF to reduce number of noisy bands associated with the multispectral images, which is represented as a dimensionality reduction method, and then the adoption of CNN classification method following selection region of interest.

IV. RESULTS

ENVI 5.3, a ground-breaking image processing program, was used in this work to produce the result. To eliminate the effects of air scattering and absorption, calibration and atmospheric reduction techniques have been used. These methods have demonstrated a surface with high reflectivity that is clear and has surface qualities that are visible.

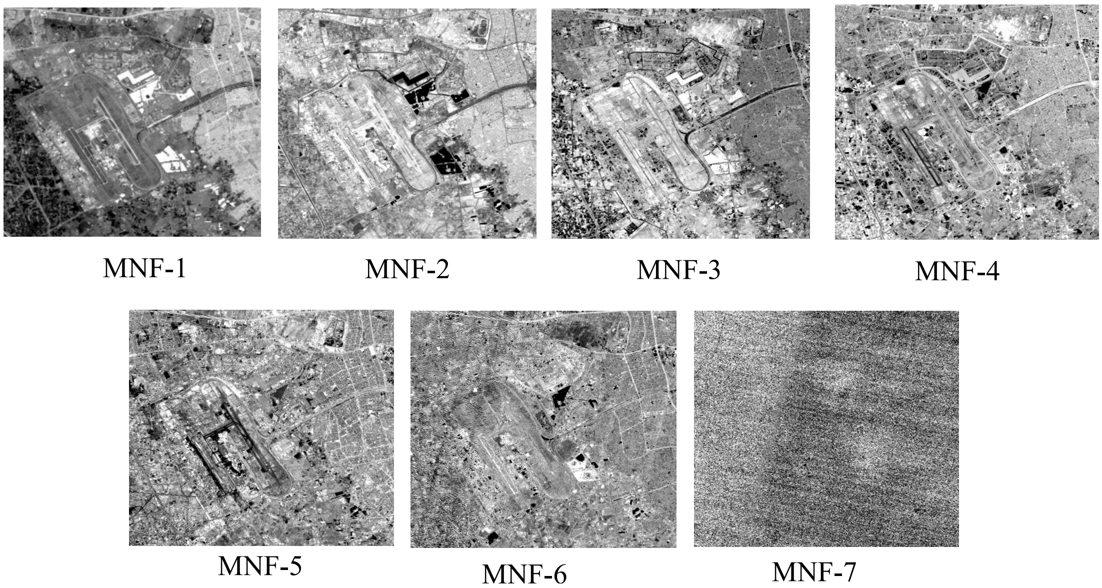

Fig. 4. The Result of MNF Transformation Method of 7 Bands

With the help of the MNF technique, noisy bands in multispectral images have been reduced. MNF demonstrated the superior representation of image bands with less noise while simultaneously reducing the number of bands used for the classification process. Seven bands have been chosen for the research region. Three bands plus a noisy residual band were produced by the MNF approach. Figure 4 shows the output of MNF method.

The first three image bands, as shown in the figure above (Fig. 4), contain the most details about the study area with the least amount of noise, whereas the residual bands contain more noise and minimal details that are unsuitable for classification.

The CNN classifier was used in the classification procedure, which was applied to MNF output. Five sorts of classes have been determined based on the region of interest for four land cover characteristics (water, vegetation, buildings, bare lands, and roads). The classification image provided an accurate depiction of land cover attributes. The CNN-classified image was 97.41% accurate.

Fig. 5 depicts the result of the classified image, whereas Table I depicts the classification confusion matrix and data.

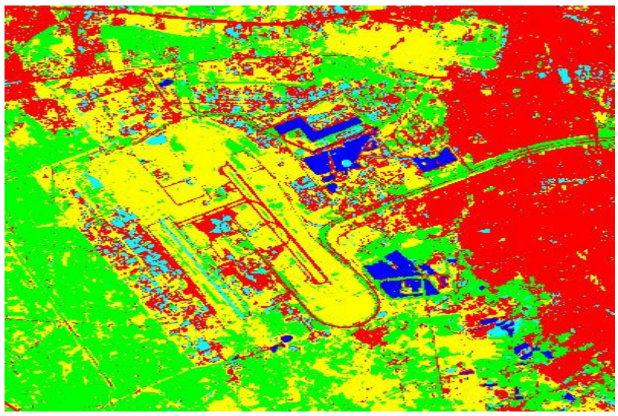

Fig. 5. Result of CNN Classifier

TABLE I. CONFUSION MATRIX OF CNN CLASSIFICATION

Overall Accuracy 97.41% of **Kappa Coefficient** = 0.9674					
	Roads	**Vegetations**	**Water**	**Bare lands**	**Buildings**
Roads	17	0	0	0	0
Vegetations	0	36	0	0	0
Water	0	0	31	9	0
Bare lands	3	0	0	32	0
Buildings	1	0	0	0	35
Total	21	36	31	32	35

V. Discussion

The article presents a novel approach to land use classification in remote sensing images. The study leverages the power of Convolutional Neural Networks combined with the Minimum Noise Fraction Transform (MNFT) to achieve accurate and efficient classification results. The research aims to improve the performance of land use classification techniques by exploiting the spatial-spectral features extracted from Landsat 8 images [1].

Comparing this article with other research in the field, it emerges as a significant contribution to the growing body of knowledge on land use classification using deep learning techniques [2-5]. The utilization of CNNs in remote sensing image classification has shown great promise in recent years [21]. However, most studies have primarily focused on exploring different CNN architectures and feature extraction methods [6], [7]. In contrast, this research introduces the MNFT as a preprocessing step to enhance the effectiveness of CNNs in land use classification.

One of the key findings of this study is the effectiveness of the MNFT in enhancing the spatial-spectral characteristics of Landsat 8 images [37], [40]. By reducing noise and improving the signal-to-noise ratio, the MNFT allows for better feature extraction, which is critical for accurate classification results. The integration of MNFT with CNNs enhances the ability of the model to capture complex spatial patterns and spectral information, resulting in improved classification accuracy [41].

The article highlights the advantages of using CNNs over traditional machine learning algorithms for land use classification [1], [42]. CNNs have shown that they are better at dealing with big and complicated datasets, like hyperspectral and multispectral pictures.

By automatically learning hierarchical features from raw pixel values, CNNs can effectively identify unique patterns and discriminate between land use classes [16], [30], [43].

Another significant contribution of this research is the evaluation of the proposed method's performance using Landsat 8 images [1]. By conducting thorough experiments and comparisons with other methods, the article demonstrates the superiority of the proposed CNN-MNFT approach in achieving higher accuracy and efficiency in land use classification [20]. The use of Landsat 8 images is particularly relevant as Landsat data provides valuable information for monitoring land cover changes and supporting various environmental and agricultural applications [23], [24].

The study showcases the significance of combining deep learning techniques with preprocessing methods to enhance the accuracy and efficiency of land use classification. Compared to other research in the field, the article stands out by focusing on the MNFT's role in improving spatial-spectral features and introducing a robust CNN architecture for land use classification using Landsat 8 images. The findings contribute to the advancement of remote sensing image analysis and offer valuable insights for future research in the domain of land use classification and environmental monitoring.

VI. Conclusion

The article presents a Convolutional Neural Network method for the classification of multispectral satellite images obtained from Landsat 8. The classification process was based on the results of the Minimum Noise Fraction Transform (MNF) method, which is a powerful technique for noise reduction and band reordering in the context of satellite image analysis.

The application of the MNF method in this study has proven to be beneficial as it reorganized the bands in the order of informativeness and noise levels. The first three bands were identified as containing the most relevant information with lower noise levels, while the latter bands were found to have less information and higher noise levels. This reordering of bands optimized the input data for the subsequent CNN classification.

The classification results using the CNN demonstrate a satisfactory depiction of various land cover classes, such as water bodies, vegetation, and bare lands. However, certain classes, such as buildings and roads, appear to overlap with each other in some regions. This issue may be attributed to the spatial resolution of the Landsat 8 images used in the study. To address this, we recommend the utilization of multitemporal images of the same research region, combined with the same methodology employed in this work. The use of multitemporal images can capture the temporal variations in land cover attributes, thereby improving classification accuracy and reducing potential misclassifications.

The proposed CNN-based classification approach combined with the MNF preprocessing technique shows promise in effectively analyzing Landsat 8 multispectral satellite images for land cover classification. The findings of this research can have valuable applications in environmental monitoring, urban planning, and land use studies, among others.

Further research and refinements to the methodology can be explored to enhance classification accuracy and address the issue of overlapping classes. Future investigations could consider incorporating additional feature extraction techniques and exploring the potential of deep learning architectures for even more accurate and robust land cover classification.

This article contributes to the field of satellite image analysis by showcasing a CNN-based classification approach and highlighting the benefits of MNF preprocessing for improved noise reduction and band reordering. With continued advancements in remote sensing technologies and machine learning techniques, the accurate classification of satellite images can be instrumental in better understanding and managing our changing environment.

References

[1] Z. Zhang, X. Cui, Q. Zheng, and J. Cao: ''Land use classification of remote sensing images based on convolution neural network'', *Arabian Journal of Geosciences*, 14, 2021

[2] L. Ghayour, A. Neshat, S. Paryani, H. Shahabi, A. Shirzadi, W. Chen, N. Al-Ansari, M. Geertsema, M. Pourmehdi Amiri, M. Gholamnia, J. Dou, and A. Ahmad: ''Performance Evaluation of Sentinel-2 and Landsat 8 OLI Data for Land Cover/Use Classification Using a Comparison between Machine Learning Algorithms'', *Remote Sensing*, 13, (7), 2021, pp. 1349

[3] J. F. Mas, and J. J. Flores: ''The application of artificial neural networks to the analysis of remotely sensed data'', *International Journal of Remote Sensing*, 29, (3), 2008, pp. 617-63

[4] N. Qasim, Y. P. Shevchenko, and V. Pyliavskyi: ''Analysis of methods to improve energy efficiency of digital broadcasting'', *Telecommunications and Radio Engineering*, 78, (16), 2019

[5] A. E. Maxwell, T. A. Warner, and L. A. Guillén: ''Accuracy Assessment in Convolutional Neural Network-Based Deep Learning Remote Sensing Studies—Part 1: Literature Review'', *Remote Sensing*, 13, (13), 2021, pp. 2450

[6] J. L. Giraudel, and S. Lek: 'Ecological Applications of Non-supervised Artificial Neural Networks', in Recknagel, F. (Ed.): 'Ecological Informatics: Scope, Techniques and Applications' (Springer Berlin Heidelberg, 2006), pp. 49-67

[7] K. L. Xin WANG, Chen NING, Fengchen HUANG.: '' Remote Sensing Image Classification Method Based on Deep Convolution Neural Network and Multi-kernel Learning[J]. '', *Journal of Electronics & Information Technology*, 41, 2019, pp. 5

[8] N. Qasim, and V. Pyliavskyi: ''Color temperature line: forward and inverse transformation'', *Semiconductor physics, quantum electronics and optoelectronics*, 23, 2020, pp. 75-80

[9] L. Liao, Y. Zhao, S. Wei, Y. Wei, and J. Wang: ''Parameter Distribution Balanced CNNs'', *IEEE Transactions on Neural Networks and Learning Systems*, 31, (11), 2020, pp. 4600-09

[10] S. Bera, and V. Shrivastava: ''Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification'', *International Journal of Remote Sensing*, 41, 2020, pp. 2664-83

[11] F. Zhang, B. Du, and L. Zhang: ''Scene Classification via a Gradient Boosting Random Convolutional Network Framework'', *IEEE Transactions on Geoscience and Remote Sensing*, 54, 2015, pp. 1-10

[12] H. Liang, and Q. Li: ''Hyperspectral Imagery Classification Using Sparse Representations of Convolutional Neural Network Features'', *Remote Sensing*, 8, (2), 2016, pp. 99

[13] O. I. Yurii Khlaponin, Nameer Hashim Qasim, Hanna Krasovska, Kateryna Krasovska: 'Management Risks of Dependence on Key Employees: Identification of Personnel', in Editor (Ed.)^(Eds.): 'Book Management Risks of Dependence on Key Employees: Identification of Personnel' (CPITS, 2021, edn.), pp. 295-308

[14] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov, ": ''Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data'', *IEEE Geoscience and Remote Sensing Letters*, 17, (5), 2017, pp. 778-82

[15] B. A. Hamida, A. Benoit, and P. Lambert, : ''3-D Deep Learning Approach for Remote Sensing Image Classification'', *IEEE Transactions on Geoscience and Remote Sensing*, 5, (8), 2018, pp. 4420–34.

[16] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. Johnson: ''Deep learning in remote sensing applications: A meta-analysis and review'', *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 2019, pp. 166-77

[17] A. M. Jawad, N. H. Qasim, H. M. Jawad, M. J. Abu-Alshaeer, R. Nordin, and S. K. Gharghan: ''NEAR FIELD WPT CHARGING A SMART DEVICE BASED ON IOT APPLICATIONS'', *TTSIIT*, 2022, pp. 12

[18] E. Paoletti, J. M. Haut, J. Plaza, and A. Plaza: ''Deep learning classifiers for hyperspectral imaging: A review'', *ISPRS Journal of Photogrammetry and Remote Sensing*, 158, 2019, pp. 279-317

[19] N. Audebert, B. Le Saux, and S. Lefèvre: ''Deep Learning for Classification of Hyperspectral Data: A Comparative Review'', *IEEE Geoscience and Remote Sensing Magazine*, 7, (2), 2019, pp. 159–73.

[20] X. Cao, J. Yao, Z. Xu, and D. Meng: ''Hyperspectral Image Classification With Convolutional Neural Network and Active Learning'', *IEEE Transactions on Geoscience and Remote Sensing*, 58, 2020, pp. 4604-16

[21] Y. Chen, H. Jiang, C. Li, X. Jia, and P. Ghamisi: ''Deep Feature Extraction and Classification of Hyperspectral Images Based on Convolutional Neural Networks'', *IEEE Transactions on Geoscience and Remote Sensing*, 54, (10), 2016, pp. 6232-51

[22] A. B. Chan, L. Zhang-Sheng John, and N. Vasconcelos: 'Privacy preserving crowd monitoring: Counting people without people models or tracking', in Editor (Ed.)^(Eds.): 'Book Privacy preserving crowd monitoring: Counting people without people models or tracking' (2008, edn.), pp. 1-7

[23] S. Ji, Z. Chi, A. Xu, and Y. Duan: ''3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images'', *Remote Sensing*, 10, 2018, pp. 75

[24] A. M. J. A.-A. Nameer Hashim Qasim, Haidar Mahmood Jawad, Yurii Khlaponin, Oleksandr Nikitchyn: ''DEVISING A TRAFFIC CONTROL METHOD FOR UNMANNED AERIAL VEHICLES WITH THE USE OF GNB-IOT IN 5G.'', *Eastern-European Journal of Enterprise Technologies*, 117, (9), 2022, pp. 53-59

[25] Y. Guo, L. Sun, Z. Zhang, and H. He,: '' Algorithm Research on Improving Activation Function of Convolutional Neural Networks'', *Chinese Control and Decision Conference, Nanchang, China, 2019*, pp. 3582-86

[26] J. Feng, J. Chen, L. Liu, X. Cao, X. Zhang, L. Jiao, and T. Yu,: '' CNN-Based Multilayer Spatial-Spectral Feature Fusion and Sample Augmentation with Local and Nonlocal Constraints for Hyperspectral Image Classification'', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12, (4), 2019, pp. 1299–313.

[27] A.-N. Sharkawy: ''Principle of Neural Network and Its Main Types: Review'', *Journal of Advances in Applied & Computational Mathematics*, 7, 2020, pp. 8-19

[28] R. Dastres, and M. Soori: ''Artificial Neural Network Systems'', *International Journal of Imaging and Robotics*, 21, 2021, pp. 13-25

[29] L. Huang, and Y. Chen: ''Dual-Path Siamese CNN for Hyperspectral Image Classification With Limited Training Samples'', *IEEE Geoscience and Remote Sensing Letters*, PP, 2020, pp. 1-5

[30] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi: ''A survey of deep neural network architectures and their applications'', *Neurocomputing*, 234, 2017, pp. 11-26

[31] I. Namatevs: ''Deep Convolutional Neural Networks: Structure, Feature Extraction and Training'', *Information Technology and Management Science*, 20, 2017

[32] A. N. Sharkawy, P. N. Koustournpardis, and N. Aspragathos: 'Variable Admittance Control for Human-Robot Collaboration based on Online Neural Network Training', in Editor (Ed.)^(Eds.): 'Book Variable Admittance Control for Human-Robot Collaboration based on Online Neural Network Training' (2018, edn.), pp. 1334-39

[33] Q. N. Hashim, A.-A. A. M. Jawad, and K. Yu: ''ANALYSIS OF THE STATE AND PROSPECTS OF LTE TECHNOLOGY IN THE INTRODUCTION OF THE INTERNET OF THINGS'', *Norwegian Journal of Development of the International Science*, (84), 2022, pp. 47-51

[34] E. Tatulli, and T. Hueber: 'Feature extraction using multimodal convolutional neural networks for visual speech recognition', in Editor (Ed.)^(Eds.): 'Book Feature extraction using multimodal convolutional neural networks for visual speech recognition' (2017, edn.), pp. 2971-75

[35] S. Jeon, A. Elsharkawy, and M. S. Kim: ''Lipreading Architecture Based on Multiple Convolutional Neural Networks for Sentence-Level Visual Speech Recognition'', *Sensors*, 22, (1), 2022, pp. 72

[36] L. Alzubaidi, J. Zhang, A. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. Fadhel, M. Al-Amidie, and L. Farhan: ''Review of deep learning: concepts, CNN architectures, challenges, applications, future directions'', *Journal of Big Data*, 8, 2021

[37] A. A. Green, M. Berman, P. Switzer, and M. D. Craig: ''A transformation for ordering multispectral data in terms of image quality with implications for noise removal'', *IEEE Transactions on Geoscience and Remote Sensing*, 26, (1), 1988, pp. 65-74

[38] A. Ghosh, B. U. Shankar, and S. K. Meher: ''A novel approach to neuro-fuzzy classification'', *Neural Netw*, 22, (1), 2009, pp. 100-9

[39] N. Hashim, A. H. Mohsim, R. M. Rafeeq, and V. Pyliavskyi: ''Color correction in image transmission with multimedia path'', 2006

[40] J. Burger, and A. Gowen: ''Data handling in hyperspectral image analysis'', *Chemometrics and Intelligent Laboratory Systems*, 108, (1), 2011,

[41] pp. 13-22

[42] N. Hashim, A. Mohsim, R. Rafeeq, and V. Pyliavskyi: ''New approach to the construction of multimedia test signals'', *International Journal of Advanced Trends in Computer Science and Engineering*, 8, (6), 2019, pp. 3423-29

[43] D.-Y. Chen, C.-C. Chen, and L.-W. Kang: ''Visual Depth Guided Color Image Rain Streaks Removal Using Sparse Coding'', *Circuits and Systems for Video Technology, IEEE Transactions on*, 24, 2014, pp. 1430-55

[44] Z. L. Li, Fan & Yang, Wenjie & Peng, Shouheng & Zhou, Jun. : ''A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. '', *IEEE Transactions on Neural Networks and Learning Systems*, 2021, pp. 1-21