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AI-Powered Land Classification: Analyzing Deep Learning Models for Urban and Desert Images

Nishpa Das , ***Fathima Hasna Zainulabdeen*** * , ***Smitha Sunil Kumran Nair***

Department of Computing and Electronics, Middle East College, Muscat 124, Oman

ABSTRACT

Land degradation and environmental concerns resulting from rapid urbanization in Oman in recent years have made innovative and advanced strategies and approaches for sustainable urban planning & environmental preservation a necessity. This research presents an AI-based classification and analysis method that utilizes Deep Learning algorithms to analyze satellite and drone images for monitoring urban growth and desertification. A Convolutional Neural Network (CNN)-based binary image classification model was developed to distinguish between urban infrastructure and natural landscapes based on the datasets retrieved from Kaggle and its performance was evaluated by accuracy, precision, recall, and F1 score. The CNN model achieved an accuracy of 53%, but the confusion matrix demonstrated poor performance for classifying urban areas with a recall of 0.00 for the Urban class. To address this issue, a pre-trained model was implemented, achieving 54% accuracy and stronger class-wise recall for both categories compared to the baseline CNN model. The results demonstrated both the potential and the limitations of deep learning models for land classification tasks, delivering valuable insights for urban planning and environmental monitoring, where visual similarities pose major challenges. Despite modest accuracy, the study demonstrates the feasibility of AI-driven land assessment as an additional tool for environmental monitoring, urban expansion tracking and desertification analysis. Furthermore, it aligns with Oman Vision 2040 digital transformation and supports Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action) and SDG 15 (Life on Land), by emphasizing data-driven approaches for sustainable development and ecological resilience.

Keywords: Urban Planning; Environmental Monitoring; Convolutional Neural Networks (CNN); ResNet; Land Cover Classification

*CORRESPONDING AUTHOR:

Fathima Hasna Zainulabdeen, Department of Computing and Electronics, Middle East College, Muscat 124, Oman; Email: 22f22703@mec.edu.om

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1. Introduction

1.1. Background & Context

Urban growth and desertification portray two contrasting yet intertwined challenges in the field of environmental sustainability and urban planning. As growing populations and economic operations are requiring expanded accommodation by cities, natural environment, like forests, mountains, etc., are appreciably modified, leading to land degradation, biodiversity loss, and raised environmental concerns [1]. Concurrently desertification, intensified by climate variations and unsustainable land use, continues to stress and threaten arable land and environmental stability [2].

Recent global trends indicate rapidly increasing urban land covers driving significant environmental consequences. Zhao et al. [3] explored global urban extents from 1992 to 2020 and found that the proportion of Urban land rose from 0.22% to 0.69% globally of Earth's surface, reflecting accelerated urban growth. Such expansion is often accompanied by urban heat island effects, increased soil degradation, and biodiversity loss. Tian et al. [4] further argue that urbanization today is not only about land expansion but also structural changes such as reduced vegetation and increased fragmentation. The United Nations also projects that 68% of the world population will live in cities by 2050, intensifying pressure on land systems [5].

The sultanate of Oman, like many other countries in the Middle East, has been witnessing increased urbanization to facilitate economic and population growth while ruralization has been gradually decreasing, as shown in **Figure 1** [6]. The rise of approximately 10% in 1950 to 80% in 2020 has been recorded and expected to go up to 85% by 2040 for urban areas. However, this growth has been transformed by compromising raised desertification risks, mainly due to poor land management planning and practices and climate changes in the Sultanate. It is very crucial to understand these contexts and implement sustainable urban planning strategies that mitigate land degradation and simultaneously promote expansion of urban areas. In Oman, land degradation remains a significant environmental challenge. According to Al-Hashmi [7] around 95% of Oman's territory is arid or vulnerable to desertification, with lands suffering from overgrazing and declining productivity. Since 1970, Oman and Sohar undergoing major expansion and rapid urban development has been documented by Benkari [6]. These insights stress the urgency of integrating monitoring tools into national urban planning.

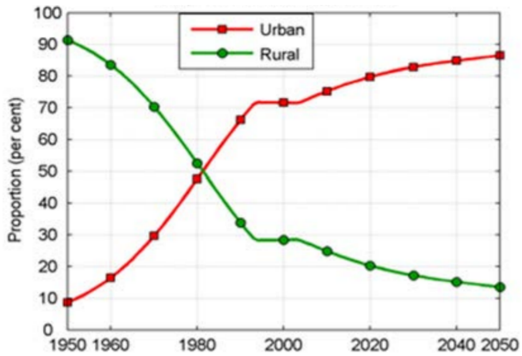

Figure 1. Urban vs Rural Growth in Oman.

Source: Adapted from Benkari [6].

Artificial Intelligence (AI) is a remarkable tool that can be utilized in environmental planning and monitoring by analyzing and classifying land use patterns. Convolutional Neural Network (CNN), is a type of deep learning architecture within the broader field of machine learning, that has the capabilities in processing and interpreting satellite and aerial images for land classification activities [8]. By utilizing AI for terrain analysis, policy makers can gain real time insights and make data-driven decision-making into urban growth trends, desert progression, and land management policies. This study explores AI-driven binary image classification and explores how it can aid sustainable urban planning by differentiating between desert and urban satellite images, to provide supportive data-driven decisions for environmental monitoring and sustainability.

Recent studies in arid environments indicate the capability of satellite-based forecasting. Mansour et al.[9] showed how thousands of hectares of desert land are projected to convert into urban zones by 2050 using satellite imagery and predictive methods in Ibri, Sultanate of Oman. On the other hand, Rivera-Marin and Ogutu[10] also reviewed global desertification monitoring, concluding that while remote sensing is widely applied, a gap in combining deep learning with desert-urban classification, particularly in Middle Eastern Regions.

1.2. Problem Statement

In this growing and developing era, regions like Oman, are victims of desertification due to rapid urban expansion which are critical environmental and development concerns. Using traditional approaches, like manual surveys and Geographic Information Systems (GIS), to monitor and keep track can be challenging due to extensive manual labor, time consumption, resources intensiveness and limited scalability[11]. The limitation of automated, real-time and high accuracy methods to classify lands prohibits the policymakers from making informed decisions about sustainable urban planning and environmental preservations.

Deep Learning models, such as Convolutional Neural Networks (CNNs), studied by Krizhevsky et al.[12] have exhibited a major potential in automating complex image classification tasks containing several images. However, using CNN method to distinguish between urbanized and desert regions and its effectiveness in Oman remains underexplored. This research article aims to address this research gap by studying and implementing such AI-based models using satellite images for land classification. Furthermore, this study provides an efficient and scalable solution along with future recommendations for urban expansion monitoring.

1.3. Objectives of the Study

The objective of this study includes the study of CNN in image classification, specifically focusing on deep learning techniques on land-type application. A built-in CNN model and a pre-trained (ResNet) model were utilized to distinguish between urban and desert images. The performance was compared using key classification metrics such as accuracy, precision, recall and F1-score. In addition, this study will explore and suggest real-world usage of AI-based land classification models. Finally, recommendations for future enhancements highlighting the possibilities for improved real-time environmental monitoring and analysis.

1.4. Significance and Contribution

This study contributes to both regional and global research on land-use and land-cover (LULC) classification using deep learning techniques. Several studies, like Said et al.[13] and Zhu[8] emphasize on challenges that are still faced by deep learning models on visually similar land types, especially in arid regions where urban areas and desert zones often look alike. However, pre-trained models can improve feature extraction in remote sensing tasks, although performance varies depending on dataset quality and region[14]. This study tests both a built-in CNN model and a pre-trained ResNet model on publicly available datasets, and provides additional evidence on how binary land classification performs n environments, where misclassification is common. This assists in filling the gap in the literature, especially for studies focused on desert-urban classes, which is not widely explored in Middle Eastern contexts.

Regionally, this study aligns with Oman Vision 2040[15], which emphasizes sustainable urban development and advancing smart technologies in Oman using AI and remote sensing, in national planning. This research supports not only Oman Vision 2040 objectives but also supports Sustainable Development Goals (SDGs) 13 (Climate Action) by upgrading and strengthening environmental monitoring and 15 (Life on Land) by assisting in natural conservation efforts[16]. Overall, this study provides both local and global value by offering insights into how deep learning models can support the monitoring of urban expansion and land degradation.

2. Literature Review

2.1. Contributors of Desertification

Desertification is the process of land degradation in arid and semi-arid areas, which poses a severe challenge in Oman and across the Middle East[17]. Approximately 95% of the Sultanate is classified as desert or hyper-arid land, with much of it experiencing significant land degradation. A recent climate analysis in Oman found a statistically significant increase in the frequency and severity of droughts over the past 40 years [15]. Due to this, Oman faces soil degradation problems. The wider Middle East and North Africa (MENA) regions face some of driest and most degrading areas on Earth. This issue troubles ecosystems and livelihoods, food and water scarcity increases as healthy ecosystems get transformed into barren and unproductive terrain [18].

Multiple drivers fuel desertification in the MENA region. A significant factor is climate change which brings intensified aridity and drought frequency. This chronic deficit in moisture reduces vegetation and water resources, destroying land resilience [19]. Other key contributors include deforestation, overgrazing and unsustainable farming, and unchecked urban expansion, all of which degrade soil and vegetative cover. Rapid population growth and economic development further increase demand for land and water [20]. As MENA population's growth climbs, the need for food security and sustainability of resources go hand in hand, making it both a socio-economic and environmental threat [16].

Swift urbanization indirectly contributes to desertification. Expansion in urban areas leads to land degradation in the following ways. First, it causes the direct loss of vegetative cover and topsoil, which may trigger the local desertification processes in case it was a previously semi-productive, but semi-arid land [21]. In dry climates, plants and topsoil are important in holding down the topsoil, when they are cleared off to build a construction the left-over bare soil is easily eroded by the wind and water. In fact, researchers observe that unplanned or inadequately planned urban sprawl in dry and semi dry areas causes loss of green cover, broken ecosystems [10].

There is also a lot of building and paving in the Gulf which enhances water runoff and decreases the natural ground water recharge, which might escalate the effects of drought on the nearby territories [22]. In Oman, the urban development occurs in most places along the coast or oasis, which were once richer in vegetation. As city centres such as Muscat, Sohar, or Salalah grow, they overtake the orchards, farms or scrubland, establishing the need for mitigation strategies [10].

It is evident that in the absence of sustainable planning, the rapid urbanisation process occurring in Oman and the MENA region has the potential of accelerating the process of desertification both in terms of land conversion and through the increased demands on water and land resources [23]. This has been identified in the literature as the necessity to incorporate land degradation concerns in urban planning and expansion policies.

2.2. Initiatives for Combating Desertification

Desertification needs to be addressed through united action in terms of restoration, sustainable management, and policy, which Oman and other MENA nations have begun to address already. Some of the important strategies include ecosystem restoration and reforestation [24]. In 2020, Oman established a national initiative to plant 10 million trees, with a clear scope to increase the green cover, regenerate unmanaged lands and combat desertification. In dry areas, native drought resistant trees are being planted in arid areas to stabilize the soils and enhance the vegetation cover [25].

On the policy level, Oman and its neighbours are aligning itself with the global structures and making long term plans. Oman Environment Authority has made periodic updates to a National Plan to Combat Desertification at regular intervals which is coordinated with the Arab Organization on Agricultural Development which keeps the local activities aligned with the best international practices. Oman is also an active signatory of the United Nations Convention to Combat Desertification (UNCCD) and it also participates in its Conference of Parties like COP16 in 2024 in order to exchange experiences and to learn how other nations can address the issue of desertification [25].

The strategy of Sultanate of Oman, which is a combination of tree planting, conserving green spaces, updating the existing policy frames, and engaging with the community, aligns well with the wider regional vision of sustainable land management.

2.3. AI-Based Models for Urban and Desert Monitoring

Recently, an emerging trend is the application of advanced technologies, including artificial intelligence (AI), to monitor and combat desertification. Geospatial analysis and remote sensing have long been needed in the measurement of land cover change in extensive deserted areas. These capabilities are being improved by AI and machine learning methods now, which enable creating more accurate mapping, prediction, and resource optimization [8,26,27]. The above challenges can be solved with promising solutions that are provided by advances in Geospatial Artificial Intelligence (AI). Specifically, Deep Learning (Convolutional Neural Networks or CNNs) have shown exceptional ability in land-use/land-cover classification of remotely sensed imagery [8,14]. In contrast to older forms of mapping using GIS or analogous surveys that require a considerable amount of human labour and are frequently slow to respond to changes, AI solutions can automatically examine high amounts of satellite and aerial data to detect urban growth and environmental change patterns in near-real-time [11,28].

In terms of recent in-depth reviews, deep learning strategies prove to be superior to the traditional ones. The traditional methods of classification have high repeatability and timeliness against visual interpretation, but the accuracy of the classification will be significantly low once the data or study area is changed [8,28]. Deep learning, unlike conventional machine learning algorithms, has special strengths in image classification. Recent architectures are highly performance efficient, and researchers have reported a high accuracy of 90 percent on fine-tuning ResNet models on satellite images datasets to perform land-use classification [28]. The conceptual comparison of performance of deep learning and traditional machine learning methods with respect to the data volume is shown in **Figure 2**.

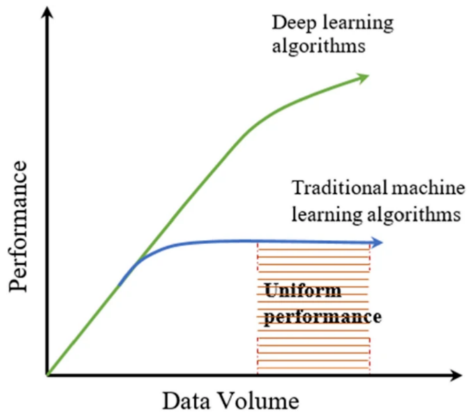

Figure 2. Performance of Deep Learning vs Traditional Learning Techniques.

Source: Adapted from Ahmed et al. [27].

In this section, prior research and studies on AI based models for urban and desert monitoring and the traditional ways of environmental monitoring and analysis are explored. Gavade and Gavade [11] explored the limitations of traditional methods for Land Use Land Cover (LULC), including human perspicacity and inconsistency in results, time and resources limitations and limitation of huge and diverse data integration. They also suggested the potential of AI-based models highlighting the advantages like integration of data from different sources, enhanced accuracy of classification of large dataset, automation of analysis in short amount of time and more. This implies a CNN-based model can outperform traditional ways of classification.

Feng et al. [26] employed different machine learning techniques, such as Support Vector Machines (SVM) and Decision Trees, and deep learning models like CNNs to classify LULC types and studied how these various techniques can be applied on remote sensing data to monitor environmental patterns in desertification. However, some challenges, like the need of high-quality dataset and complication in differentiating desert and barren land has been highlighted. This research paper aligns with the idea of the proposed work with the significance of deep learning's potential in land classification, although lacks an analysis on different CNN based transfer learning model.

The scarcity of labeled data in dry areas has motivated scientists to gravitate towards transfer learning methods [26]. Transfer learning (TL) is the use of information acquired in the old domain (source domain) to the new domain (target domain) that offsets the adverse effect of sample scarcity and enhances the generalization capability of the model resulting in more accurate classification. This especially applies to Omani contexts in which the ground truth data might be minimal [29].

Addressing the usage of ResNet, Douass and Kbir[14] carried out a study by applying a deep learning architecture for land use images classification on Tangier region in Morocco. The methodology includes extracting the images from Flickr API, transforming it and loading them in a pre-trained model ResNet 18 model. The training results obtained an accuracy of 94%, implying AI model's effectiveness in large scale urban monitoring. A confusion matrix was used to assess the classification performance, emphasizing areas where the model struggles, yet another similar study conducted to highlight the impact of AI in land classification.

Despite AI-based land classification have numerous advantages, like ability in capturing and analysing of large and complex dataset, integration of multiple data sources[29], etc., some challenges have been recognized, including limited data diversity, overfitting due to small training dataset, lower quantity of recent land images[30] which can hinder the generalization ability of the model. Moreover, most research done priorly, has been centralized on urban and rural classification only and not between desert and urban regions, which is critical for Middle East countries like Oman, where desert is a major region and desertification is a growing concern lately[13].

This research aims to address these gaps by developing an image classification CNN-based models to improve urban and desert classification, using diverse datasets from various sources, applicable for real-world problems in urban planning and environmental monitoring.

2.4. Data Challenges and Regional Limitations

A critical gap in current research is the lack of region-specific datasets for Middle Eastern contexts[26]. Pixel-level samples lack a large and high-quality dataset like the patch-level. The samples in pixels do not have a high and large dataset as the patch-level. In addition, the covered areas are quite homogeneous and can only be applied to particular areas, and the generalizability should be enhanced. The patch-level dataset has lesser spectral bands, and this reduces the capability of the model to derive spectral information of the features and thereby restricts the application[29].

It is difficult to monitor desertification in arid lands where sustainable development is held back[26]. Remote sensing plays a crucial role in monitoring changes in land surfaces and ecosystems, but spatial and temporal data is very demanding and cannot be readily acquired by field surveys only[13].

2.5. The Critical Perspective

The limitations of AI-based land classification systems come from a few practical and environmental reasons. The models may sometimes reduce complex ecological processes into very simple classifications, so important environmental details can be left out. Another limitation is data dependency. Since large and diverse training samples are required, areas with limited satellite images or little ground-truth information may not be monitored properly. Difficulties also appear during validation, especially in dry regions where conditions can change quickly. This means the land seen during data collection may not look the same when the model is checked later, which affects how reliable the results are. Interpretability is another concern, as deep learning models are not always easy to understand, making it harder for environmental managers to know why a certain classification was made.

3. Materials and Methods

3.1. Dataset and Preprocessing

This study addresses the clear knowledge gap in the existing literature, especially in deep learning applications for separating desert and urban landscapes in arid regions, by building a classification model prototype, where we used satellite and drone images extracted from multiple publicly available sources on Kaggle, representing desert or urban. The images were then shuffled and stored in Google Drive. Around 7080 images were collected and split into 80% training, 20% testing and 16% validation, to build a strong model to mitigate overfitting problems and ensure strong evaluation. As a preprocessing step, all images were resized 256 × 256 pixels, ranging between 0 and 1 assuring normalization, to enhance the model's performance. A validation split was applied, where a portion of the dataset was automatically separated and used to monitor the model's performance, helping in identifying fit issues during the training stage.

To enhance the diversity of the dataset and decrease overfitting, data augmentation methods were used, which are common in the remote sensing application[31]. Techniques included rotation (0°, 90°, 180°, 270°), horizontal and vertical flipping, and brightness adjustment (±20%) to simulate different lighting conditions commonly encountered in satellite imagery. Image normalization was done according to ImageNet preprocessing norms, having the pixel values normalized to fall within [1] range and normalized using mean = [0.485, 0.456, 0.406] and standard deviation = [0.229, 0.224, 0.225] of RGB channels. Stratified sampling was applied to divide the dataset in an equal number of each of the two classes in the training, validation, and test sets to adhere to the best practices in binary classification tasks. The limitation of the study was that cross-validation was not applied because of the computational constraints.

3.2. Model Architecture

To address this problem of limited development of AI-based models to track urban expansion and assesses desertified areas, two deep learning models have been developed: a built-in Convolutional Neural Network (CNN) and a pre-trained ResNet model. The built-in CNN model included 3 convolutional layers with 32, 64, and 128 filters, along with layers of max-pooling and batch normalization to mitigate overfitting. These layers helped capture low level features, raising generalization of the model.

The model developed using ResNet, has more advanced architecture and was effective for training deeper networks. The top layers were frozen, and an average pooling layer was added. Both the models had a learning rate of 0.0001 and the final layer had a sigmoid function to output a binary classification: Urban and Desert. The models were trained using Adam optimizer and validated 15 times to improve the model's accuracy by learning from the data multiple times. The model's performance was evaluated on the basis of accuracy, precision, recall and F1-score.

4. Results and Discussion

4.1. Performance Metrics

The performance of both models was evaluated using metrics, consisting of accuracy, precision, recall, and F1-score. The built-in CNN model achieved 99% accuracy on the training dataset and 99% on the validation dataset, however, the accuracy dropped to 52% during real-world testing performance using testing dataset. Similar direction has been noticed in ResNet model's performance too, with stronger generalization in validation with 96% accuracy, followed by a decline in testing accuracy with 47% (shown in **Table 1**).

Table 1. CNN and ResNet Performance.

Tool	Accuracy	Precision	Recall	F1-Score
Proposed CNN Model	52%	52% (0) and 52% (1)	52% (0) and 52% (1)	52% (0) and 52% (1)
ResNet (Pre-trained) Model	47%	47% (0) and 48% (1)	43% (0) and 51% (1)	45% (0) and 49% (1)

In these models, 0 is Desert and 1 is Urban. Further limitations of testing dataset were highlighted and perceived using confusion metrics. The proposed CNN model has obtained equal precision of 52%, recall and F1-score for both classes, implying the model's difficulty to distinguish between the two classes competently. Whereas the ResNet model displayed precision value of 47% and 48%, recall values of 43% and 51%, and F1-score of 45% and 49%, for urban and desert respectively, which is slightly lower in accuracy compared with CNN model.

Given that the accuracy of both models is close to 50%, the results display the models performed only slightly above random chance. This indicates that the technology isn't very suitable yet for practical use. A major contributing factor is the limited and non-ideal dataset: the satellite images used in this study were of relatively low quality and lacked clear features, making it difficult for the models to learn meaningful patterns. To achieve reliable classification between desert and urban landscapes, future work will require much larger, more diverse and high-resolution images. Additionally, deeper training, improved pre-processing and more accurate labelling will be essentials for obtaining consistent accuracy.

Due to computational limitations, this study does not implement cross-validation. This reduces the reliability of the results, as the model was tested on only one split of the dataset. Implementing multiple folds in future work would offer a more stable and generalised estimate of the model's performance and help identify the accuracy across the folds.

4.2. Confusion Matrix Analysis

The analysis of confusion matrix showed that there were certain failure patterns in the two models. The CNN model presented the same misclassification (48% false positives and false negatives), which reflected the systematic failure to differentiate between classes and not a preference of one of the classes.

The ResNet model had a small bias to the desert classification (51% recall on desert vs 43% recall on urban) which may be attributed to the fact that the pre-trained features are more fitted to the natural landscape patterns compared to urban forms. This is consistent with using ImageNet-trained models on tasks that are more specific to remote sensing.

Analysis of loss curve during training showed that both models overfitted quickly after epoch 3, and validation loss was also growing, and training loss was still decreasing. This trend implies that the regularization is not sufficient, and the size of the dataset used might not be sufficient to use the complexity of the model.

The McNemar's test of significance ($p = 0.67$) did not reveal any statistical significance in the differences between CNN and ResNet performance, which indicated that model architecture was not the constraint in the present study.

4.3. Comparison: CNN and ResNet Performance

The comparison between CNN model and ResNet model (as shown in **Table 1**) emphasizes the challenges in applying deep learning to real-world classification. From the results, it may seem contrary that ResNet model's accuracy (47%) is lower than CNN model's accuracy (52%), given that ResNet has deeper architecture, but class-wise performance, its apparent that ResNet had slightly better recall for desert areas with 51% recall value. This implies the pre-trained model was able to extract more complex features for desert images. Several factors could have influenced the model's performance, such as:

- Insufficient generalization: Due to limited diversity in datasets and low-resolution images, the models struggled to generalize, therefore it was unable to learn the pattern as required and apply in new or unseen data.
- Poor Feature Extraction: The models couldn't distinguish properly between the two classes, possibly due to similar visuals or texture.
- Shortage of Specific Data: Dataset tailored to urban and desert classification, specifically Oman, were publicly unavailable, leading to reduced model accuracy.

These results and their interpretation suggest further improvements and fine-tuning to enhance both model's ability to generalize on real-world test data. Despite the models showing moderately promising performance, additional optimization will enhance their accuracy and make the geospatial applications more effective for environmental monitoring and land use analysis.

4.4. Critical Analysis and Contributing Factors

The lack of performance of the model could be explained by a number of systematic problems that are typical of remote sensing applications, but were not sufficiently considered in this study:

- To begin with, the heterogeneity of the data must have added a lot of noise because pictures obtained in various Kaggle datasets could portray various geographical areas, sensor types, and conditions of acquisition.
- The spectral similarity between some urban locations (especially construction sites or paved areas) and desert locations is a major problem of RGB-based classification. The earth-toned materials used in desert cities tend to resemble the natural desert spectral signs, and the spectral bands or contextual clues are needed to discriminate them correctly.
- Patch-based classification removes the spatial context and thus, important information that can be used by human interpreters is removed. Cities have typical spatial structures (road systems, city plan) that cannot be represented by individual patches of images.

The next step in work should take into account semantic segmentation methods that do not break the spatial relations. The mismatch of scales between training and application data can have been the cause of poor generalization. Model features might not transfer effectively, when training images are obtained at other spatial resolutions or on other sensor platforms than the application scenarios. This highlights the importance of utilizing domain-specific training data in operational remote sensing applications.

4.5. Real-World Application and Potential Impact

Integrating AI in land classification model can contribute to major implications in sustainable urban planning & environmental preservation. This research contributes to real world concepts like:

- Environmental Monitoring: AI-based applications can assist in detecting land degradation and urbanization efficiently and rapidly.
- Urban Planning & Infrastructure Development: Policymakers, like governments and city planners, can track urbanization and sustainable planning through these AI-powered models.
- Ecological Research: Using information through these models, soil quality and ecosystem health can be monitored.

5. Conclusions and Future Work

5.1. Recommendations

To enhance the performance of the AI-based land classification system in Oman or Middle East countries, the following recommendations are proposed:

- Expand Dataset Diversity: Further studies should collect larger quantity of images with higher resolution and with unique topography, so the models learn excessive and detailed features to minimize overfitting.
- Incorporate Geospatial Layers: Additional environmental concepts, such as elevation maps, land surface temperature, soil types, and GIS metadata [32], should be incorporated to uplift the classification of the model.
- Enhance Deep Learning Architecture: Lighter or hybrid models, such as MobileNet or ViTs could be explored and deployed to obtain higher performance.
- Assemble Local & Specific Dataset: Data collected from government or satellite providers or even open-source contributions, that specific to Middle East or Oman shall be better to get better deliverables to learn about environmental and urban patterns in Oman.

5.2. Real-World Applications and Impact

Although the results show limited accuracy, the study still shows conceptual potential of AI-based land monitoring systems. However, due to the nearly random classification performance, the current model should not be applied in real-world scenarios. The use cases outlined below represent long-term possibilities rather than immediate applications, and significant improvements in model accuracy and dataset quality are required before operational use.

- Urban Expansion Monitoring
  The yearly expansion of urban areas can be tracked using automated image classification, providing planners with updates and real-time insights on sprawl and land conversion. Such monitoring is important, as global projections indicate the urban land cover to increase by more than 200% by 2030, placing an unprecedented pressure on environment [1].
- Smart City Planning
  AI-driven land cover maps can support smart city strategies by offering accurate spatial data to guide infrastructure development. Using these tools government entities can predict growth patterns, reduce inefficiencies and ensure the new projects align with sustainable objectives. Data driven intelligence forms the foundation of smart city planning, enabling cities to adapt dynamically to emerging challenges.
- Climate Adaptation
  Vulnerable areas such as heat stress, water scarcity and land degradation can be identified by monitoring land use changes, which is an essential component of climate change and adaptation. Classification systems can help guide interventions such as afforestation, greening programs and soil rehabilitation. Hagenlocher et al. [33] highlight the integration of LULC monitoring system into adaptation planning is essentials for building urban resilience to climate risks.
- Disaster Risk Management
  AI-based land monitoring can also support in preparing for disaster by identifying hazard prone zones such as floodplains, or erosion sensitive slopes. Integrating AI intelligence into risk frameworks strengthens the ability of government to design early warning systems and allocate resources effectively [34].

5.3. Conclusion

Deep Learning techniques, specifically the built-in Convolutional Neural Network (CNN) and ResNet architecture model, have been explored in this study for classifying and distinguishing satellite and drone images into desert and urban classes, to support AI-based automated land analysis for sustainable development initiatives, tracking urban expansion and assessing desertified areas to provide data-driven insights for the policymakers. The models successfully achieved high performance on training and validating data, although real world testing data faced challenges as overfitting and less generalization, resulting in poor performance.

The results highlight the importance of improving dataset diversity and applying effective data preprocessing techniques. This research also underscores the expansion of Artificial Intelligence, Machine Learning and Deep Learning in environmental applications to monitor and track the expansion of urbanization and mitigation of natural ecosystems. The data collection that relies on several sources in Kaggle, although offering a considerable amount of data, probably caused the inclusion of a high level of variability in the quality of the images, the conditions of their acquisition, and their geographical representativeness, which hinders effective learning of the models. The binary classification framework itself may be overly simplistic for the complex reality of land cover in arid regions. The boundary between urban and desert areas is often gradual, with mixed-use areas, construction sites, and sparse urban development, making it ambiguous for applying binary classification approaches.

Although the model performance was poor and close to random, the study provides valuable insights for environmental monitoring applications in Oman and similar arid regions. Moreover, this study contributes to the major aim of integrating AI into sustainable planning and land use planning policies by demonstrating how AI can automate landscape classification using real-time data. These results highlight the necessity to continue to invest in the technological development as well as capacity-building in the sphere of environmental monitoring. The complex issues revealed indicate that the effective implementation will depend on the strong interdisciplinary partnership that will include remote-sensing experts, environmental scientists and the local experts in the field.

The overall objective is the creation of viable, implementable solutions that will assist in monitoring the environment and sustainable development in Oman. To achieve this objective, the research activities will have to contain ongoing efforts, improved datasets to be used, and academic and environmental-management practitioners will have to cooperate on a regular basis.

Author Contributions

Conceptualization, N.D. and S.S.K.N.; methodology, N.D. and F.H.Z.; software, N.D. and F.H.Z.; validation, N.D., F.H.Z. and S.S.K.N.; formal analysis, N.D.; investigation, N.D. and F.H.Z.; resources, N.D.; data curation, N.D.; writing—original draft preparation, N.D. and F.H.Z.; writing—review and editing, N.D., F.H.Z. and S.S.K.N.; visualization, N.D.; supervision, S.S.K.N.; project administration, S.S.K.N. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets analyzed in this study were obtained from publicly available repositories on Kaggle (https://www.kaggle.com/). The authors merged multiple open-access image datasets related to urban and desert environments for model training and evaluation. Since these datasets are freely accessible, interested researchers can obtain them directly from Kaggle and upload them in the Supplementary Materials section. The processed/merged dataset and code used in this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

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