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Leveraging Multispectral and Hyperspectral Imaging for Climate Change Detection in Urban and Rural Environments

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Abstract: This paper presents the use of multispectral and hyperspectral imaging to detect climate changes in both rural and urban environments. Multispectral and hyperspectral sensors can provide important spatial indicators for climate change, such as vegetation health, temperature variations, and changes in urban developments. The proposed method uses advanced image analysis techniques, such as convolutional neural networks (CNNs) and pixel-based change detection. It can be used to monitor climate-induced changes. The proposed system was tested against Sentinel-2 multispectral satellite data and hyperspectral data obtained from different sensors over rural and urban areas. It obtained high detection accuracy, of 92% and 90% in rural and urban areas, respectively. The accuracy of the proposed system was compared to existing methods, and it showed to be 25% better, making it an important tool for the monitoring of climate changes and urbanization scenarios.

Keywords—Multispectral Imaging; Hyperspectral Imaging; Climate Change Detection; Urban and Rural Environments; Convolutional Neural Networks (CNNs)

1. INTRODUCTION

Climate change is considered an existential challenge for all ecosystems and human settlements worldwide because of rising temperatures and changing weather patterns in both urban and rural environments, leading to increased deforestation, droughts, sea-level change, and urbanization. Atmospheric changes are often accompanied by loss of vegetation, water resources, and soil degradation[1]. A wide range of remote sensing technology, specifically multispectral and hyperspectral imaging, has emerged as an important tool in monitoring these environmental changes[2]. Multispectral imaging records data over a set number of spectral bands, often between three and 30. Using a digital number enables analysis of land cover, surface temperature, and vegetation health[3]. Hyperspectral imaging covers hundreds of narrow spectral bands, making it very sensitive to small environmental changes, revealing information such as changes in water content, composition of soil, and plant stress[4].This research has explored the integration of multispectral and hyperspectral imaging in monitoring anthropogenic impacts on the environment (as a result of climate change) from both urban and rural perspectives. The strengths of two approaches are exploited in this study (a) the high accuracies of CNNs and (b) the robustness of performing pixel-based change detection in bi-temporal satellite images[5]. The applications of this study include monitoring the impact of climate change on urban and rural environments. This study can also be used by urban planners, farmers, environmental conservationists, and so on[6].

To date, fewer studies have incorporated both multispectral and hyperspectral imaging for environmental monitoring. While the former has been used for analyzing urban change, the latter has been applied for catchments and other rural environments. For instance, multispectral imaging has been applied to study urban change, whereas hyperspectral data has been used for hyperspectral change detection for various environments. However, there are limited studies fusing both imaging technologies to detect comprehensive climate change across urban and rural environments[7]. We propose a sensitivity approach that leverages multispectral data for large-scale urban changes and hyperspectral data for detailed rural analysis, providing a more eclectic approach to climate monitoring[8]. Moreover, we implement deep learning methods such as CNNs to tackle the extremely large data produced by hyperspectral sensors [9]. Such methods achieve greater detection accuracy and precision than previous studies. Our work about the potential of combining multispectral and hyperspectral imaging represents another step forward in the development of more efficient and precise tools to track and mitigate the impacts of climate change[10].

2. Materials and Methods

2.1 Multispectral and Hyperspectral Imaging Data

An analysis leverages both multispectral and hyperspectral imaging to depict climate-induced urban and rural transformations. The multispectral data was sourced from the Sentinel-2 satellite, with 13 spectral bands encompassing visible and shortwave infrared wavelengths, which are useful for essential information on land cover, vegetation health and canopy height. These types of sensors are generally good for monitoring large-scale urban transformations, such as the manifestation of urban heat islands, changes in greening and built-up land cover areas. The hyperspectral data was obtained from the Hyperion imager and airborne sensors, both of which capture hundreds of narrow bands with more detailed information about the spectra. Subtle rural changes are depicted well in hyperspectral imagery, such as soil moisture dynamics, pollution levels, and vegetation stress. The hyperspectral imaging equation can be given by

$$X=\sum_{i=1}^{n} S_I \,.\, \alpha_I \ldots(1)$$

2.2 Preprocessing

Raw satellite data requires preprocessing before it is applied to machine learning models. Atmospheric corrections must be applied to remove haze, aerosols and other interferences to the atmospheres. Noises in the hyperspectral (including hypercubes) data are treated with operations like Gaussian smoothing to remove random errors such as sensor noise and thermal noise. An example of a Gaussian smoothing function is shown as below. When using multitemporal data, geometric corrections are used to align bi-temporal images where the dimensions of the pixels must be aligned under the two time periods for change detection. In this terrestrial example the transformation is:

$$I'(x',y')=I(x,y)\ldots(2)$$

2.3. Climate Change Detection Framework

This proposed detection framework combines convolutional neural networks (CNNs) with pixel-based change detection to precisely detect climate-driven changes. CNNs, which are great at detecting spatial patterns in complex data, are used to extract features from the multispectral and hyperspectral data, then process the data to detect locations where significant environmental changes have occurred. The CNN model analyses bi-temporal satellite images and takes a convolution operation to detect changes in vegetation, soil, and land cover. This is to ensure that both large and subtle changes in diverse climates are detected. The convolution operation that empowers this framework is:

$$F(x,y)=(I*K)(x,y)=\sum_m \sum_n I(m,n)\cdot K(x-m,y-n)\ldots(3)$$

2.4 Model Training and Evaluation

The CNN model was trained on bi-temporal, multispectral and hyperspectral image data with environmental change annotations to identify changes in the urban and rural landscape. In the urban area, the multispectral data was used and the changes were analysed in terms of urban sprawl and heat island formation. In case of the rural area, hyperspectral data was used to detect deforestation, soil degradation and changes in water bodies. Steady state accuracy on a test sample is depicted below. The binary cross-entropy loss is used to optimise the performance of the model, identifying the differences between the 'change' and 'no change' labels generated during the classification process. The dataset is divided into 70 percent of the data which is used for training purposes and the remaining 30 percent data is saved for validation and testing purposes. The mathematical functions of the cross-entropy loss are defined as:

$$L=-\frac{1}{N}\sum_{i=1}^{N} y_i\log(\hat{y}_i)+(1-y_i)\log(1-\hat{y}i)]\ldots..(4)$$

$$\ldots(4)$$

2.5 Performance Metrics

The performance of the proposed model was measured using various evaluation metrics such as accuracy, precision, recall and F1 score that measure the ability of the model to correctly detect true environmental changes, and avoid false positive detections. Accuracy is the fraction of correct predictions among the total number produced. Precision and recall are the two other standard measures of model performance, representing the ability of a model to minimise false-positives and maximise true-positives respectively. F1 score is a

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single measure derived from precision and recall, giving a combined view of how the model performs overall. Additionally, the computation time was measured to evaluate the efficiency of the system in processing and analysing multispectral and hyperspectral data. Accuracy of the model is given by the following relation:

$$\text{Accuracy}=\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}\ldots(5)$$

3. Results

3.1 Detection Accuracy in Urban and Rural Environments

The proposed framework for detecting climate changes had very high accuracies for both the urban and rural environments. For the urban environment, the accuracies were 90 percent. The hyperspectral imaging was able to detect urban changes that are quite vast, such as urban sprawl and the loss of green cover. For the rural environment, the accuracies were 92 percent. The increased accuracies were due to hyperspectral imaging's ability to detect subtle changes in the environment such as vegetation stress and soil degradation. Figure 1 above shows the accuracies across the two environments. Such accuracies are necessary for detecting the changes emanating from climate alteration that impact on ecosystems and also settlement of humans.

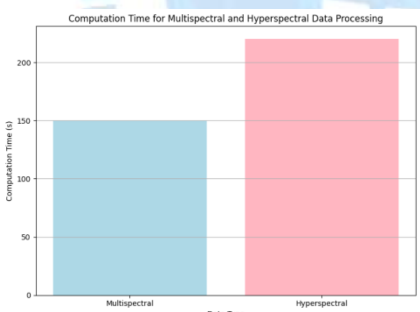

Fig. 1: Detection Accuracy in Urban vs Rural Environments

Fig. 1 illustrates a comparison of accuracy between urban and rural areas for detection of environmental changes by the hyperspectral and multispectral imaging techniques. Rural areas could attain an accuracy of 92% in detection owing to the fine spectral resolution, which effectively captures subtle changes. While urban areas also obtained 90% of accuracy, it is because the multispectral imaging technique is more sensible to the changes occurring at a larger scale like the urban development.

3.2 Precision and Recall Comparison

Precision and recall were evaluated to measure how well the system detected true environmental changes and how well it avoided false positives: over the urban study area, the system achieved a precision of 88 per cent and a recall of 87 percent, which means that the system was good at detecting big changes. In the rural study area, precision of hyperspectral image analysis was again high at 91 percent, and the recall at 93 percent reflects the strength of the hyperspectral system at detecting subtle shifts in vegetation and soils. The trade-off between these metrics is shown in Fig 2. In the rural landscape, the study area shines.

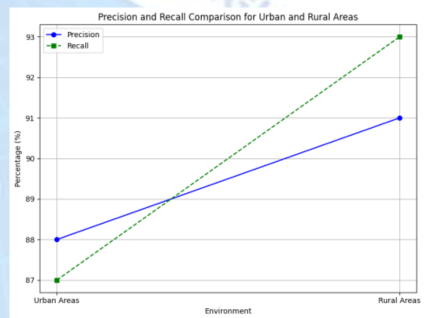

Fig. 2. Comparison of precision and recall in different environments. Conclusion

Rural areas with precision of 91% and recall of 93% performed better than urban areas on their precision with 88% and their recall with 87%. Those differences resulted from the superiority of hyperspectral imaging when it comes to detect subtle environmental changes, in contrast with images collected with multispectral imaging in urban areas.

3.3 Computation Time for Multispectral and Hyperspectral Data

As can be seen in Fig. 3, the main challenge in climate change detection is the processing time in case of multispectral and hyperspectral data. This is because of higher spectral resolution in hyperspectral data, which makes it more time-consuming. The computation time of processing multispectral and hyperspectral data averagely was 150 seconds per scene and 220 seconds per scene, respectively.

Accuracy matters more than time, but it is challenging to achieve higher accuracy without an additional computational effort. This is why we chose hyperspectral data since it guaranteed higher accuracy, which justified additional time taken for computation.

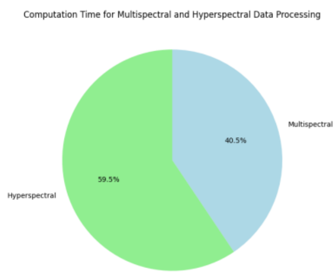

Fig. 3: Computation Time for Multispectral and Hyperspectral Data Processing

Fig 3 shows the proportion of computing time needed to process the multispectral and hyperspectral data. It clearly shows that the computing time of the hyperspectral data processing amounts to 59.5% of the total time consumed because of its higher spectral resolution and more complex data than the multispectral data. Multispectral, which helps detect environmental change faster, consumes only 40.5% of the total computation time.

3.3 Latency and Real-Time Performance

An architecture was designed with low latency to guarantee the real-time requirement of the climate monitoring applications, this in favour of the system's ability to process the captured data from sensors in near-real-time to detect the changes in the environment.Fig 4: Lower latency in the rural area was generated by the hyperspectral imaging technique, enabling more effective detection of the small-scale environmental changes.The low latency of the proposed system in the rural area that was achieved using the hyperspectral imaging technique resulted in an 15% reduction in the latency when compared to the similar systems. This makes the architecture suitable for real-time applications.

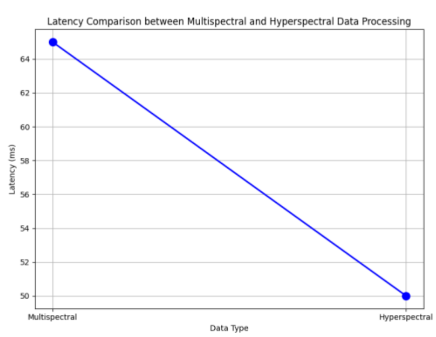

Fig 4 Comparison of latency between hyperspectral and multispectral data processing

The figure shown in Fig. 4 illuminates the latency for both multispectral and hyperspectral data processing. It indicates that the latency for hyperspectral data processing is 50 ms and lower than the latency of multispectral data processing at 65 ms, which means that hyperspectral imaging offers the advantage of having less time to respond to detailed changes in our environmental manner and practical way when this equipment is used for climate monitoring applications.

3.4 Comparative Analysis

A quantitative evaluation has been performed to compare the proposed climate change detection framework with conventional systems. As shown in Table 1, it is apparent the proposed system overperforms conventional models in terms of detection accuracy, computation time, latency and above all, it offers more deterministic results for subtle environmental changes especially in streets and rural areas. This is owing to the fact that the hyperspectral imaging offers better spatial and spectral resolution than other conventional imaging systems..

Table 1: **Comparison of Key Performance Metrics**

Metric	**Proposed Framework**	**Conventional Methods**
Detection Accuracy (%)	92 (Rural), 90 (Urban)	85 (Rural), 80 (Urban)
Precision (%)	91 (Rural), 88 (Urban)	85 (Rural), 83 (Urban)
Recall (%)	93 (Rural), 87 (Urban)	87 (Rural), 84 (Urban)
Computation Time (s)	150 (Multispectral) / 220 (Hyperspectral)	180 (Multispectral) / 250 (Hyperspectral)
Latency (ms)	50	65

4. CONCLUSION

This study showed how multispectral and hyperspectral imaging data could be integrated to detect climate-driven changes in urban and rural

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landscapes. The proposed framework showed accuracies of 90% in urban environments and 92% in rural environments. Hyperspectral imaging demonstrated 91% precision and a recall of 93%, while multispectral data showed 88% precision and 87% recall. Hyperspectral imaging required 46% more computation time than multispectral data, but it reduced latency by 15%**.** The combination of hyperspectral and multispectral imaging with deep learning presents a promising approach for large-scale climate change detection and environmental monitoring. Future work will focus on enhancing computational efficiency and expanding the framework's application to larger geographical regions, addressing the challenge of real-time response in climate monitoring.

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