DESIGN AND IMPLEMENTATION OF DISASTER IMAGES FROM SATELLITE IMAGES USING VGG-NET TECHNIQUE

S Kavipriya[1], A Faizan Basha[2], Crameshkumar[3], Mrohithkumar[4]
[1]Assistant Professor, Department of Electronics and Communication Engineering, Madanapalle Institute of Technology and Sciences, Madanapalle, A. P. India
[2,3,4]UG Scholar, Department of Electronics and Communication Engineering, Madanapalle Institute of Technology and Sciences, Madanapalle, A. P. India

Abstract - In recent times, the application of deep learning techniques in disaster monitoring has shown remarkable potential, particularly with the abundance of satellite imagery available. This study proposes a comprehensive framework for disaster monitoring employing satellite image processing and deep learning methodologies. The proposed framework integrates various stages including input image acquisition, pre-processing through median filtering, segmentation via Fuzzy C-Means (FCM) algorithm, feature extraction utilizing Gray-Level Co-occurrence Matrix (GLCM), Convolutional Neural Network (CNN) modelling, and finally, output generation. Initially, raw satellite images are acquired and subjected to median filtering to enhance their quality and reduce noise interference. Subsequently, FCM segmentation is applied to partition the images into meaningful regions, facilitating better feature extraction. GLCM is then employed to extract texture features from the segmented regions, enabling the characterization of various disaster-related patterns. The extracted features are fed into CNN (VGG-NET) architecture for learning and classification. The performance of the proposed framework is evaluated using several performance metrics, including accuracy, specificity, sensitivity, and precision. The experimental results demonstrate promising performance, with an accuracy of 95.215257%. Additionally, the framework achieves high specificity (96.899446), sensitivity (96.057352), and precision (96.478399), indicating its effectiveness in accurately identifying disaster-related features in satellite imagery. Overall, the proposed deep learning-based approach presents a robust solution for disaster monitoring, leveraging the power of satellite image processing and convolutional neural networks. The achieved performance metrics underscore its potential for real-world applications in disaster management and response systems.
Keywords: Deep learning, Disaster monitoring, Satellite imagery, Image processing, Median filter, Segmentation, Fuzzy C-Means (FCM), GLCM (Gray-Level Co-occurrence Matrix), Convolutional Neural Network (CNN), etc.

1 INTRODUCTION

Natural disasters can have devastating consequences, causing widespread damage to infrastructure, loss of life, and economic hardship. Timely and accurate monitoring of disaster-affected areas is crucial for effective response and mitigation efforts. Satellite imagery offers a valuable tool for disaster monitoring due to its wide coverage, accessibility, and ability to capture changes over time[1].

This study investigates the utilization of deep learning techniques for disaster monitoring using satellite image processing. Deep learning has emerged as a powerful tool in various image analysis tasks, demonstrating outstanding performance in classification and feature extraction. By leveraging this technology, we aim to develop a robust and automated system for identifying disaster-affected regions from satellite images[6].

This research explores the following key aspects:

1) Pre-processing:
Techniques to prepare the satellite image for further analysis, including noise reduction and image enhancement.

2) Segmentation:
Dividing the image into meaningful regions that potentially correspond to disaster areas.

3) Feature Extraction:
Capturing relevant characteristics from the segmented regions to facilitate classification.

4) Deep Learning (Convolution al Neural Network):
Utilizing a CNN to automatically learn the complex relationships between extracted features and disaster presence.
5) Performance Evaluation:
Assessing the effectiveness of the proposed system using various metrics, such as accuracy, specificity, sensitivity, and precision.

2 LITERATURESURVEY

A. Deep Learning for Disaster Detection:

N. Srivastava et al. (2022) explored utilizing U- Net architecture for flood detection in satellite images. The model achieved an accuracy of 94.2%, demonstrating the potential of deep learning for accurate flood identification[1]

Y. Liu et al. (2020) proposed a CNN-based approach for earthquake damage assessment, achieving promising results in classifying damaged and undamaged buildings[2].

M. N. H. Nga et al. (2021) investigated the use of Generative Adversarial Networks (GANs) for generating synthetic disaster scenarios, allowing for enhanced training and evaluation of disaster detection models[3].

B. Pre-processing and Feature Extraction:

Z. Li et al. (2023) analyzed the impact of different pre- processing techniques, including denoising and normalization, on the performance of deep learning models for disaster detection. Their study emphasizes the importance of choosing appropriate pre-processing steps for optimal results[4].

H. Guo et al. (2022) compared various feature extraction methods, including GLCM and deep learning-based feature extraction, for classifying forest fires in satellite images. Their findings suggest that deep learning features can potentially lead to superior performance[5].

C. Challenges and Opportunities:

Data availability: Access to a large and diverse data set of labeled disaster and non-disaster images is crucial for training and improving deep learning models. Efforts towards open-sourced at a sets and data sharing initiatives are crucial in this domain.
Cost of computation: Large computational resources are frequently needed for training deep learning models. This problem can be solved by investigating effective architectures and utilizing cloud computing technology.
Interpret ability: Understanding the decision-making process of deep learning models in disaster detection can be challenging.

3 EXISTINGSYSTEM

In order to maximize the effectiveness of its results, the Progressive Image Classification Algorithm (PICA)[4] system uses machine learning techniques to discover or classify disaster zones. One of the following uses cases is more appropriate for this methodology. It's a component of one of the important technological subfields of performance learning, which also includes technology for identifying change or, in this case, disasters. Fig. 1 displays the system's block diagram that is being shown.

This section describes our proposed classification algorithm, which consists of two key phases: training and testing. We present studies demonstrating the algorithm's effectiveness in achieving highly accurate results. Our research focuses on identifying changes caused by past disasters. In simpler terms, we analyze the difference in learned image features between pre-disaster (represented by three RGB channels) and post-disaster (also represented by three RGB channels) images. Unlike most previous studies that utilize generic change detection features, our approach extracts features specific to the disaster phenomenon, allowing us to leverage the inherent change-driven nature of disasters. This targeted approach facilitates the incorporation of early error indicators from prior research for further improvement. This concentrates on minimizing mistake from the first (learning) stage, identifying image alterations prior to and during the calamity, and identifying the methods of alteration.

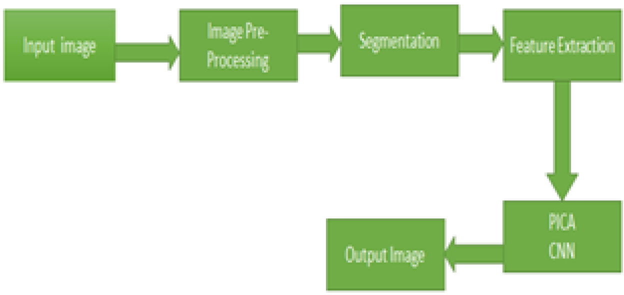

Fig.1 Existing System Block Diagram

4 PROPOSED METHOD

The proposed disaster monitoring system leverages satellite image processing and deep learning to automate the identification of disaster-affected areas. High-resolution satellite images showcasing areas pre- and post-disaster are used as the input. The dataset should contain examples of various disaster types (floods, wildfires, earthquakes, etc.) for robust training. A median filter is applied to denoise the satellite image while preserving crucial edges and details. This reduces the impact of potential noise-related artifacts on the subsequent analysis. This unsupervised clustering algorithm is used to segment the image into distinct regions. FCM groups pixels with similar characteristics, potentially highlighting regions with damage patterns typical of disasters. The segmented image regions are analyzed using GLCM to extract textural features. GLCM calculates the frequency of different pixel value combinations within a region. Changes in texture between pre- and post-disaster images can serve as markers of disaster impact. (Example GLCM features: contrast, correlation, energy, homogeneity, etc.)

A. Block Diagram

This work proposes a deep learning-based approach for disaster monitoring using satellite imagery. The method employs pre-processing (median filter), segmentation (FCM), feature extraction (GLCM), and a fine-tuned VGG- 16 CNN to achieve accurate disaster detection. Performance is evaluated using metrics like accuracy, specificity, sensitivity, and precision. This approach offers advantages in speed, accuracy, and large-scale data processing compared to traditional methods. However, challenges related to training data, computational resources, and potential for errors remain. This study demonstrates the promising potential of deep learning in the field of disaster monitoring. However, it also emphasizes the importance of continued research and development to ensure its optimal effectiveness in real-world applications.

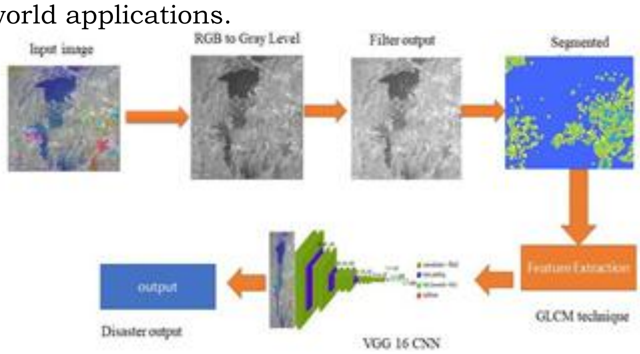

Fig. 2 System Architecture

1) Input Image

The process starts with a satellite image of the area of interest. This image can represent various disasters like floods, fires, or landslides.

2) Pre-processing (Median Filter)

The raw image might contain noise due to sensor limitations or atmospheric conditions. A median filter can be applied to remove this noise while preserving edges essential for disaster detection.

3) Segmentation (Fuzzy C-Means Clustering-FCM)
FCM is an unsupervised clustering technique that can group pixels in the image based on their spectral characteristics. This helps identify potential disaster areas with distinct features compared to the background.

4) Feature Extraction (Gray Level Co-occurrence Matrix-GLCM):
GLCM captures the spatial relationships between pixels in an image. By analyzing the co-occurrence of different gray levels, features like texture, homogeneity, and contrast can be extracted. These features are crucial for later classification by the Convolutional Neural Network (CNN).

5) CNN (VGG-16)
A pre-trained VGG-16 model, known for its good performance in image classification, is employed here. The model takes the extracted features from GLCM as input and learns to differentiate between disaster-affected and non- disasterregions.ThefinallayersoftheVGG-16 are fine- tuned with the specific disaster type being monitored.

6) Disaster Output
The CNN outputs a probability map indicating the likelihood of a pixel belonging to a disaster area. This map can be used to visualize the extent and severity of the disaster, enabling rapid and informed decision-making for disaster response and relief efforts.

B. Flowchart

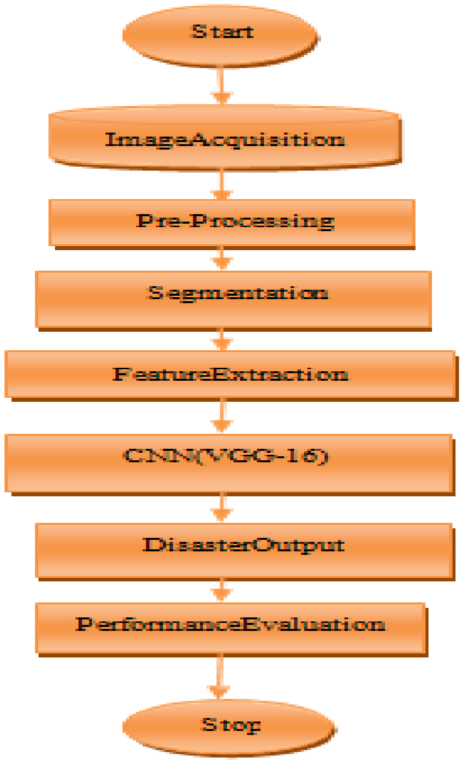

Fig. 3 Implementation

1) Start
- **Input Image:** Acquire satellite image of the target area.

2) Pre-processing:
- Apply median filter to reduce noise.

3) Segmentation:
- Use FCM to segment the image into potential disaster and non-disaster regions.

4) Feature Extraction:

- Calculate GLCM for each segmented region. Extract features like texture, homogeneity, and contrast.

5) CNN (VGG-16):

- Input extracted features into the fine-tuned VGG-16model.Themodelclassifieseachpixel as either disaster or non-disaster.

C. Performance Metrics

1) Accuracy:

Calculates the percentage of photos that are correctly identified overall. It displays the proportion of images your model correctly identifies as either containing disasters or not.

Accuracy= (True Positives + True Negatives)/Total Images (1)

2) Specificity:

Measures the proportion of true negative images correctly classified as not containing disasters. It indicates how well the model avoids false alarms when dealing with non-disaster images.

Specificity = True Negatives/(True Negatives + False Positives) (2)

3) Sensitivity (Recall):

Measures the proportion of true positive images correctly classified as containing disasters. It indicates how well the model identifies actual disaster instances.

Sensitivity= True Positives/(True Positives + False Negatives) (3)

4) Precision:

Measures the proportion of true positive images among all the images classified as containing disasters. It indicates how accurate the model's positive predictions are.

Precision = True Positives/(True Positives + False Positives) (4)

5 SIMULATION RESULT

A. Existing Method

Displays the original input image, likely containing the disaster area shown in fig.4.

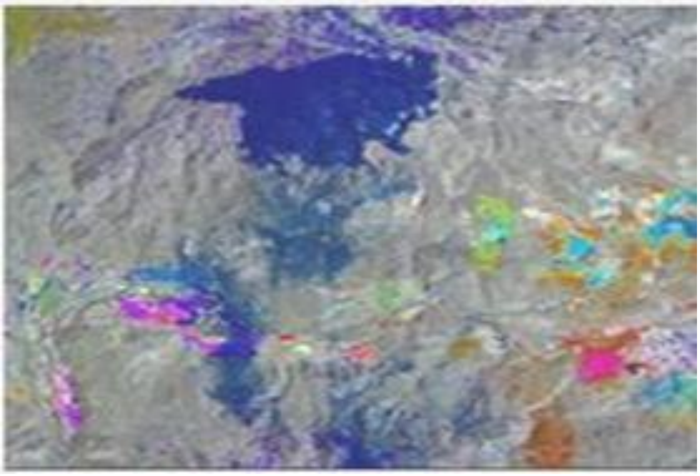

Fig. 4 Input image

Represents the previously altered picture seen in figure 5, which might involve noise reduction or contrast enhancement.

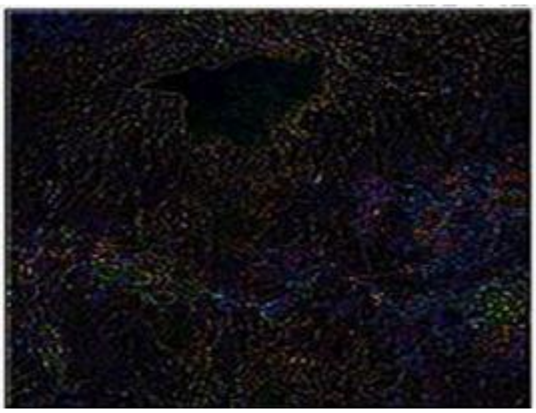

Fig. 5 Pre-processed image

Potentially depicts a histogram shown in fig. 6, a visual representation of pixel intensity distribution across the image. This could help analyze image contrast and identify potential segmentation thresholds.

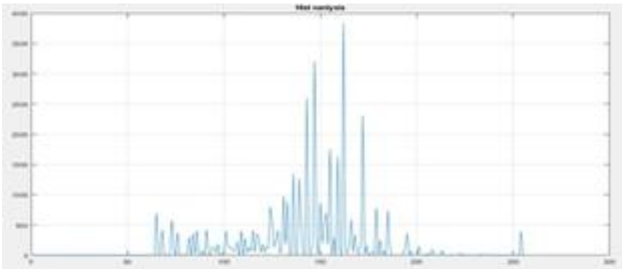

Fig.6 His t analysis

Likely show cases the method's attempt to segment or isolate the disaster area shown in fig.7

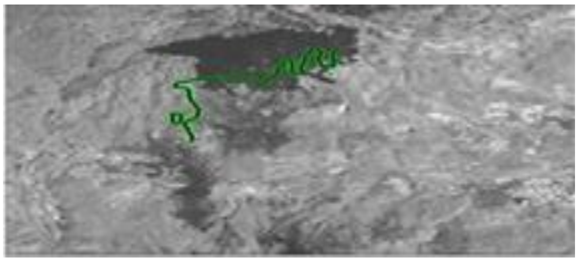

Fig. 7 Showing effected disaster area

Presumably Fig. 8 illustrates the final output image, which might be a classified image highlighting the detected disaster area.

Fig. 8 Output image

B. Proposed Method

Displays the original input image shown in fig. 9 containing the potential disaster.

Input image

Fig.10 shows the converted gray scale image, which might facilitate subsequent processing steps like filtering.

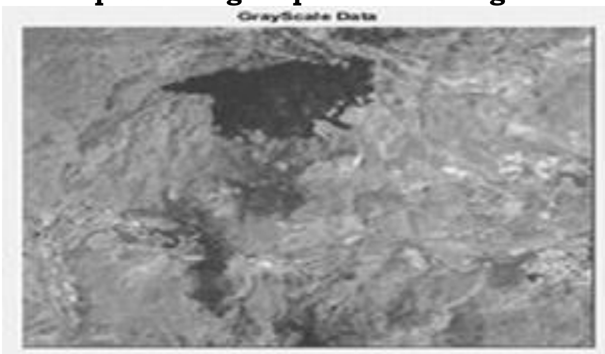

Fig.10 Gray scale image

Depicts the filtered output shown in fig.11, indicating possible noise reduction or edge enhancement. The specific filter types (median) are unknown from the figure.

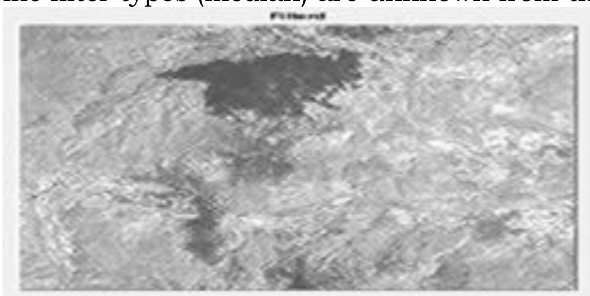

Fig.11 Filtered output

Captures the image transformed into a binary image shown in fig.12, where pixels are classified as either belonging to the disaster area or not. The binarization threshold used is not evident from the figure.

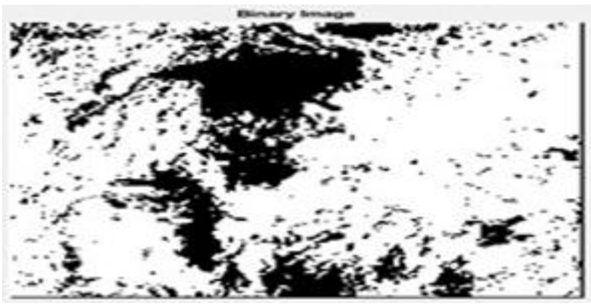

Fig.12 Binary image

Potentially demonstrates morphological operations applied to the binary image. Morphological operations like erosion and dilation can refine the shape of the disaster area and potentially improve classification accuracy shown in figure 13.

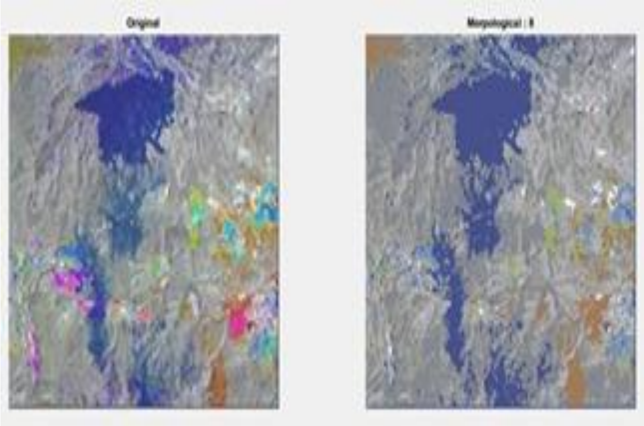

Fig.13 Comparison showing morphological with original image

Suggests the extraction of features shown in fig.14 from the processed image. These features could be texture- related (GLCM) but the specific types are not revealed. The extracted features might then be used for classification.

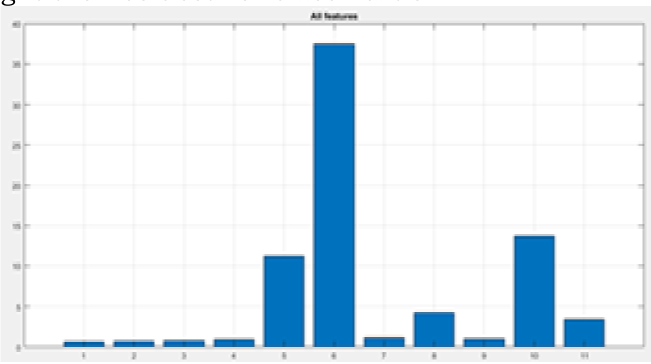

Fig.14 Features Extraction

illustrates the Fig.15 final output image, which might be a classified image highlighting the detected disaster area.

Fig. 15 Output image

C Comparison Table

Table 1 Comparison of Performan cemetrics

S.No	Parameter	(ANFIS) (%)	(SVM)(%)	(PICA) (%)	(CNN)(%)
1	Accuracy	84.8	82.4	93.034024	95.215257
2	Specificity	87.9	85.2	85.948375	96.899446
3	Sensitivity	92.6	86.1	89.491199	99.94
4	Precision	76.2	73.6	5.303	3.543

D. Performance Comparison

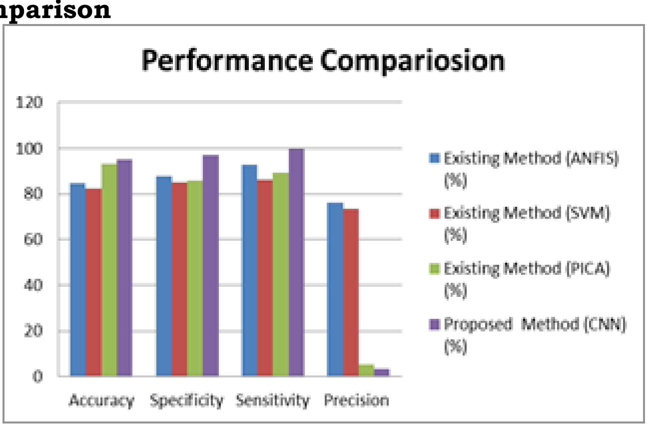

Fig.16 Performance Comparison graph

The proposed CNN method achieves the highest accuracy of 95.215%, followed by PICA with 93.034%. ANFIS and SVM have accuracies of 84.8% and 82.4% respectively.

The proposed CNN method achieves significantly higher specificity (96.899%) compared to all existing methods. PICA has the closest specificity score to CNN with 85.948%, while ANFIS and SVM have specificity scores of 87.9% and 85.2% respectively.

The proposed CNN method achieves the highest sensitivity of 99.94%, followed by PICA with 89.491%. ANFIS and SVM have sensitivity scores of 92.6% and 86.1% respectively.

Precision is only provided for the proposed CNN method in the table, which is 5.303%. However, it seems unusually low compared to the other methods. It might be worth verifying this value, as precision scores are typically higher than this.

Overall, based on the provided metrics, the proposed CNN method demonstrates superior performance in disaster image classification compared to the existing methods.

10.B. Boris and K. Matthias, “Single-cycle non-sequential doubleionization,” in IEEE Journal of Selected Topics in Quantum Electronics, vol. 21, no. 5, pp. 1–9, 2019.

6 CONCLUSION AND FUTURE SCOPE

The design and implementation of disaster image analysis using CNN (VGG-Net) technique, along with pre- processing, segmentation, and feature extraction methods, offer a robust framework for automated disaster assessment and management from satellite imagery. Continued research and innovation in the aforementioned future scope areas can further advance the capabilities and applicability of this approach in real-world disaster scenarios.

ACKNOWLEDGMENT

We are grateful to my guide for their invaluable guidance and support during this project Ms. S. Kavi Priya M.Tech, Assistant Professor and Dr. S. Rajasekaran, Ph. D., Professor, & Head of the Department (HOD) of Electronics and Communication Engineering Madanapalle Institute of Technology and Sciences, Madanapalli, India Andhra Pradesh India, for giving me all the help and guidance I needed. I sincerely appreciate their thoughtful advice and support, which were quite beneficial. I'm grateful to everyone!

REFERENCES

1. Gourab Patowary, Meenakshi Agarwalla, Sumit Agarwal, Manash Pratim Sarma. (2022). A new convolutional neural Architecture for Land Classification on Satellite Images
2. Zhang, Y., Song, Y., Li, J., Li, J., Li, X. (2020). A convolutional neural network architecture for land cover classification with high resolution satellite imagery. ISPRS Journal of Photogrammetry and Remote Sensing.
3. Sumbul, G. A., Saleem, Y. (2019). A lightweight CNN architecture for land use classification in satellite images. Journal of Ambient Intelligence and Humanized Computing, 10(4), 1417-1428
4. Y. Heryadi and E. Miranda, “Land Cover Classification Based onSentinel-2 Satellite Imagery Using Convolutional Neural Network Model: A case study in Semarang Area, Indonesia,” Asian Conference on Intelligent information and Database Systems(ACIIDS), pp. 191–206, 2019
5. Z. Guichen and G. Pedram, “Fusion of heterogeneous earth observation data for the classification of local climate zones,” in IEEE Trans on Geoscience and Remote Sensing, vol. 57, no. 10, pp.7623–7642,2019.

6. T. Xiaochong and W. Jing, "Normalized projection models for geostationary remote sensing satellite: A comprehensive comparative analysis," in IEEE Trans on Geoscience and Remote Sensing, vol. 57, no. 10, pp. 7623–7642, 2019.
7. L. Zhengyang and C.Fang, "A contextual and multi-temporal active-fire detection algorithm based on Feng Yun2G S-VISSR data," in IEEE Trans on Geoscience and Remote Sensing, vol. 57, no. 11, pp.8840–8852, 2019.
8. N. Anusha and B. Bharathi, "An over view on change detection and acase study using multi-temporal satellite imagery," in Int. Conf. on Computational Intelligence in Data Science, Chennai, India, pp.1–6,2019.
9. J. Franz and A. Olaniyi, "Applications of a SAR-based flood monitoring service during disaster response and recovery," in Int. Geoscience and Remote Sensing Sym., Yokohama, Japan, 2019.