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Wildfire Detection Based on Satellite Information Processing Using Convolutional Neural Network

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Abstract:
The exponential growth in satellite data availability and the need for more advanced processing methods have led to significant advancements in satellite information processing in recent years. This article provides a comprehensive review of the current trends and future directions in satellite information processing. Various processing techniques are employed for satellite imagery and remote sensing data. This includes preprocessing steps such as radiometric and geometric correction, as well as advanced processing methods like image classification, change detection, and feature extraction. In conclusion, satellite information processing is a multifaceted domain encompassing various techniques and applications critical for modern society. Understanding and advancing these processing methods are essential for harnessing the full potential of satellite data in addressing global challenges and fostering innovation across industries.

Keywords:
Wildfire, Convolutional Neural Networks, deep learning, aerial images satellite images

1. Introduction

Satellite information processing stands at the forefront of modern technological advancements, facilitating many applications critical to our interconnected world [1]. The rising incidence and intensity of wildfires have become a critical concern worldwide, impacting ecosystems, air quality, and human lives. The urgency to detect and manage these fires early has driven advancements in detection technology. Placing this research within the global context of wildfire management highlights its potential contribution to addressing a significant environmental challenge. With the proliferation of satellites orbiting the Earth, ranging from communication and navigation to remote sensing and scientific research, the volume and complexity of satellite data have surged exponentially. Harnessing the vast potential embedded within this data necessitates sophisticated processing techniques capable of extracting actionable insights efficiently and accurately.

The Onboard Computer (OBC) of a typical satellite is connected to numerous subsystems [2]. The OBC manages the satellite's operations, processes data and commands, and keeps up digital

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*Corresponding author: anggy.pradiftha@nusaputra.ac.id connection. Our study demonstrates the data flowing within the satellite, discusses the communication protocols when the satellite is in contact with the Ground Station (GS), and exhibits the protocols utilized to connect the various subsystems with the OBC. Additionally, this work shows how to use the CubeSat Space Protocol (CSP) in place of other widely used protocols like Serial Peripheral Interface (SPI) and Controller Area Network (CAN).

Satellites have become indispensable tools for communication, enabling global connectivity through telecommunications networks that span continents and oceans. They serve as relays for transmitting voice, data, and multimedia content, bridging geographical barriers and empowering individuals and organizations with instant, ubiquitous communication capabilities.

Satellite information processing [4] has emerged as a critical field at the intersection of technology, science, and societal needs. The proliferation of satellites orbiting the Earth has led to an exponential increase in the volume and variety of data acquired from space, spanning diverse applications such as communication, navigation, remote sensing, and scientific research. Understanding the background of this field provides insights into its evolution, challenges, and transformative impacts.

Traditional wildfire detection methods, such as ground-based sensor networks, often suffer from limitations including delayed response times, limited coverage, and high operational costs. These weaknesses can hinder timely detection and intervention, especially in remote or rapidly spreading fires. By leveraging Convolutional Neural Networks (CNNs), the proposed approach can improve detection speed, accuracy, and scalability, presenting a more effective solution to mitigate the devastation caused by wildfires. This focus on addressing specific limitations in current methods underscores the novelty and impact of the research presented.

2. Literature Review

This article [5] explores the current landscape of quantum computing in Earth observation and satellite imagery. It discusses the potential of quantum learning models, considering challenges in harnessing quantum advantage and optimizing resource sharing between high-performance and quantum computing. The analysis includes parameterized quantum circuit models, particularly focusing on T-gates' quantum resources. Quantum machine learning models demonstrate quantum advantage when outperforming classical counterparts on unseen data points and breaking weight symmetries, especially for hyperspectral satellite images with limited input qubits. Cloud detection in optical remote sensing images is crucial, but existing methods face challenges due to translucent clouds. This study [6] introduces a genetic reinforcement learning-based method. By analyzing pixel environmental states and integrating actions, it achieves accurate cloud detection with an impressive 97.15% overall accuracy.

Furthermore, the design and execution of flight software for an OBC of a nanosatellite was described in another study conducted at the Norwegian University of Science and Technology [7]. CSP over CAN was utilized for subsystem communication. The tasks (processes operating on the OBC) communicated with one another via CSP as well. Nevertheless, CSP is not being used for task-to-task communication. Use the more effective message queues in its place. The same author claimed that CSP might be viewed as a viable solution for both inter- and intra-satellite communication" in a different publication [8].

3. Methodology

A lot of planning and discussion is carried out before the start of this work. A general overview of the work is established. To ensure that the work matches the flow, a great deal of preparation and planning is required before it can begin. It also ensures that the project runs smoothly. This work's time management is meticulously planned, and a flowchart is used to create the process. The process flow is as in Figure 1.

3.1 Flowchart for Overall Process in This Study

Figure 1 shows the flowchart for the overall operation of this project. The flowchart has the following steps.

i. **Upload data in Google Colab**: Satellite data is uploaded to Google Colab, a cloud-based platform that allows you to write and execute code.
ii. **Train and compile using model CNN**: The CNN model is trained and compiled with the uploaded satellite data. CNNs are a type of deep learning model particularly effective for image and pattern recognition.
iii. **Evaluate the model**: After training, the model's performance is evaluated to ensure it accurately processes and classifies the satellite information.
iv. **Classification**: The model classifies the data, likely into different categories based on features learned during training.
v. **Result**: The outcome of the classification process is obtained, which could be used for various applications like weather forecasting, environmental monitoring, etc.

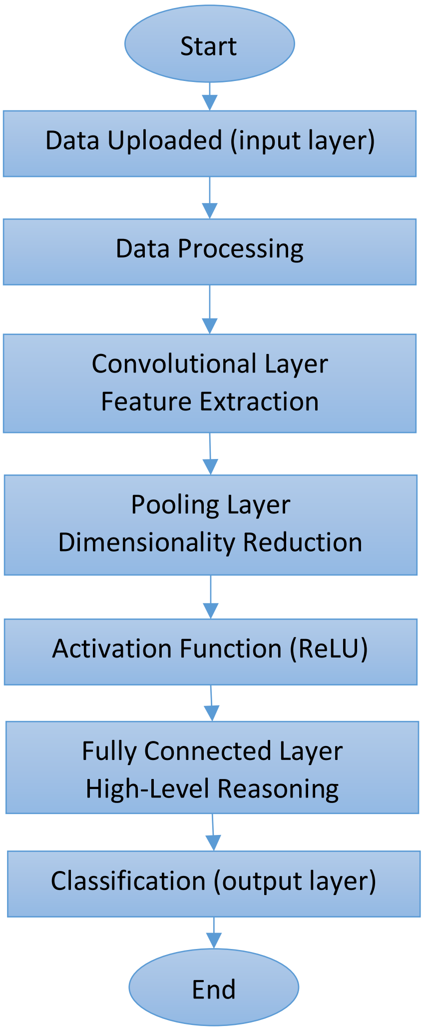

Figure 1: The flowchart of the work process

3.2 Design Architecture

Deep learning architectures are increasingly being applied to satellite information processing for various tasks such as image classification, object detection, semantic segmentation, change detection, and more. These architectures leverage the massive amount of data collected by satellites to extract meaningful information for different applications.

Convolutional Neural Networks (CNN) are widely used for tasks like image classification, object detection, and semantic segmentation in satellite imagery. They have proven to be effective in automatically learning hierarchical features from raw image data. Here are some common CNN architectures used in satellite information processing.

- **Input Preprocessing**: Satellite images often come in different resolutions and formats. Preprocessing steps such as normalization, resizing, and augmentation may be applied to the input images to ensure consistency and improve the robustness of the model.
- **Convolutional Layers**: CNNs are made up of several convolutional layers, each of which processes the input image using a set of learnable filters. These filters identify patterns at many spatial scales, including edges, textures, and forms. These filters aid in the extraction of useful spatial elements from satellite data that are pertinent to the current task, such as different types of land cover, infrastructure, or natural phenomena.
- **Pooling Layers**: To downsample the feature maps and capture the most pertinent characteristics, pooling layers are inserted between convolutional layers. This lowers computational cost. The most noticeable features are often retained while noise or less important information is discarded using max pooling or average pooling.
- **Activation Functions**: Non-linear activation functions like ReLU (Rectified Linear Unit) are applied after each convolutional and pooling layer to introduce non-linearity into the network and enable the model to learn complex relationships between features.
- **Fully Connected Layers**: Using the retrieved features as a basis, fully connected layers are usually used towards the end of the CNN architecture to carry out high-level reasoning and categorization. These layers link the output classes or regression targets to the flattened output from the convolutional layers that came before it.
- **Output Layer**: The output layer depends on the specific task. For classification tasks, it often consists of a softmax layer, which produces probability distributions over the different classes. For regression tasks, a single output neuron with an appropriate activation function (e.g., linear for numerical predictions) may be used.
- **Training and Optimization**: To minimize a selected loss function, such as mean squared error for regression or categorical cross-entropy for classification, CNNs are trained using gradient descent and backpropagation methods. To enhance generalization and avoid overfitting, strategies such as weight regularization, dropout, and batch normalization may be used.
- **Deployment**: After training, the CNN model is tested using a different validation or test dataset to determine how well it performs in terms of accuracy, precision, recall, and F1-score. Once the model reaches a reasonable level of performance, it can be used for inference on fresh satellite photos to provide forecasts or extract useful data for later uses.

Detailed list of the hyperparameters used in this CNN model:

i. Number of Filters:
    - First Convolutional Block: 8 filters
    - Second Convolutional Block: 16 filters

ii. Kernel Size: Both convolutional layers use a kernel size of 3x3

iii. Pooling Size: Pooling layers use a size of 2x2 for max pooling

iv. Number of Units in Dense Layers:

  - First Dense Layer: 16 units
  - Second Dense Layer: 8 units

v. Activation Functions:
  - ReLU (Rectified Linear Unit) for all hidden layers
  - Softmax for the output layer

vi. Optimizer: Adam optimizer with a learning rate of 1×10-5 and a decay rate of 1×10-7
vii. Loss Function: Categorical Crossentropy
viii. Batch Size: 100 samples per batch
ix. Number of Epochs: 30 epochs
x. Data Normalization: Image data is normalized to the range [0, 1] by dividing pixel values by 255
xi. Data Type Conversion: Input images and labels are converted to float32 format for normalization and processing

4. Results and Discussion

This study about satellite information processing typically involves examining the methodology, results, implications, and potential future directions of the research.

4.1 Result

Table 1: Accuracy and loss for evaluation result

	Training Loss:	Training Accuracy:	Validation Loss:	Validation Accuracy:
Epoch 1	0.7954	70.69%	0.3252	87.47%
Epoch 2	0.2778	88.28%	0.2340	89.93%
Epoch 3	0.2142	91.19%	0.1756	93.26%
Epoch 4	0.1880	92.29%	0.1558	93.80%
Epoch 5	0.1662	93.60%	0.2202	91.28%
Epoch 6	0.1470	94.33%	0.1408	94.65%
Epoch 7	0.1313	95.03%	0.1579	93.33%
Epoch 8	0.1218	95.40%	0.1011	96.26%
Epoch 9	0.1136	95.64%	0.0985	96.63%
Epoch 10	0.1090	95.63%	0.1013	96.36%
Evaluation Result		Test Loss: 0.1013		Test Accuracy: 96.36%

Table 1 shows the model's training accuracy steadily improves over epochs, reaching 95.93% by the last epoch. An epoch refers to one complete pass through the entire training dataset during the training phase of the machine learning model. The training process consists of multiple epochs, where the model iteratively updates its parameters to minimize the difference between predicted outputs and actual ground truth labels. Training loss decreases significantly, indicating that the model is learning effectively. Validation accuracy also improves consistently, reaching 96.36% on the last epoch. The model performs well on the test set, achieving a test accuracy of 96.36% and a low test loss of 0.1013. There is a slight gap between training and validation accuracy, but it doesn't seem to be a significant overfitting issue. The model appears to be effective for wildfire detection, as evidenced by high accuracy and low loss on both validation and test sets.

Table 2: Result of Confusion matrix

426	0	0	3	138	3
1	2662	1	109	1	0
0	2	2066	100	0	0
0	93	10	1751	2	0
5	0	0	11	280	3
0	0	0	0	0	4483

Table 3: Result of each class

Class	Precision	Recall	F1-score
0	0.99	0.75	0.85
1	0.97	0.96	0.96
2	0.99	0.95	0.97
3	0.89	0.94	0.91
4	0.67	0.94	0.78
5	1	1	1
Accuracy			0.96
Macro Avg	0.92	0.92	0.91
Weighted avg	0.96	0.96	0.96

Table 2 shows the confusion matrix provides a detailed breakdown of the model's predictions across different classes. Diagonal elements represent the true positive counts for each class. Meanwhile, Table 3 shows the class which is precision, recall, F1-score, and support. Precision is the proportion of true positive predictions among all positive predictions. Recall is the proportion of true positive predictions among all actual positives. F1-score is the harmonic mean of precision and recall. Support is the number of actual occurrences of each class. Classes 1, 2, and 5 have high precision, recall, and F1-score, indicating accurate and reliable predictions. Class 0 has high precision but lower recall, suggesting potential room for improvement in detecting instances of this class. Class 4 has a relatively lower precision and F1-score, indicating some difficulty in correctly identifying instances of this class.

The model achieves an overall accuracy of 96%, which is a good performance metric. The weighted average precision, recall, and F1-score are all high, indicating a well-performing model across all classes. Macro average considers each class equally, providing an overall performance metric. Weighted average considers the number of instances of each class, giving more weight to larger classes. The model demonstrates strong performance, especially in classes 1, 2, and 5. Further investigation and potential improvement may be needed for class 0 and class 4 to enhance the model's overall performance.

4.2 Comparison of CNN model in Satellite Information Processing

Table 4 shows the comparison of the examined CNN models with different hyperparameter settings. CNN1 uses parameters with 16 layers. CNN2 consists of three convolutional blocks with increasing filter sizes (16, 128, and 256), followed by max-pooling layers. Meanwhile, CNN3 utilizes 64 layers without dropout. The results show that CNN3 has the highest accuracy, with a score of 97.59%

Table 4: Comparison of each CNN model

CNN model	Result accuracy	Comparison
CNN1	Test accuracy: 96.36%	Use 16 layers
CNN2	Test accuracy: 97.07%	CNN2 consists of three convolutional blocks with increasing filter sizes (16, 128, and 256), followed by max-pooling layers.
CNN3	Test accuracy: 97.59%	For CNN3, total layer increased from 16 layers to 64 layers, and no dropout

5. Discussion

5.1 Practical Implication:

High values of accuracy, precision, recall, and F1-score in the context of wildfire detection have significant practical implications in this case as mention as following;

- **High Accuracy**: Indicates that the model reliably distinguishes between wildfire and non-wildfire instances. This reliability can lead to faster and more confident detection, thus reducing response times and allowing emergency services to allocate resources more effectively.
- **High Precision**: Ensures that most of the detected wildfires are true positives, meaning the model has a low rate of false alarms. This is crucial for avoiding unnecessary resource deployment, which could strain emergency services and divert attention from actual threats.
- **High Recall**: Reflects the model's ability to identify a large proportion of actual wildfires. This is essential for minimizing the risk of undetected fires, which could spread uncontrollably and cause extensive damage.
- **High F1-Score:** Balances precision and recall, demonstrating that the model is both effective and efficient in detection. A high F1-score means the system can be relied upon to detect and respond to wildfires promptly and accurately, enhancing overall wildfire management and control."

5.2 Limitation

Limitations to address in this research include:

- **Data Constraints:** The model's performance may be limited by the quality and diversity of satellite imagery used. Issues such as inconsistent image resolution, cloud cover, and varying environmental conditions can introduce bias or inaccuracies in detection.
- **Geographical Bias**: The dataset may not represent all types of landscapes or climate conditions equally, which could affect the model's generalizability to different regions worldwide.
- **Real-Time Limitations**: Despite high detection accuracy in controlled tests, the model may face challenges in real-time deployment due to satellite data transmission delays or the computational power required for processing.
- **Future Research Directions**: Suggestions for future research include expanding the dataset to include more diverse environments, incorporating real-time data streams, and exploring integration with other detection methods (e.g., drone surveillance or ground-based sensors) to improve robustness and reliability."

6. Conclusion

Satellite information processing stands as a cornerstone in modern technological advancements, offering invaluable insights into our planet and enabling a myriad of applications critical for societal well-being. Through this comprehensive review, we have explored the fundamental components, challenges, and transformative impacts of satellite information processing.

In essence, satellite information processing continues to evolve as a dynamic and indispensable field, driving innovation, fostering collaboration, and shaping the way we understand and interact with our planet. As we navigate the complexities of an increasingly interconnected world, satellite information processing remains a beacon of progress, guiding us toward a brighter and more informed future.

6.1 Potential for Future Research:

This research opens up exciting avenues for further exploration and practical advancements in wildfire detection. One significant area of future research is the integration of this CNN-based detection system into comprehensive disaster response frameworks. Such integration could enable automated, real-time alerts for emergency services, thereby streamlining response efforts and optimizing resource allocation. Additionally, expanding the system's capabilities to work seamlessly with other technologies, such as drone surveillance or IoT sensor networks, would enhance its accuracy and coverage. Another promising research direction involves exploring the fusion of satellite data with other environmental datasets to improve predictions of wildfire behavior and facilitate proactive intervention strategies.

6.2 Novelty and Effectiveness:

This study demonstrates the novelty and effectiveness of employing Convolutional Neural Networks (CNNs) for analyzing satellite imagery in the context of wildfire detection. The model's ability to quickly and accurately extract meaningful features from complex image data sets it apart from traditional detection methods, which often struggle with speed and scale. The use of CNN not only enhances detection accuracy but also provides a scalable solution adaptable to various geographical regions and conditions. Looking ahead, advancements such as the integration of more sophisticated neural architectures (e.g., attention mechanisms or hybrid models) and improvements in computational hardware will further bolster the potential of CNN-based systems for real-time and large-scale wildfire monitoring. These developments will pave the way for even more efficient and impactful applications in environmental disaster management.

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