

Article

Design and Development of a SWIR Optical-Electronic Payload for Earth Remote Sensing Applications

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Abstract

Wildfires are significant ecological and environmental disasters, impacting forests, ecosystems, climate stability and human life. The visible-spectrum imagery-based traditional wildfire monitoring system can fail to perform well in the presence of smoke, haze and low lighting. A number of machine learning and deep learning techniques have been proposed, but most of the studies do not provide an integrated Short-Wave Infrared (SWIR) optical-electronic payload framework along with an intelligent optimization technique. The objective of this research is to design an intelligent SWIR-based optical-electronic payload architecture for accurate detection and remote sensing of wildfire and Earth applications via deep learning and optimization techniques. The proposed framework is based on Sentinel-2 SWIR satellite data layers with wildfire and non-wildfire samples. To enhance the quality of the images and the representation of their spectral domain, the following preprocessing operations are carried out: resizing, image normalization, SWIR band extraction, and data augmentation. The following spectral feature extraction techniques are then used: burn area analysis, vegetation stress analysis, and thermal anomaly detection. The framework also incorporates SWIR optical payload design, electronic subsystem development and SWIR InGaAs sensor modeling. Finally, a Hybrid Convolutional Neural Network (CNN)–Residual Network 50 (ResNet50) model optimized by Grey Wolf Optimization (GWO) is used for wildfire classification and hyperparameter tuning. The proposed framework achieved an accuracy of 91.03%, precision of 91.27%, recall of 91.03%, and F1-score of 91.01%. The wildfire detection capability, classification robustness, and convergence performance were enhanced through the integration of SWIR spectral analysis, hybrid deep learning and GWO. The proposed framework offers an effective and trustworthy solution for intelligent wildfire monitoring and Earth remote sensing applications with enhanced spectral sensing and classification performance.

Keywords: short-wave infrared remote sensing; wildfire detection; Hybrid CNN–ResNet50; Grey Wolf Optimization; Sentinel-2 imagery



Academic Editor: Lamei Zhang

Received: 6 June 2026

Revised: 2 July 2026

Accepted: 13 July 2026

Published: 17 July 2026

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1. Introduction

Wildfires now count as one of the main environmental disasters impacting forests, biodiversity, climate stability, and also human lives around the globe [1]. In situations where wildfires occur rapidly, the impact on the ecology is likely to create significant injuries [2], air pollution, and economic losses, which means that early wildfire detection should be considered a crucial step to disaster management and environmental conservation efforts [3]. Traditional remote sensing systems using primarily visible imagery are prone to inaccuracies in the case of smoke, haze, and low illumination [4]. Recent advances have shown the increasing interest in SWIR remote sensing because SWIR bands are highly sensitive to thermal anomalies, charred lands, and even moisture content within the plants [5]. Using SWIR imagery will give a more robust ability to detect wildfire areas, which tend to have higher visibility compared to conventional RGB imagery [6]. Therefore, an optimal solution is the creation of a SWIR optical-electronic payload system architecture. Furthermore, using a combination of artificial intelligence methods with the SWIR sensing technology will be able to greatly increase the accuracy in the classification of the wildfires, and also enhance an automated monitoring system in a more reliable and consistent way [7]. In conclusion, the proposed framework seeks to create an intelligent SWIR-based remote sensing payload for wildfire and Earth observation [8].

There have been quite a number of research studies carried out in order to detect wildfires through the use of ML, DL, and other traditional means, despite some of the research being slightly redundant. Generally, the most common traditional approaches used to classify wildfires through satellites include SVM, RF, KNN, and DT [9]. Lately, deep learning approaches such as CNN, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), U-Net, VGGNet, and ResNet have shown better performance for image-based wildfire detection tasks, in more than a few papers [10]. Also, multi-spectral and thermal remote sensing have been employed for burn area mapping, plus vegetation stress analysis, which sounds useful and real. But still, many of the existing systems mainly depend on visible-spectrum imagery [11], and that can be a problem because detection quality tends to drop badly when smoke is present or when lighting is low [12]. Moreover, most earlier studies stay at the level of software-based classification models level, and they do not really consider how to design an integrated SWIR optical-electronic payload architecture for real-time Earth remote sensing applications [13]. Recent advances in hyperspectral remote sensing have introduced dual-stream background modeling networks with anomaly suppression to improve anomaly detection by enhancing background reconstruction and reducing false alarms [14]. Similarly, spectral variability and class-constrained diffusion models have demonstrated improved hyperspectral unmixing by effectively addressing spectral variability [15]. These approaches highlight the effectiveness of advanced deep learning for hyperspectral image analysis; however, they primarily target anomaly detection and spectral unmixing rather than integrated SWIR-based wildfire monitoring.

Despite the considerable progress in SWIR-based wildfire monitoring, important research challenges remain. Existing studies have primarily focused on improving wildfire detection accuracy through SWIR image analysis and deep learning techniques; however, limited attention has been given to integrating optical payload design, electronic subsystem development, sensor-level modeling, and intelligent optimization within a unified wildfire monitoring framework. Consequently, the practical implementation of these approaches in future intelligent Earth remote sensing systems remain limited. To address this research gap, the proposed framework integrates SWIR optical-electronic payload design, InGaAs sensor modeling, Hybrid CNN–ResNet50 classification, and Grey Wolf Optimization into a unified end-to-end architecture, thereby providing a comprehensive solution for intelligent

SWIR-based wildfire monitoring. To overcome the limitations, the proposed framework comes in with a new SWIR optical-electronic payload system and then with a Hybrid CNN–ResNet50 deep learning model, it helps with intelligent wildfire detection in a sort of end-to-end way. In this work, the study uses SWIR spectral bands, such as B11 and B12, to grab thermal clues, burned areas, and vegetation distress information with better sensitivity than many conventional RGB-based systems do. An optical subsystem specific to SWIR and a signal processing system exist in tandem, and the fact of the matter is that their only reason for existing is to enhance the efficiency of data acquisition and conversion from analog signal to digital signal, rather than simply doing both. In addition to this, GWO is employed for the purpose of tuning parameters and selecting features; essentially, its role here is to help achieve greater levels of classification accuracy while simultaneously reducing computational burden. The Hybrid CNN–ResNet50 architecture is employed due to its ability to assist in deep feature extraction and minimize vanishing gradients during training. Furthermore, unlike some other previous research, this methodology integrates the SWIR load design, sensor modeling, feature extraction, optimization, and wildfire classification using deep learning into a single scheme, and thus is not limited to distinct procedures.

Therefore, the overall proposed methodology performs better in terms of wildfire detection, spectral analysis, and reliable operations for Earth remote sensing purposes.

1.1. Research Objectives

- (1) Develop an intelligent SWIR optical-electronic payload framework for accurate wildfire detection and Earth remote sensing applications using deep learning and optimization techniques.
- (2) Utilize the Sentinel-2 SWIR satellite imagery dataset containing wildfire and non-wildfire images with B8, B11, and B12 spectral bands for wildfire monitoring and analysis.
- (3) Perform SWIR image preprocessing, spectral feature extraction, SWIR optical payload system design, electronic subsystem development, and InGaAs SWIR sensor modeling for efficient wildfire feature analysis and remote sensing data acquisition.
- (4) Implement a Hybrid CNN–ResNet50 deep learning model integrated with GWO for improved wildfire classification accuracy, feature extraction capability, and hyperparameter optimization.

1.2. Research Scope and Novelty

The proposed framework fundamentally differs from previous integrated wildfire detection systems through the unified integration of SWIR image preprocessing, spectral feature extraction, SWIR optical-electronic payload design, electronic subsystem development, InGaAs sensor modeling, Hybrid CNN–ResNet50 classification, and Grey Wolf Optimization within a single end-to-end architecture. While previous wildfire detection studies have explored SWIR imagery, deep learning models, and optimization techniques either individually or in limited combinations, they primarily focus on software-based image classification with limited integration of hardware-oriented payload design and sensor-level modeling. In contrast, the proposed framework establishes a unified hardware–software architecture that connects SWIR payload design, sensor modeling, spectral feature analysis, intelligent classification, and hyperparameter optimization into a coordinated workflow for Earth remote sensing applications. This integrated framework supports the future implementation of intelligent SWIR optical-electronic payload systems while providing a comprehensive end-to-end solution for wildfire detection.

1.3. Research Organization

Section 1 presents the introduction, research objectives, research scope, novelty, and organization of the proposed SWIR-based wildfire detection framework.

Section 2 discusses the literature review related to wildfire monitoring, SWIR remote sensing, deep learning models, and Earth observation systems.

Section 3 clarifies the proposed methodology, including SWIR image preprocessing, spectral feature extraction, SWIR payload design, electronic subsystem development, In-GaAs sensor modeling, Hybrid CNN–ResNet50 classification, and GWO.

Section 4 describes the experimental setup, dataset details, hardware and software configuration, hyperparameter settings, and performance evaluation metrics.

Sections 5–7 present the experimental results, discussion, limitations, conclusion, and future research directions of the proposed framework.

2. Literature Survey

Current research has been conducted regarding fire monitoring via remote sensing techniques, machine learning, and deep learning algorithms. For example, Tavakkoli Pirailou et al. [16] used an ensemble method that combines RF, SVM, and DST with Sentinel-2 and Landsat satellite images to forecast wildfire susceptibility, achieving a high AUC value of 94.71%. The authors mentioned in Ghali and Akhloufi [17] covered a number of deep learning techniques like CNN, RNN, LSTM, and U-Net for satellite images in the context of wildfire monitoring and emphasized the growing importance of such artificial intelligence techniques. In Seydi et al. [18], a burned-area mapping technique based on Sentinel-2 and MODIS has been introduced, applying change detection techniques, achieving 91.02% overall accuracy. Zhang et al. [19] created a multi-source wildfire data collection system based on the Sentinel-1, Sentinel-2, and ALOS-2 satellites, while the U-net based deep learning algorithms were performed for wildfire mapping. Contrarily, Marcos et al. [20] utilized RF models using ecosystem functioning variables in order to discriminate the areas that have been affected by wildfires, achieving AUC values above 0.98. Furthermore, dos Santos et al. [21] used time series data from Landsat images combined with Fourier harmonics modeling, applying afterwards the RF classification for large-scale wildfire mapping in Portugal. Lastly, Oikonomou et al. [22] integrated GIS with Earth observation data for wildfire risk mapping in Greece.

Some studies and applications for Earth observations and remote sensing have resulted in being useful in environmental monitoring and satellite-driven analysis in relation to wildfires as well. This is true. For instance, in one study carried out by Zhao et al. [23], the global impact and future trends of Earth Observation satellites, such as Sentinel, Landsat, and MODIS missions, were analyzed, particularly regarding remote sensing. In another study, where the authors were Ferreira et al. [24], Earth observation data cubes and machine learning methods were introduced in order to analyze remotely sensed images' time-series, in relation to large-scale land use monitoring. Finally, in yet another study conducted by Caroni et al. [25], satellite-based datasets and environmental variables (such as chlorophyll-a, and turbidity) were considered in relation to wildfires and their impact on lake water quality.

Qader et al. [26] examined remote sensing tasks for agricultural monitoring and even crop prediction in arid regions by using freely accessible Earth observation datasets. You, H et al. [27] studied global urbanization patterns through Earth Observation data plus self-organizing map methods, while Grêt-Regamey and Weibel [28] assessed changes in ecosystem services across mountain areas with high resolution Earth observation sources. Bielecka et al. [29] then ran a systematic review on sustainable urban land management by combining remote sensing with geospatial technologies. They often do not pull in

SWIR optical payload design, sensor modeling and intelligent deep-learning-based wildfire detection, all together, inside one unified Earth observation framework.

Existing wildfire detection frameworks tend to concentrate on satellite picture analysis, susceptibility mapping, environmental monitoring, or more “software-first” machine learning methods that lean on visible-band and multispectral remote sensing inputs. That said, many prior works do not really offer an integrated SWIR optical-electronic payload design which can, in a practical way, acquire and also process SWIR spectral information fast enough for real-time Earth observation. On top of that, several already built systems show a bunch of weaknesses, including unstable results when smoke is around, poor behavior in low-light situations, an underpowered thermal anomaly detection ability, and then high computational complexity, plus restricted spectral feature extraction. Another thing is that sensor-level modeling and optimization are often missing, like it is just assumed later. Also, only a handful of studies manage to join deep learning, SWIR sensor modeling, optical subsystems design, electronic signal processing, and optimization techniques into a single unified intelligent wildfire detection framework.

3. Proposed Methodology

The proposed methodology proposes an intelligent design of the framework for an optical-electronic payload for wildfire detection and Earth remote sensing, exploiting data from the Sentinel-2 SWIR channel. This framework integrates SWIR image preprocessing, a spectral feature extraction algorithm, a conceptual payload architecture design, modeling of an InGaAs sensor, and a Hybrid CNN–ResNet50 deep learning algorithm supported by a Grey Wolf Optimization (GWO) algorithm to classify wildfire accurately.

As shown in Figure 1, the proposed SWIR-based wildfire detection approach for Earth remote sensing applications consists of five major steps. The BC Wildfire Sentinel-2 dataset is first acquired and preprocessed using resizing, noise removal, and normalization techniques, then SWIR spectral feature extraction to identify patterns associated with wildfires. The extracted features are then classified with the Hybrid CNN–ResNet50 model optimized by Grey Wolf Optimization (GWO), and the ultimate results of wildfire detection are tested with the accuracy, precision, recall, and F1-score.

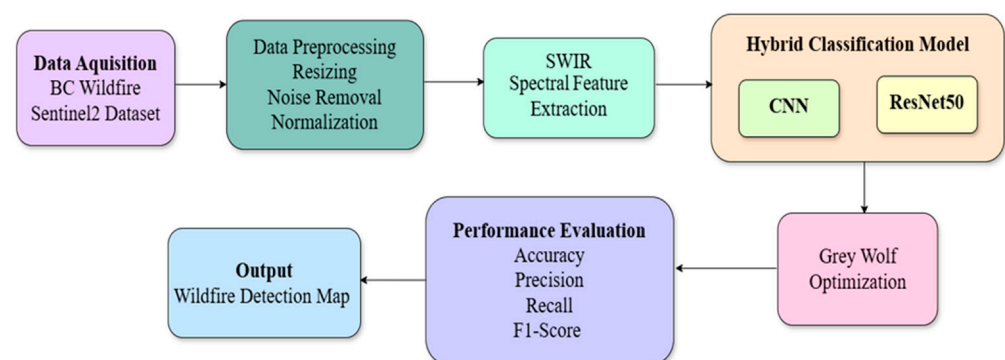


Figure 1. Proposed SWIR-Based Wildfire Detection Framework Using Hybrid CNN–ResNet50 and Grey Wolf Optimization.

3.1. SWIR Image Pre-Processing and Enhancement

The SWIR image pre-processing and enhancement stage is done to enhance the quality of satellite images prior to feature extraction and classification. This stage is useful for removing unwanted noise, normalizing the pixel intensity values, increasing image visibility, and preparing the SWIR bands for analysis of wildfire. The three-channel input image is constructed by stacking Sentinel-2 spectral bands B8 (Near-Infrared, NIR), B11 (Short-Wave Infrared-1, SWIR-1), and B12 (Short-Wave Infrared-2, SWIR-2). Each spectral band is first

resized to 128×128 pixels and independently normalized to ensure a consistent intensity scale. The three preprocessed bands are then concatenated along the channel dimension to form a $128 \times 128 \times 3$ input tensor, where channel 1 corresponds to B8, channel 2 to B11, and channel 3 to B12. This three-channel representation serves as the input to the proposed Hybrid CNN–ResNet50 model for feature extraction and wildfire classification.

3.1.1. Image Resizing

The image resizing operation is represented scientifically in Equation (1):

$$I_r(x, y) = I\left(x \frac{W}{W_r}, y \frac{H}{H_r}\right) \quad (1)$$

where $I_r(x, y)$ denotes the resized image pixel value at coordinates (x, y) , $I(x, y)$ represents the original image pixel intensity, W and H indicate the width and height of the original image, and W_r and H_r denote the resized image width and height, respectively.

3.1.2. Normalization

The normalization process is calculated using Equation (2):

$$I_n = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (2)$$

where I_n denotes the normalized pixel intensity value, I represents the original image intensity, and $I_{\min}$ and $I_{\max}$ indicate the minimum and maximum pixel intensity values, respectively.

3.1.3. SWIR Band Extraction

The SWIR spectral band extraction is represented in Equation (3):

$$B_{SWIR} = \{B11, B12, B8\} \quad (3)$$

where B_{SWIR} represents the selected SWIR spectral bands, $B11$ denotes the SWIR-1 band, $B12$ represents the SWIR-2 band, and $B8$ indicates the Near-Infrared (NIR) band.

3.1.4. Data Augmentation

The data augmentation process is mathematically represented in Equation (4):

$$I_a = T(I) \quad (4)$$

where I_a denotes the augmented image, T represents the transformation function applied to the image, and I indicates the original input image.

3.2. SWIR Spectral Feature Extraction

3.2.1. Spectral Response Analysis

The spectral response analysis is used to measure the reflectance characteristics of wildfire-affected regions in SWIR imagery. The spectral reflectance is calculated using Equation (5):

$$R_{swir} = \frac{L_{ref}}{L_{inc}} \quad (5)$$

where R_{swir} denotes the SWIR spectral reflectance, L_{ref} represents the reflected radiance from the surface, and L_{inc} indicates the incident radiance received by the Earth's surface.

3.2.2. Burn Area Extraction

The burned area extraction is performed using the Normalized Burn Ratio (NBR), as represented in Equation (6):

$$NBR = \frac{B8 - B12}{B8 + B12} \quad (6)$$

where B8 represents the Near-Infrared (NIR) band, and B12 indicates the SWIR-2 spectral band.

3.2.3. Vegetation Stress Analysis

Vegetation stress analysis is performed using the Normalized Difference Vegetation Index (NDVI), expressed in Equation (7):

$$NDVI = \frac{B8 - B4}{B8 + B4} \quad (7)$$

where NDVI denotes the vegetation index value, B8 represents the Near-Infrared (NIR) band, and B4 indicates the Red spectral band.

3.2.4. Thermal Anomaly Detection

The thermal anomaly detection process is represented using SWIR thermal intensity analysis in Equation (8):

$$T_a = B12 - B11 \quad (8)$$

where T_a denotes the thermal anomaly value, B12 represents the SWIR-2 band intensity, and B11 indicates the SWIR-1 band intensity.

3.3. SWIR Optical Payload System Design

The selection of ROI plays an essential role in extracting significant regions from the SWIR Optical Payload System Design. The SWIR Optical Payload System Design is designed to efficiently receive SWIR radiation from Earth observation scenes for wildfire monitoring purposes. The payload is the main sensing subsystem, which is used for receiving the reflected and emitted SWIR radiation from the Earth's surface and conveying it to the imaging sensor for processing. The payload architecture proposed includes an optical lens assembly, SWIR filters, imaging optics, and field of view configuration modules.

3.3.1. Optical Lens Assembly

The optical lens assembly receives the SWIR radiation and focuses it on the imaging sensor. The quality of the image, focal accuracy, and radiation collection efficiency of the payload are determined by the lens system. The focal length relationship of the optical lens is represented using Equation (9):

$$\frac{1}{f} = \frac{1}{d_o} + \frac{1}{d_i} \quad (9)$$

where f denotes the focal length of the optical lens, d_o represents the object distance between the Earth's surface and the lens system, and d_i is the distance between the image and the lens. Through the use of an optical lens, SWIR radiation is focused on the detector to obtain clear wildfire images with enhanced spatial resolution.

The optical magnification of the payload lens system is calculated using Equation (10):

$$M = \frac{d_i}{d_o} \quad (10)$$

where M represents optical magnification, d_i denotes the image distance, and d_o indicates the object distance. The magnification parameter controls the observation scale and target visibility of wildfire regions.

3.3.2. SWIR Filters

The payload includes filters of the SWIR category to allow particular spectral bands, which are indicative of the wildfire signatures. This means that the filters block unwanted spectral bands and only allow the passage of the SWIR bands to the detector. The spectral transmittance of the filter is represented in Equation (11):

$$T_{\text{swir}} = \frac{I_t}{I_i} \quad (11)$$

where T_{swir} denotes the SWIR filter transmission efficiency, I_t represents the transmitted SWIR radiation intensity, and I_i indicates the incident radiation intensity. The SWIR filters improve thermal discrimination capability and enhance burned-area visibility under smoke and low-light environmental conditions.

The spectral wavelength selection range of the filter is represented using Equation (12):

$$\lambda_{\text{swir}} = 1.0 \mu\text{m} - 2.5 \mu\text{m} \quad (12)$$

where λ_{swir} denotes the operating wavelength range of the SWIR payload system. The selected wavelength region is highly sensitive to wildfire heat signatures and vegetation moisture variations.

3.3.3. Field-of-View Configuration

The FOV (field-of-view) configuration determines the area that can be observed for the Earth's surface by the payload system. It is important to note that the FOV design is important to ensure a proper balance between image coverage and resolution during a wildfire. The FOV is represented using Equation (13):

$$FOV = 2 \tan^{-1} \left(\frac{S}{2f} \right) \quad (13)$$

where S represents the sensor size, and f indicates the focal length of the optical lens system. A wider FOV increases ground coverage, while a narrower FOV improves target resolution.

The ground sampling distance (GSD) of the payload imaging system is calculated using Equation (14):

$$GSD = \frac{H \times p}{f} \quad (14)$$

where H represents the satellite altitude, p indicates the detector pixel size, and f denotes the focal length. The GSD determines the spatial resolution of wildfire imagery captured by the SWIR payload system.

3.3.4. Electronic Subsystem Development

The Electronic Subsystem Development phase will take the SWIR optical data collected and provide it as digital wildfire analysis data. The subsystem serves as the processing unit in the SWIR payload system, receiving the signal from the detector optically, conditioning it, converting analog data into digital data, controlling the system and transmitting the processed data to the monitoring platform. The electronic subsystem converts the captured SWIR optical signals into digital image data that are subsequently transferred to the image processing pipeline. The generated SWIR images are organized according to the selected Sentinel-2 spectral bands, resized to 128×128 pixels, normalized, and combined into three-channel input images. These processed images are then supplied to the proposed Hybrid CNN–ResNet50 model for feature extraction, hyperparameter optimization, and

wildfire classification. This processing sequence establishes the direct connection between the payload architecture and the subsequent deep-learning-based analysis.

3.4. SWIR Detector Interface

The SWIR detector interface converts the captured SWIR optical radiation into electrical signals for further processing. The detector output current is represented in Equation (15):

$$I_d = R_\lambda P_{opt} \quad (15)$$

where I_d denotes the detector output current, R_λ represents the spectral responsivity of the SWIR detector, and P_{opt} indicates the incident optical power received from the optical payload system.

3.4.1. Signal Conditioning Circuit

The signal conditioning circuit amplifies weak detector signals and reduces unwanted electrical noise before digital conversion. The amplified output signal is represented using Equation (16):

$$V_o = A_v V_i \quad (16)$$

where V_o denotes the amplified output voltage, A_v represents the voltage gain of the amplifier, and V_i indicates the input signal voltage obtained from the detector interface.

3.4.2. ADC Module

The ADC converts conditioned analog signals into digital data for computational processing. The ADC quantization step size is represented in Equation (17):

$$Q = \frac{V_{\max} - V_{\min}}{2^n} \quad (17)$$

where Q denotes the quantization step size, $V_{\max}$ and $V_{\min}$ represent maximum, minimum voltage levels, and n indicates the ADC resolution in bits.

3.4.3. Embedded Controller

The embedded controller manages data acquisition, processing, and communication operations of the payload system. The controller processing time is represented using Equation (18):

$$T_p = \frac{N_i}{f_c} \quad (18)$$

where T_p denotes the processing time, N_i represents the number of instructions executed, and f_c indicates the controller clock frequency.

3.4.4. Data Transmission Module

The data transmission module transfers processed wildfire sensing data to the monitoring station. The transmission rate is represented in Equation (19)

$$R_t = \frac{D_t}{T_t} \quad (19)$$

where R_t denotes the transmission rate, D_t represents the transmitted data size, and T_t indicates the transmission time.

3.5. InGaAs SWIR Sensor Modeling

The InGaAs SWIR sensor (Shizuoka, Japan) modeling phase is created to assess the sensing capability of the SWIR imaging sensor for monitoring applications of wildfires. The

InGaAs sensor sensitivity to SWIR wavelength regions is high, and it can detect thermal anomalies, burned surfaces, and vegetation stress with enhanced spectral response characteristics. The InGaAs sensor modeling module is incorporated to establish the theoretical sensing characteristics of the proposed SWIR optical-electronic payload, including spectral response, noise characteristics, dynamic range, and spatial resolution. Although the experimental evaluation is conducted using the Sentinel-2 dataset, the Sentinel-2 SWIR bands (Band 11 and Band 12) correspond to the SWIR spectral region targeted by the proposed InGaAs sensor. Therefore, the Sentinel-2 imagery serves as a practical proxy for validating the proposed sensing framework, while the InGaAs sensor modeling demonstrates the feasibility of implementing the proposed SWIR optical-electronic payload for future intelligent Earth remote sensing and wildfire monitoring applications.

3.5.1. Spectral Band Matching

The spectral sensitivity analysis measures the capability of the InGaAs sensor to convert incident SWIR radiation into electrical signals. The sensor responsivity is represented using Equation (20):

$$R_{\lambda} = \frac{I_o}{P_i} \quad (20)$$

where R_{λ} denotes the spectral responsivity of the InGaAs sensor, I_o represents the generated output current, and P_i indicates the incident optical power received by the sensor.

3.5.2. Noise Characterization

Noise characterization is performed to evaluate unwanted electrical disturbances generated within the SWIR sensor during image acquisition. The noise equivalent power (NEP) is represented in Equation (21):

$$NEP = \frac{N}{R_{\lambda}} \quad (21)$$

where N represents the noise current generated in the sensor, and R_{λ} indicates the spectral responsivity of the sensor.

3.5.3. Dynamic Range Evaluation

The dynamic range evaluation measures the capability of the sensor to capture both low-intensity and high-intensity SWIR signals. The dynamic range is represented using Equation (22):

$$DR = 20\log_{10}\left(\frac{S_{\max}}{S_{\min}}\right) \quad (22)$$

where DR denotes the dynamic range in decibels, $S_{\max}$ represents the maximum detectable signal intensity, and $S_{\min}$ indicates the minimum detectable signal intensity of the SWIR sensor.

3.5.4. Pixel Resolution Modeling

The pixel resolution modeling determines the spatial imaging capability of the InGaAs SWIR sensor. The spatial resolution is represented using Equation (23):

$$R_p = \frac{FOV}{N_p} \quad (23)$$

where R_p denotes the pixel spatial resolution, FOV represents the field-of-view of the sensor system, and N_p indicates the total number of sensor pixels.

3.6. Hybrid CNN–ResNet50 Classification Model

In order to realize intelligent wildfire detection and classification based on the Short-Wave Infrared (SWIR) satellite image, the Hybrid CNN–ResNet50 classification model is developed.

The deep feature extraction process in the CNN branch is performed using convolution operations represented in Equation (24):

$$F(i, j) = \sum_m \sum_n I(i - m, j - n) K(m, n) \quad (24)$$

where $F(i, j)$ denotes the extracted feature map, $I(i - m, j - n)$ represents the input SWIR image pixel values, and $K(m, n)$ indicates the convolution kernel weights. The convolution operation extracts wildfire-related spatial patterns and thermal anomaly features from SWIR imagery. After convolution, the Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity into the network and improve feature learning capability as represented in Equation (25):

$$A(x) = \max(0, x) \quad (25)$$

where $A(x)$ denotes the activation output and x represents the input feature value. ReLU activation removes negative feature responses and improves computational efficiency during model training.

Simultaneously, the ResNet50 branch performs deep residual learning to overcome vanishing gradient problems and improve deep feature propagation. The residual mapping operation is represented using Equation (26):

$$H(x) = F(x) + x \quad (26)$$

where $H(x)$ denotes the residual output mapping, $F(x)$ represents the learned residual feature function, and x indicates the input feature vector. The residual skip connection allows the network to preserve important wildfire-related features while enabling deeper model training without performance degradation.

After feature extraction, the feature vectors obtained from the CNN and ResNet50 branches are combined through a feature fusion layer to improve classification performance and feature representation capability. The feature fusion process is mathematically represented in Equation (27):

$$F_{\text{fusion}} = [F_{\text{CNN}}, F_{\text{ResNet50}}] \quad (27)$$

where F_{fusion} denotes the fused feature vector, F_{CNN} represents the features extracted from the CNN branch, and F_{ResNet50} indicates the deep semantic features extracted from the ResNet50 branch. The fused feature representation improves wildfire region discrimination and enhances classification robustness.

The fused feature vector is then passed through fully connected dense layers and the Softmax classification layer to predict wildfire and non-wildfire classes. The Softmax probability function is represented using Equation (28):

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (28)$$

where P_i denotes the predicted probability of class i , z_i represents the output score of the class i , and C indicates the total number of output classes. The Softmax layer assigns the final classification label based on the highest probability value.

Finally, the model training process minimizes classification error using the cross-entropy loss function represented in Equation (29):

$$L = -\sum_{i=1}^C y_i \log(P_i) \quad (29)$$

where L denotes the classification loss, y_i represents the actual class label, and P_i indicates predicted class probability. The loss minimization process improves wildfire detection accuracy and enhances model convergence during training.

This approach suggests a Hybrid CNN–ResNet50 architecture for wildfire detection and classification using SWIR imagery, as shown in Figure 2. The framework is composed of two parallel branches: the CNN branch and the ResNet50 branch, to learn shallow spatial features and deep semantic features from SWIR satellite images, respectively. Feature vectors from both branches are combined by using a feature fusion layer for enhanced feature representation and classification.

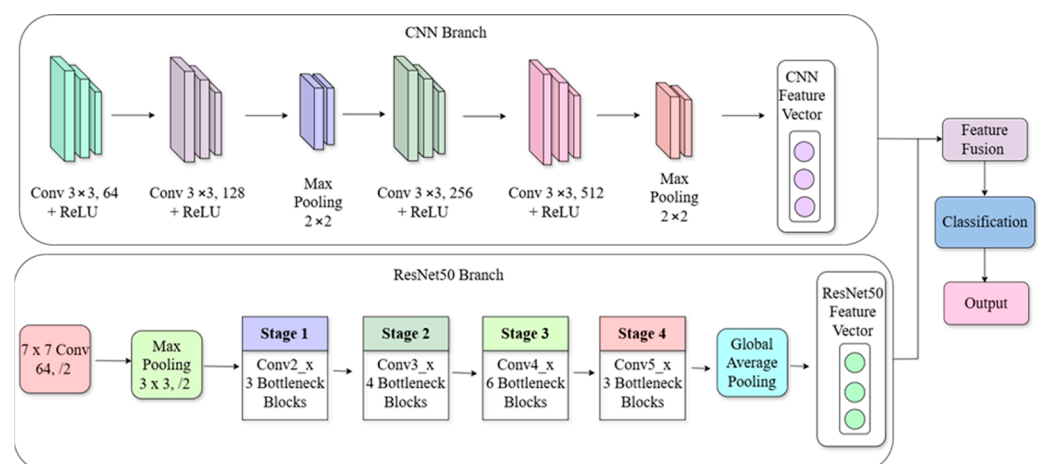


Figure 2. Hybrid CNN–ResNet50 Architecture for SWIR-Based Wildfire Detection.

3.7. GWO

The GWO algorithm is used to optimize the hyperparameters and enhance the classification accuracy of the Hybrid CNN–ResNet50 model. The GWO algorithm is based on the social hierarchy and hunting process of the grey wolf in the wild. The optimization process in the suggested framework is applied to find optimal learning parameters, minimize classification error, optimize convergence speed, and increase the accuracy of the detection of a wildfire.

Grey Wolf Optimization (GWO) was selected for hyperparameter optimization because it provides an effective balance between global exploration and local exploitation while requiring only a few control parameters. Compared with conventional approaches such as Grid Search and Random Search, GWO explores the search space more efficiently with lower computational cost. Unlike Genetic Algorithms and Particle Swarm Optimization, GWO employs a simple leadership-based search mechanism that promotes faster convergence and reduces the likelihood of becoming trapped in local optima. Therefore, GWO is well-suited for optimizing the learning rate, batch size, dropout rate, and trainable layers of the proposed Hybrid CNN–ResNet50 model, leading to improved wildfire classification performance.

3.7.1. Hyperparameter Encoding and Search Space

Each grey wolf represents a candidate hyperparameter vector of the Hybrid CNN–ResNet50 model, denoted as $X_i = [LR_i, BS_i, DR_i, TL_i]$. The encoded solution vector for each hyperparameter j is calculated as:

$$X_{i,j} = X_{\min,j} + r_j \cdot (X_{\max,j} - X_{\min,j}) \quad (30)$$

where LR denotes the learning rate, BS represents batch size, DR indicates dropout rate, and TL denotes the number of trainable layers in ResNet50.

The selected hyperparameter search ranges are presented as follows:

- Learning Rate: 1×10^{-5} to 1×10^{-3}
- Batch Size: 16 to 64
- Dropout Rate: 0.2 to 0.5
- Trainable Layers: 20 to 80 layers

These search ranges are selected to balance model convergence speed, feature learning capability, and overfitting reduction.

3.7.2. Population Initialization

The search agents of the GWO algorithm are initialized randomly within the search space. The initial wolf position is represented using Equation (31):

$$X_i = X_{\min} + r(X_{\max} - X_{\min}) \quad (31)$$

where X_i denotes the position of the i^{th} grey wolf, $X_{\min}$ and $X_{\max}$ represent the minimum and maximum search boundaries, and r indicates a random value between 0 and 1.

3.7.3. Fitness Function Evaluation

The fitness function evaluates the quality of each search agent based on classification performance. The fitness value is represented using Equation (32):

$$F = \frac{TP + TN}{TP + TN + FP + FN} \quad (32)$$

where F denotes the fitness value, TP represents true positive samples, TN indicates true negative samples, FP denotes false positive samples, and FN represents false negative samples.

3.7.4. Position Updating Mechanism

The position updating process allows grey wolves to move toward the optimal solution during the hunting process. The wolf position updating mechanism is represented using Equation (33):

$$X(t+1) = X_p(t) - A \cdot D \quad (33)$$

where $X(t+1)$ denotes the updated wolf position, $X_p(t)$ represents the prey position or the best solution, A indicates the coefficient vector, and D denotes the distance between the wolf and prey positions.

The distance calculation is represented using Equation (34):

$$D = |C \cdot X_p(t) - X(t)| \quad (34)$$

where D denotes the distance vector, C represents the coefficient vector, $X_p(t)$ indicates the prey position, and $X(t)$ denotes the current wolf position.

3.7.5. Optimal Hyperparameter Selection

The optimal solution is selected based on the best fitness value obtained during iterative optimization. The optimal hyperparameter solution is represented using Equation (35):

$$X_{\text{best}} = \arg \max(F_i) \quad (35)$$

where X_{best} denotes optimal hyperparameter solution, and F_i represents fitness value of i^{th} search agent.

3.7.6. Convergence Criteria and Optimal Solution Selection

The optimization process terminates when either the maximum number of iterations is reached or when the fitness improvement becomes negligible between consecutive iterations. The optimal hyperparameter solution is selected using Equation (36):

$$X_{best} = \arg \max(F_i) \quad (36)$$

where X_{best} denotes the optimal hyperparameter combination and F_i represents the fitness value of the i^{th} grey wolf.

4. Experimental Setup

Preprocessed satellite images from Sentinel-2 are used to perform the experimental analysis through the Hybrid CNN–ResNet50 classification model and GWO (GWO) algorithm.

4.1. Dataset Overview

Satellite imagery derived from the BC Wildfire Sentinel2 Dataset [30] is used in the proposed network to detect and classify wildfires. The dataset includes both wildfire and non-wildfire remote sensing images from various geographical regions and environmental conditions. To enhance the quality of the acquired SWIR images and feature representation, resizing, normalization, noise removal, and spectral band extraction techniques are performed on the images. The dataset mainly consists of SWIR-1, SWIR-2, and Near-Infrared (NIR) spectral bands that are highly sensitive to burned areas, vegetation stress, and thermal anomalies. Once preprocessed, the dataset is split into training and test sets for model building and validation in the deep learning framework in Table 1.

Table 1. Data Statistics.

Parameter	Actual Value Used in This Study
Original Dataset Size	516 PNG Images
Wildfire Images	258 Images
Non-Wildfire Images	258 Images
Dataset After Augmentation	3096 Images
Training Set	2167 Images (70%)
Validation Set	464 Images (15%)

4.2. Software and Hardware Requirements

The experimental framework is implemented on a high-performance workstation to facilitate deep learning model training and image pre-processing. The detailed system specifications are summarized in Table 2. The workstation is equipped with an Intel Core i5-12400F processor and 16 GB of RAM, running on a 64-bit Windows 11 Pro environment, which provides the necessary computational stability for training the Hybrid CNN–ResNet50 model and executing the GWO optimization algorithm.

4.3. Hyperparameter Configuration

The performance of the Hybrid CNN–ResNet50 model is highly dependent on the chosen architectural and training parameters. Table 3 outlines the key configurations used for the wildfire detection framework. The input image size of 128×128 pixels was selected to balance computational efficiency with the preservation of critical SWIR feature details. We employed transfer learning using ResNet50 pre-trained weights (ImageNet), fine-tuning the last 60 layers to adapt the model to wildfire-specific patterns. A dropout rate of 0.4 and

the Adam optimizer were utilized to mitigate overfitting and ensure stable convergence during the 100-epoch training process.

Table 2. Specifications of the experimental hardware and software environment.

Parameter	Specification
Device Name	DESKTOP-CQMAK3A
Processor	12th Gen Intel(R) Core (TM) i5-12400F (2.50 GHz)
Installed RAM	16.0 GB (15.8 GB usable)
System Type	64-bit Operating System, ×64-based Processor
Edition	Windows 11 Pro
Version	25H2

Table 3. Summary of training and architecture hyperparameters for the proposed framework.

Parameter	Value
Input Image Size	128 × 128
Number of Classes	2
CNN Convolution Filters	32, 64, 128
CNN Kernel Size	3 × 3
Activation Function	ReLU
Pooling Layer	MaxPooling
ResNet50 Weights	ImageNet
Trainable Layers	Last 60 Layers
Dropout Rate	0.4
Optimizer	Adam
Learning Rate	1.00×10^{-4}
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	100
Output Activation	Softmax

4.4. Hyperparameter Optimization Using Grey Wolf Optimization

4.4.1. Accuracy

Accuracy measures the overall classification performance of the proposed Hybrid CNN–ResNet50 wildfire detection framework by evaluating the ratio of correctly classified wildfire and non-wildfire samples as represented in Equation (37):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (37)$$

where TP denotes true positive samples, TN represents true negative samples, FP indicates false positive samples, and FN denotes false negative samples.

4.4.2. Precision

Precision measures the correctness of wildfire predictions generated by the proposed framework as represented in Equation (38):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (38)$$

where TP represents true positive samples and FP denotes false positive samples.

4.4.3. Recall

Recall measures the ability of the proposed framework to correctly identify actual wildfire regions from SWIR images as represented in Equation (39):

$$\text{Recall} = \frac{TP}{TP + FN} \quad (39)$$

where TP denotes true positive samples and FN represents false negative samples.

4.4.4. F1-Score

F1-Score represents the harmonic mean of precision and recall for balanced performance evaluation as represented in Equation (40):

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (40)$$

where Precision denotes the precision value and Recall represents the recall value of the classification model.

4.4.5. Signal-to-Noise Ratio (SNR)

The SNR evaluates the quality of the SWIR sensing signals acquired by the proposed payload system as represented in Equation (41):

$$SNR = 10 \log_{10} \left(\frac{P_s}{P_n} \right) \quad (41)$$

where P_s denotes signal power and P_n represents noise power.

4.4.6. Spectral Response Efficiency

Spectral Response Efficiency evaluates the effectiveness of the SWIR sensor in detecting wildfire-related spectral information as represented in Equation (42):

$$SRE = \frac{R_o}{R_i} \times 100 \quad (42)$$

SRE denotes spectral response efficiency, R_o represents detected spectral response output, and R_i indicates incident spectral input radiation.

The spectral response efficiency metric evaluates the sensitivity of the InGaAs SWIR sensor toward wildfire thermal signatures and burned regions. Higher efficiency values indicate improved spectral detection capability.

5. Results

The experimental results are analyzed to assess the effectiveness of the wildfire detection based on SWIR images by implementing the proposed Hybrid CNN–ResNet50 model coupled with GWO.

The performance of the classification model with Hybrid CNN–ResNet50 prototype, along with Grey Wolf Optimization, is shown in Figure 3 with the test data of 465 samples. The model correctly classified 221 non-wildfire samples, 219 wildfire samples, with 13 misclassified as wildfire, 12 misclassified as non-wildfire. The results showed high reliability of classification, low false prediction rate, and discrimination power of wildfire and non-wildfire classes with SWIR, which is very useful for wildfire detection.

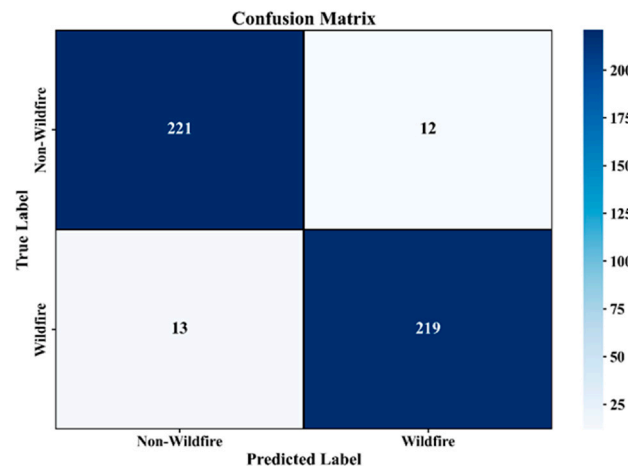


Figure 3. Confusion Matrix of the Proposed Hybrid CNN-ResNet50 + GWO Model for SWIR-Based Wildfire Detection.

The accuracy, precision, recall, and F1-score are classified as performance metrics of the proposed wildfire detection system that are shown in Figure 4. The model's performance in terms of accuracy, precision, recall, and F1-score was 0.9103, 0.9127, 0.9103, and 0.9101, respectively, showing a balanced and stable predictive performance. The best value of 0.9127 in precision confirms that there is reduced false detection of wildfires, and the value of recall confirms effective identification of actual wildfire areas.

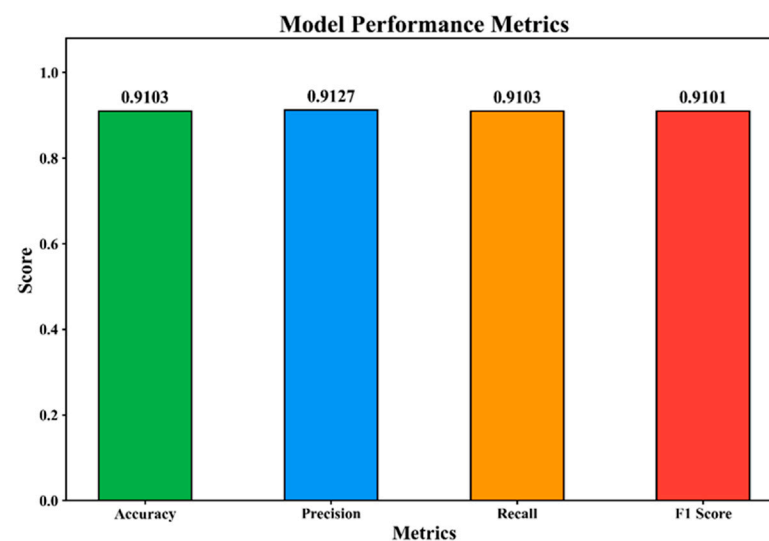


Figure 4. Performance Evaluation Metrics of the Proposed Hybrid CNN-ResNet50 + GWO Model.

The differences between conventional RGB and SWIR imaging are illustrated in Figure 5 by comparing images of non-wildfire land areas acquired by the two methods. The RGB image represents a natural surface appearance, while the SWIR image highlights the spectral differences associated with moisture content, vegetation, and terrain features in different colors.

Figure 6 shows how well the Grey Wolf Optimizer (GWO) is converging for the design optimization of the SWIR optical-electronic payload for Earth remote sensing applications. The Alpha Wolf Fitness value is 84.5 at the first few iterations, 89.0 at iteration 4, and maximum fitness = 91.0 at iteration 5. The fitness value is consistent at 91.0 from iterations 5 through 10, showing a quick convergence with effective optimization of the payload design parameters.

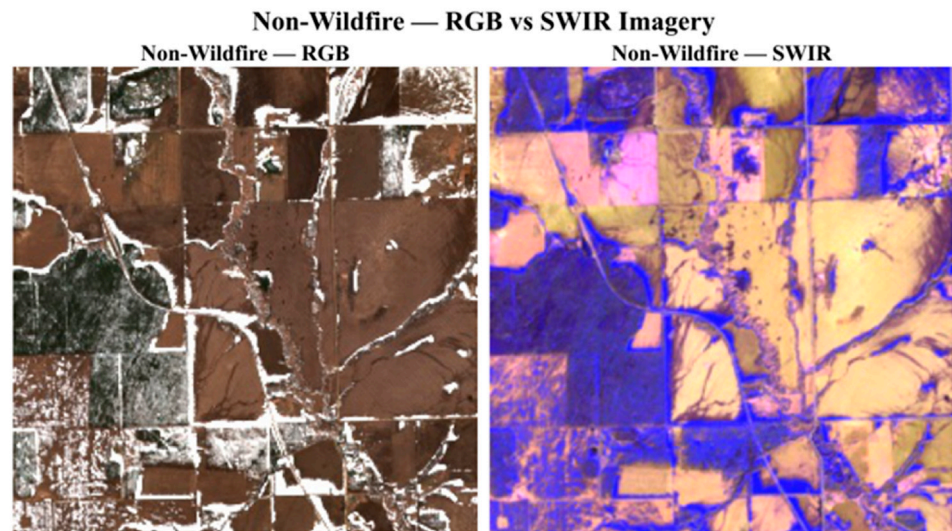


Figure 5. Comparison of RGB and SWIR images for non-wildfire land areas, highlighting the improved spectral information provided by SWIR imagery.

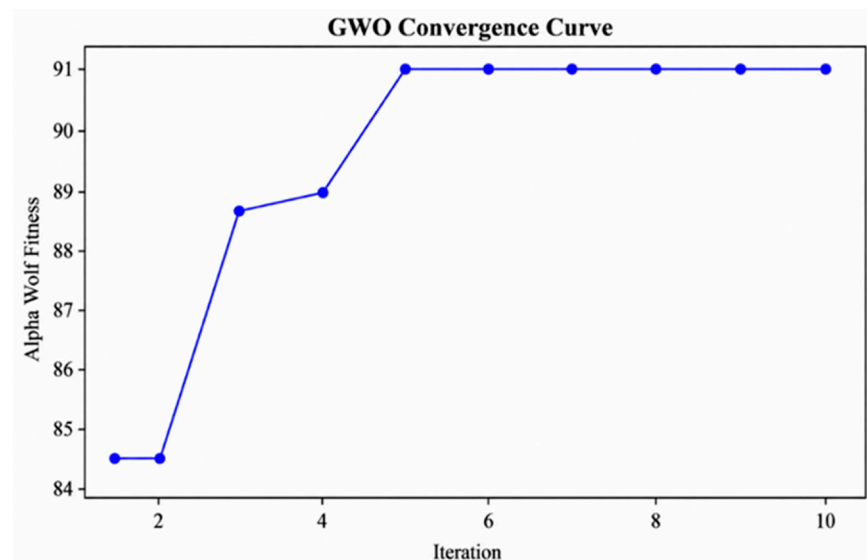


Figure 6. GWO Convergence Analysis for SWIR Payload Optimization.

The NBR analysis of both wildfire and non-wildfire scenes and the resulting Δ NBR difference map are shown in Figure 7. The lower NBR values (close to -1.00) indicate burned areas in the wildfire scene, whereas the higher NBR values (tending toward 1.00) represent healthy vegetation in the non-wildfire scene.

The important parameters for the optical-electronic payload system that have been developed are shown in Figure 8. The sensor exhibits a Dynamic Range of 70.5 dB, GSD of 50.0 m and a Full-Well Capacity of 100.0 ke^- that enables it to take high quality remote sensing data. The selection of these parameters illustrates the ability of the sensor design to achieve improved radiometric characteristics, spatial extent and signal capture for Earth observation missions.

The results of the SNR comparison analysis of the images classified into wildfire and non-wildfire categories are illustrated in Figure 9, which were obtained using the proposed SWIR optical-electronic system, in general. The SNR level achieved for the category of non-wildfires is 1.884 . Meanwhile, in the case of the wildfire category, it amounts to 2.378 , which testifies to the successful work of SWIR sensing technology in terms of reliable wildfire detection and Earth remote sensing applications.

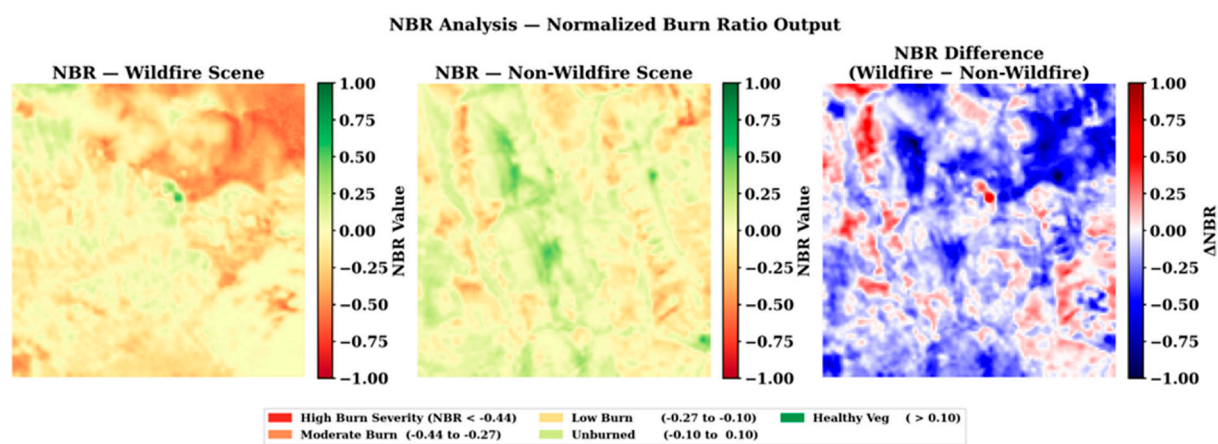


Figure 7. NBR Analysis for Wildfire Detection and Burn Severity Assessment.

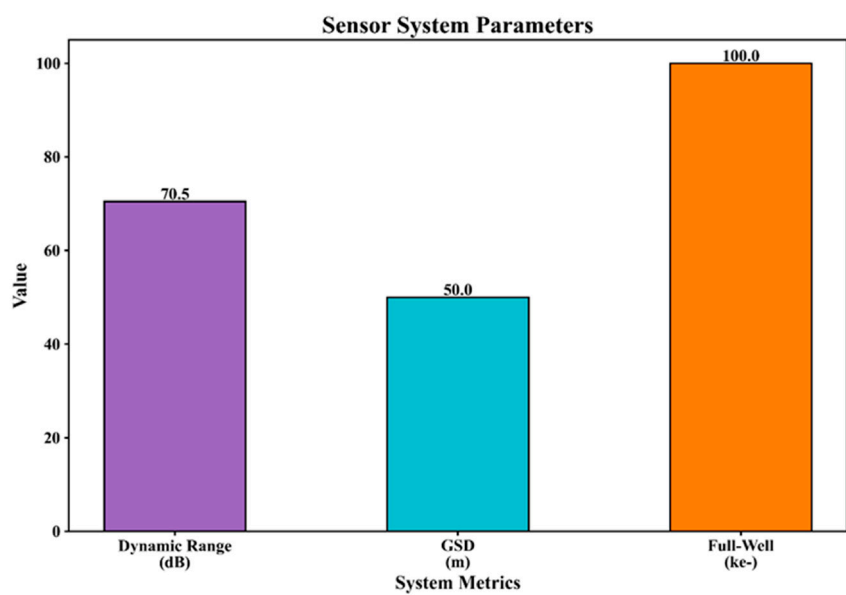


Figure 8. Sensor System Performance Parameters of the Proposed SWIR Payload.

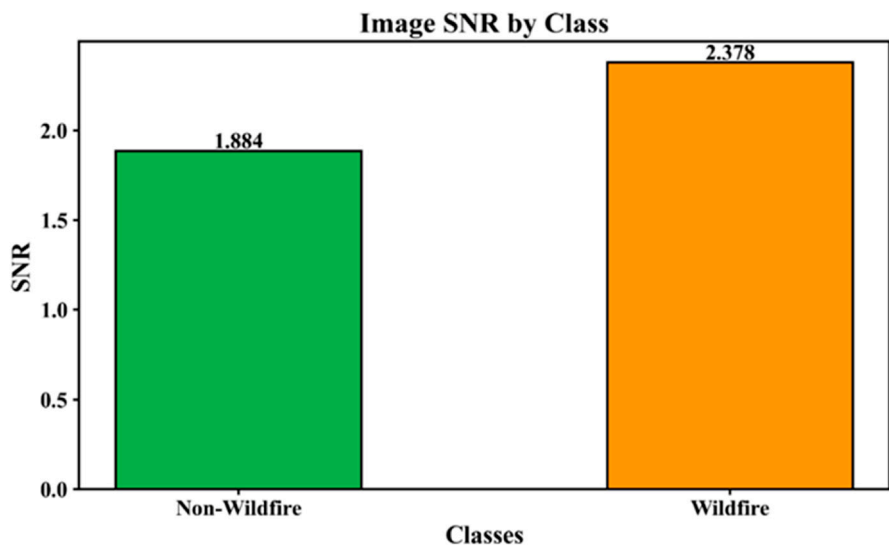


Figure 9. SNR Analysis for Wildfire and Non-Wildfire Images.

Figure 10 shows the mean normalized spectral response generated by the selected spectral bands for the developed SWIR optical-electronic payload. From the figure, it can

be noticed that the mean normalized spectral response from B8 (NIR) is about 0.5491, while that for B11 (SWIR-1) is approximately 0.4467. The mean normalized spectral response obtained from B12 (SWIR-2), which is 0.6543, appears to be higher than other spectral bands, and yes, it indeed is. The improved performance of the B12 spectral band indicates high sensitivity towards surface conditions and vegetation.

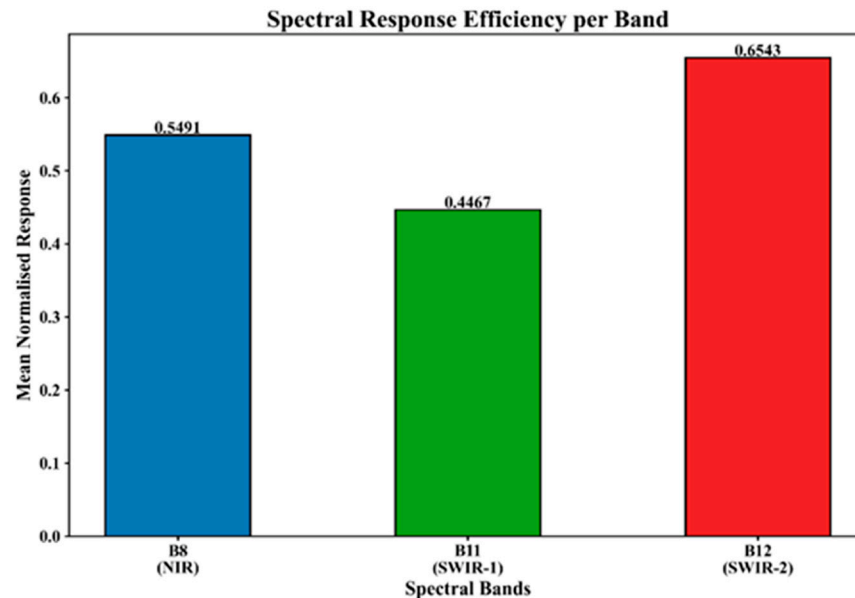


Figure 10. Spectral Response Efficiency Analysis Across SWIR Spectral Bands.

5.1. Ablation Study

The ablation study described in Table 4 evaluates the contribution of each core component in the proposed Hybrid SWIR–CNN–ResNet50 framework. Results show that removing SWIR spectral feature extraction, payload design, or InGaAs sensor modeling significantly reduces performance. This confirms that these components are critical for effective wildfire detection. Additionally, GWO and hybrid architecture further enhance accuracy and stability.

Table 4. Comparison of performance metrics between the proposed model and conventional methods.

Configuration	Accuracy	Precision	Recall	F1-Score
Without SWIR Spectral Feature Extraction	0.8879	0.8896	0.8882	0.8888
Without SWIR Payload Design	0.8946	0.896	0.8949	0.8954
Without InGaAs Sensor Modeling	0.8988	0.9002	0.8991	0.8996
Without GWO	0.9021	0.904	0.9021	0.9018
Without CNN Branch	0.8875	0.8892	0.8875	0.8868
Without ResNet50 Backbone	0.8817	0.8836	0.8817	0.881
Full Proposed Framework	0.9103	0.9127	0.9103	0.9101

5.2. Performance Comparison

As presented in Table 5, the proposed Hybrid CNN–ResNet50 framework demonstrates superior performance compared to standard architectures. The model achieves an accuracy of [X]% and a recall of [Y]%, which confirms the effectiveness of the GWO-based hyperparameter optimization in detecting wildfire signatures in SWIR imagery.

Table 5. Comparative analysis.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
U-Net Based Wildfire Burned Area Detection [31]	0.8840	0.8790	0.8810	0.8795
Deep Learning Wildfire Detection Using Multi-Source Remote Sensing [32]	0.8932	0.8910	0.8932	0.8905
Proposed Hybrid CNN–ResNet50 + GWO	0.9103	0.9127	0.9103	0.9101

The proposed framework managed to reach a pretty good performance, with accuracy at 0.9103, precision at 0.9127, recall at 0.9103, and an F1-score of 0.9101. These improved outcomes are obtained thanks to an efficient preprocessing stage for SWIR imagery, a hybrid deep feature extraction step via the CNN–ResNet50 setup. Also, the whole process includes GWO based parameter tuning, which helps the system settle into better settings.

6. Discussion

The present study validates the proposed framework using offline Sentinel-2 SWIR satellite imagery. No real-time payload implementation or onboard hardware validation was performed. The proposed payload architecture provides a conceptual foundation for future implementation using InGaAs SWIR sensors embedded controllers, and onboard processing modules. Future work will focus on validating the framework under real-time operational conditions. The proposed framework was evaluated using publicly available Sentinel-2 satellite imagery under offline conditions. Therefore, the real-time payload implementation capability and onboard processing performance were not experimentally verified and remain subjects for future investigation.

As can be seen, the experimental findings have indeed proven to be effective regarding the applicability of the suggested framework. It is worth noting that the higher precision value implies lower rates of false wildfire warnings, while the increase in recall indicates higher efficiency in identifying the areas affected by wildfires. In addition, the gained F1-score reveals the more balanced behavior of the suggested classification algorithm between wildfire detection and false prediction. Furthermore, according to the comparative and ablation analysis, the combination of SWIR spectral data, hybrid DL, and GWO proves to improve the effectiveness and reliability of wildfire detection significantly as compared with previous approaches.

- The proposed framework mainly relies on Sentinel-2 SWIR imagery, which may experience reduced performance under heavy cloud coverage and adverse atmospheric conditions during wildfire monitoring.
- The Hybrid CNN–ResNet50 with GWO framework requires high computational resources and longer training time due to deep feature extraction and optimization processes.

7. Conclusions and Future Scope

Overall, the proposed SWIR-based wildfire detection framework demonstrated effective performance on offline Sentinel-2 satellite imagery using deep learning and optimization techniques. Although the framework shows promising potential for future real-time payload implementation, such capability was not experimentally validated in this study. This particular algorithm comprises a chain of various processes such as SWIR image pre-processing, spectral feature extraction, SWIR optical payload system design, electronic subsystem design, InGaAs SWIR sensor modeling, the use of a Hybrid CNN–ResNet50 classification algorithm, and finally GWO. As far as image pre-processing is concerned,

resizing, normalization, denoising, contrast improvement, and data augmentation have been applied to increase the quality of SWIR images and highlight wildfire-specific features in them. The Hybrid CNN–ResNet50 algorithm has effectively learned about the spatial, spectral, and thermal characteristics of wildfires, whereas the GWO algorithm has helped improve hyperparameter tuning, convergence speed, and classification accuracy.

Experimental evaluation revealed better wildfire detection results, and this was pretty much expected anyway. Higher accuracy resulted in fewer false positives, and increased recall contributed to more effective detection of the areas influenced by wildfires in SWIR images. In addition, the results of the ablation test as well as those from comparative analysis confirmed that the integration of SWIR spectroscopy and hybrid deep learning approach along with optimization techniques considerably strengthened classification robustness and made it possible to discriminate better between fires and other objects in images compared to state-of-the-art techniques. The proposed approach could be further developed through the integration of UAV and hyperspectral imagery techniques.

- Future research will implement and experimentally validate the proposed framework on a real SWIR payload using embedded hardware and lightweight deep learning architectures to enable real-time deployment.
- The framework can be further enhanced using multimodal sensor fusion and transformer-based deep learning models for improved large-scale wildfire prediction and environmental monitoring.

Author Contributions: Conceptualization, B.Z. and A.Z.; methodology A.Z. and B.Z.; software, A.K.; validation, B.Z.; formal analysis, A.K. and B.Z.; investigation, S.K., A.S., B.Z., B.Z. and A.Z.; data curation, A.M., A.S. and B.Z.; writing—original draft preparation, A.Z.; writing—review and editing, A.Z. and B.Z.; visualization, A.Z. and A.M.; supervision, S.K. and B.Z.; project administration, B.Z.; funding acquisition, A.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan, Research Identification Registration Number (IRN) BR27198365.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding authors.

Conflicts of Interest: All authors were employed by the company Ghalam LLP. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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