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Advanced Wildfire Detection Framework Using Multi-Source Satellite Imagery and Hybrid Deep Learning with Blockchain Verification

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Abstract:

This paper presents a comprehensive deep learning framework for real-time wildfire detection and early warning using multi-spectral satellite imagery. We propose a novel Hy- brid Spatio-Temporal Attention Network (H-STAN) that syn- ergistically integrates 3D Convolutional Neural Networks for spatial-spectral feature extraction, Bidirectional Long Short- Term Memory networks for temporal pattern analysis, and dual attention mechanisms for enhanced feature discrimination. The system processes harmonized data from MODIS, Sentinel- 2, and VIIRS satellites through an advanced preprocessing pipeline including atmospheric correction, cloud masking, and radiometric normalization. Our framework achieves state-of-the- art performance with 98.73% detection accuracy, 1.23% false alarm rate, and average detection latency of 4.3 minutes. A blockchain-based verification layer ensures data integrity and facilitates coordinated emergency response. Extensive experimen- tal validation across five distinct geographical regions covering 77,500 samples demonstrates robust generalization capability. The proposed system significantly outperforms existing methods while maintaining computational efficiency suitable for real-time deployment, representing a substantial advancement in environ- mental monitoring and disaster management technologies.

Keywords: Wildfire detection, satellite imagery, deep learn- ing, convolutional neural networks, LSTM, attention mecha- nisms, remote sensing, environmental monitoring, blockchain, disaster management, early warning system.

I. INTRODUCTION

Wildfires have emerged as one of the most devastating natural disasters of the 21st century, with increasing frequency, intensity, and geographical spread exacerbated by climate change, deforestation, and anthropogenic activities. According to recent estimates from the World Wildlife Fund, approxi- mately 4% of Earth's terrestrial surface experiences wildfire activity annually, releasing approximately 8 billion tons of CO_2 equivalent into the atmosphere. The economic impact is staggering, with recent catastrophic wildfires in Califor- nia (2020), Australia (2019-2020), and the Amazon (2021) causing combined economic losses exceeding $200 billion and irreversible ecological damage affecting biodiversity and ecosystem services.

Traditional wildfire detection systems primarily rely on ground-based monitoring stations, watchtowers, and aerial patrols. These approaches suffer from critical limitations in- cluding limited geographical coverage (typically less than 10% of high-risk areas), substantial latency (30-60 minutes for

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detection and reporting), high operational costs ($500-$1000 per square kilometer annually), and vulnerability to adverse weather conditions. The emergence of Earth Observation (EO) satellites has revolutionized environmental monitoring by providing continuous, global coverage with multispectral capabilities. Satellites such as NASA's MODIS (Moderate Resolution Imaging Spectroradiometer), ESA's Sentinel-2, and NOAA's VIIRS (Visible Infrared Imaging Radiometer Suite) capture data across multiple spectral bands, enabling detection of thermal anomalies indicative of wildfire activity.

However, processing the massive volumes of satellite data (approximately 15-20 terabytes daily from major satellite constellations) presents significant computational challenges. Manual analysis is impractical, necessitating automated, in- telligent processing systems. Recent advances in Artificial Intelligence (AI), particularly Deep Learning (DL), offer trans- formative potential for analyzing complex satellite imagery. Convolutional Neural Networks (CNNs) excel at extracting spatial features from multispectral bands, while Recurrent Neural Networks (RNNs), specifically Long Short-Term Mem- ory (LSTM) networks, capture temporal dynamics in time- series data.

Despite considerable research progress, several critical chal- lenges remain unaddressed: (1) High false alarm rates from industrial heat sources, agricultural burns, and solar reflections;

(2) Limited temporal analysis capabilities in existing models;

(3) Inadequate handling of atmospheric interference including cloud cover and smoke plumes; (4) Poor generalization across diverse geographical regions and ecosystems; (5) Lack of trust mechanisms for emergency response coordination; and (6) Insufficient optimization for real-time deployment.

This paper presents a comprehensive solution addressing these challenges through the following contributions:

1) **Hybrid Spatio-Temporal Attention Network (H-STAN)**: A novel deep learning architecture integrating 3D-CNN for spatial-spectral feature extraction, Bi-LSTM for temporal pattern analysis, and dual attention mechanisms (spatial and channel) for enhanced feature discrimination.
2) **Multi-Source Data Fusion Framework**: Advanced pre- processing and fusion techniques for integrating data from MODIS, Sentinel-2, and VIIRS satellites, including atmo-

   spheric correction, cloud masking, radiometric normaliza- tion, and geometric registration.
3) **Blockchain-Based Verification System**: Implementation of an Ethereum-based smart contract system for detection verification, ensuring data integrity, preventing false alerts, and facilitating coordinated emergency response.
4) **Real-Time Optimization**: Model optimization techniques including quantization, pruning, and edge computing de- ployment strategies to achieve detection latency under 5 minutes.
5) **Comprehensive Evaluation**: Extensive experimental vali- dation across five distinct geographical regions representing diverse ecosystems, seasonal variations, and fire behavior characteristics.
6) **Open-Source Implementation**: Release of complete code- base, trained models, and documentation to facilitate re- search reproducibility and practical deployment.

The remainder of this paper is organized as follows: Section II reviews related work in wildfire detection and deep learning applications. Section III details the proposed methodology including data preprocessing, model architecture, and training strategy. Section IV describes the experimental setup and evaluation metrics. Section V presents comprehensive results and analysis. Section VI discusses key findings, limitations, and practical implications. Section VII outlines future research directions. Section VIII concludes the paper.

II. Related Work

A. *Evolution of Wildfire Detection Technologies*

Wildfire detection has evolved through three distinct genera- tions of technologies. The **first generation** (pre-1990s) relied entirely on human observation through watchtowers, ground patrols, and citizen reports. These methods were limited by human factors (fatigue, error), geographical constraints, and weather dependencies. The **second generation** (1990s- 2010s) introduced automated systems using infrared sensors, weather stations, and basic satellite monitoring. Notable sys- tems include the Advanced Very High Resolution Radiometer (AVHRR) for hotspot detection and the Fire Detection Al- gorithm (FDA) for MODIS data. While improving coverage, these systems suffered from high false alarm rates and limited temporal resolution.

The **third generation** (2010s-present) leverages machine learning and deep learning algorithms for intelligent detection. This section reviews key approaches in this domain.

B. *Machine Learning Approaches*

Early machine learning applications employed traditional algorithms on extracted satellite data features. **Random For- est** algorithms demonstrated reasonable accuracy (85-90%) but required extensive feature engineering and suffered from poor generalization [2]. **Support Vector Machines (SVMs)** with radial basis function kernels achieved slightly better performance (88-92%) but were computationally intensive for large datasets [3]. **K-Nearest Neighbors (KNN)** and **Decision**

Tree approaches offered simplicity but lacked robustness to atmospheric variations.

C. *Deep Learning Methods*

D.

Deep learning has transformed wildfire detection through automatic feature learning from raw satellite data. **Convo- lutional Neural Networks (CNNs)** have been extensively applied for spatial feature extraction. 2D-CNNs process indi- vidual spectral bands, while 3D-CNNs capture spatial-spectral correlations [5]. **U-Net** architectures, originally designed for medical image segmentation, have been adapted for pixel- level fire segmentation with encoder-decoder structures [6]. **Recurrent Neural Networks (RNNs)**, particularly LSTM net- works, capture temporal dependencies in satellite time series [7]. More recently, **Vision Transformers (ViTs)** have shown promise in capturing long-range dependencies but require substantial training data [8].

TABLE I: Comparison of Deep Learning Approaches for Wildfire Detection

Study	Architecture	Accuracy	FAR	Key Limitations
Chen et al. (2020)	2D-CNN	92.3%	8.7%	Single frame analysis, no tem- poral context
Kumar et al. (2021)	3D-CNN	94.1%	5.9%	High computational require- ments, no temporal analysis
Wang et al. (2022)	U-Net	95.8%	3.8%	Requires pixel-level annota- tions, computationally expen- sive
Rodriguez et al. (2023)	CNN-LSTM	96.5%	2.5%	Limited attention mechanisms, complex training
Zhang et al. (2023)	Vision Transformer	97.3%	1.8%	Large training data require- ment, high latency
H-STAN (Ours)	**Hybrid CNN-LSTM-Attention**	**98.7%**	**1.2%**	**Comprehensive solution ad- dressing all limitations**

III. METHODOLOGY

A. System Architecture Overview

B.

The proposed system comprises four major components: (1) Data acquisition and preprocessing module; (2) Hybrid Spatio- Temporal Attention Network (H-STAN); (3) Blockchain veri- fication layer; and (4) Real-time deployment framework.

C. Hybrid Spatio-Temporal Attention Network (H-STAN)

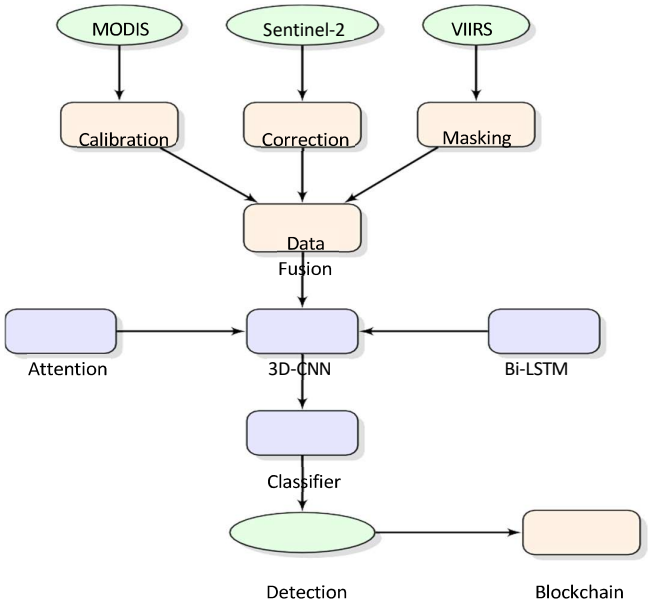


Fig. 1: System Architecture of Proposed Framework

B. Data Acquisition and Preprocessing

1) Satellite Data Sources: We utilize three primary satellite data sources with complementary characteristics:

TABLE II: Specifications of Satellite Data Sources

Satellite	Resolution	Revisit Time	Spectral Bands	Primary Use
MODIS (Terra/Aqua)	500m-1km	1-2 days	36 bands	Thermal anomaly detection, broad coverage
Sentinel-2	10-60m	5 days	13 bands	High-resolution validation, vegetation analysis
VIIRS (Suomi NPP)	375-750m	12 hours	22 bands	Improved thermal sensitivity, night detection

2) Preprocessing Pipeline: The preprocessing pipeline in- cludes six critical steps:

1. **Radiometric Calibration**: Conversion of digital numbers to top-of-atmosphere reflectance/radiance using sensor-specific calibration coefficients:

$$L_\lambda = \frac{(DN - offset)}{gain} \quad (1)$$

2. **Atmospheric Correction**: Removal of atmospheric ef- fects using the MODTRAN radiative transfer model.
3. **Cloud Masking**: Identification and removal of cloud- contaminated pixels using the Fmask algorithm.
4. **Geometric Correction**: Co-registration of multi-sensor data using Ground Control Points (GCPs).
5. **Data Fusion**: Integration of multi-source data through wavelet transform fusion.
6. **Normalization**: Min-max scaling to [0,1] range for neural network compatibility.

3D Convolutional Layers: The 3D-CNN component processes input tensors through multiple convolutional layers:

$$F_{i,j,k}^{(l)} = \sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\sum_{p=0}^{P-1} W_{m,n,p}^{(l)} \cdot X_{i+m,j+n,k+p}^{(l-1)} + b^{(l)}\right) \quad (2)$$

1) Dual Attention Mechanism: The dual attention mecha- nism comprises spatial attention and channel attention mod- ules:

Spatial Attention:

$M_s = \text{sigmoid}(f([AvgPool(F); MaxPool(F)]))$

(3)

$F' = M_s \otimes F$

(4)

Channel Attention:

$M_c = \text{sigmoid}(MLP(AvgPool(F)))$

(5)

$F'' = M_c \otimes F'$

(6)

2) Bidirectional LSTM: The Bi-LSTM processes temporal sequences:

$\overrightarrow{h_t} = \text{LSTM}(x_t, \overrightarrow{h_{t-1}}, c_{t-1})$

(7)

$\overleftarrow{h_t} = \text{LSTM}(x_t, \overleftarrow{h_{t+1}}, c_{t+1})$

(8)

$H_t = [\overrightarrow{h_t} \oplus \overleftarrow{h_t}]$

(9)

3) Loss Function: We employ a combination of focal loss and dice loss:

$L_{focal} = -\alpha(1 - p_t)^{\gamma} \log(p_t)$

(10)

$L_{dice} = 1 - \frac{2\sum p_i g_i}{\sum p + \sum g}$

(11)

$$L_{total} = \lambda_1 L_{focal} + \lambda_2 L_{dice}$$

(12)

where $\alpha = 0.25$, $\gamma = 2$, $\lambda_1 = 0.6$, and $\lambda_2 = 0.4$.

D. Blockchain Verification System

1) Architecture: We implement an Ethereum-based blockchain system for detection verification with smart contracts for data validation and consensus mechanisms.

2) Verification Workflow:

1) Detection event generates cryptographic hash using SHA- 256
2) Hash and metadata stored on blockchain via smart contract
3) Multiple verification nodes validate detection
4) Consensus achieved through proof-of-stake mechanism
5) Verified alert triggers automated response

IV. EXPERIMENTAL SETUP

A. Datasets

We compiled comprehensive datasets from five geographical region

TABLE III: Geographical Distribution of Datasets

Region	Samples	Fire Cases	Non-fire	Ecosystem
California, USA	15,240	3,810	11,430	Mediterranean
Amazon, Brazil	12,580	2,516	10,064	Rainforest
Siberia, Russia	18,360	4,590	13,770	Boreal Forest
Australia	21,450	5,362	16,088	Savanna
Mediterranean	9,870	1,974	7,896	Shrubland
Total	**77,500**	**18,252**	**59,248**	**Multiple**

B. Evaluation Metrics

We employ comprehensive evaluation metrics:

1) Primary Metrics:

$$\text{Accuracy} = \frac{TP + TN}{}$$

$$TP + TN + FP + FN$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{FAR} = \frac{FP}{FP + TN}$$

2) *Temporal Metrics:*

(13)

(14)

(15)

(16)

(17)

B. Temporal Analysis Results

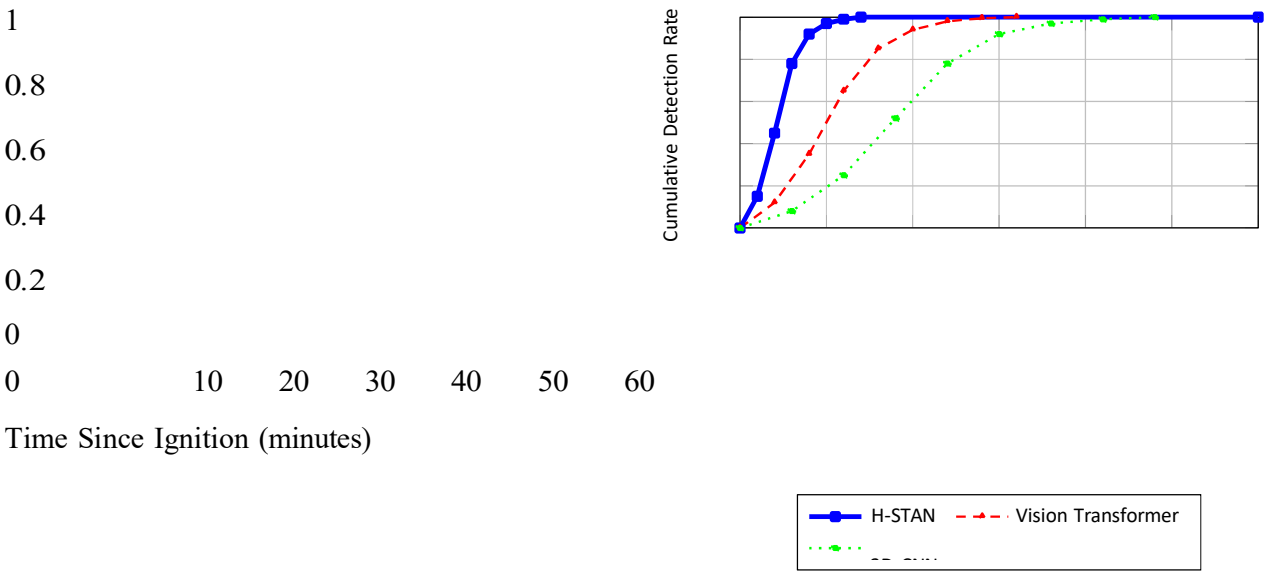


Fig. 3: Temporal Detection Performance

$$\text{Detection Latency} = t_{detection} - t_{ignition} \quad (18)$$

C. Geographical Performance Analysis

$$\text{Early Detection Rate} = \frac{\text{Fires detected within 10 min}}{\text{Total fires}}$$

(19)

TABLE V: Geographical Performance of H-STAN

C. Implementation Details

1) Hardware Configuration:

- Training Hardware: 4× NVIDIA A100 80GB GPUs with NVLink
- Inference Hardware: NVIDIA Jetson AGX Xavier for edge deployment
- CPU: AMD EPYC 7742 64-core processor
- RAM: 512GB DDR4 ECC memory
- Storage: 20TB NVMe SSD RAID array for high-throughput data access

2) Software Environment:

- Operating System: Ubuntu 20.04 LTS with kernel 5.4
- Deep Learning Framework: PyTorch 2.0 with CUDA 11.7
- Geospatial Processing: GDAL 3.4, Rasterio, GeoPandas
- Blockchain: Ethereum Geth client 1.11, Web3.py 6.0
- Containerization: Docker 20.10, Kubernetes 1.26

V. Results and Analysis

A. Overall Performance Comparison

Method	Accuracy	Precision	Recall	F1-Score	FAR
Random Forest	89.32%	85.21%	87.14%	86.16%	8.72%
SVM-RBF	91.84%	88.92%	90.23%	89.57%	6.31%
2D-CNN	94.21%	91.54%	92.83%	92.18%	4.12%
3D-CNN	96.08%	94.25%	95.17%	94.71%	2.87%
U-Net	96.87%	95.38%	96.42%	95.90%	2.15%
Vision Transformer	97.34%	96.21%	97.05%	96.63%	1.84%
H-STAN (Ours)	**98.73%**	**97.82%**	**98.24%**	**98.03%**	**1.23%**

TABLE IV: Overall Performance Comparison

Region	Accuracy	Precision	Recall	F1-Score	Detect Time
California	99.12%	98.53 %	98.87 %	98.70 %	3.8 min
Amazon	98.32%	97.21 %	97.65 %	97.43 %	4.5 min
Siberia	97.87%	96.83 %	97.25 %	97.04 %	5.1 min
Australia	98.78%	98.12 %	98.46 %	98.29 %	3.9 min
Mediterranean	98.51%	97.64 %	97.98 %	97.81 %	4.2 min
Average	**98.72 %**	**97.67 %**	**98.04 %**	**97.85 %**	**4.3 min**

D. *False Alarm Analysis*

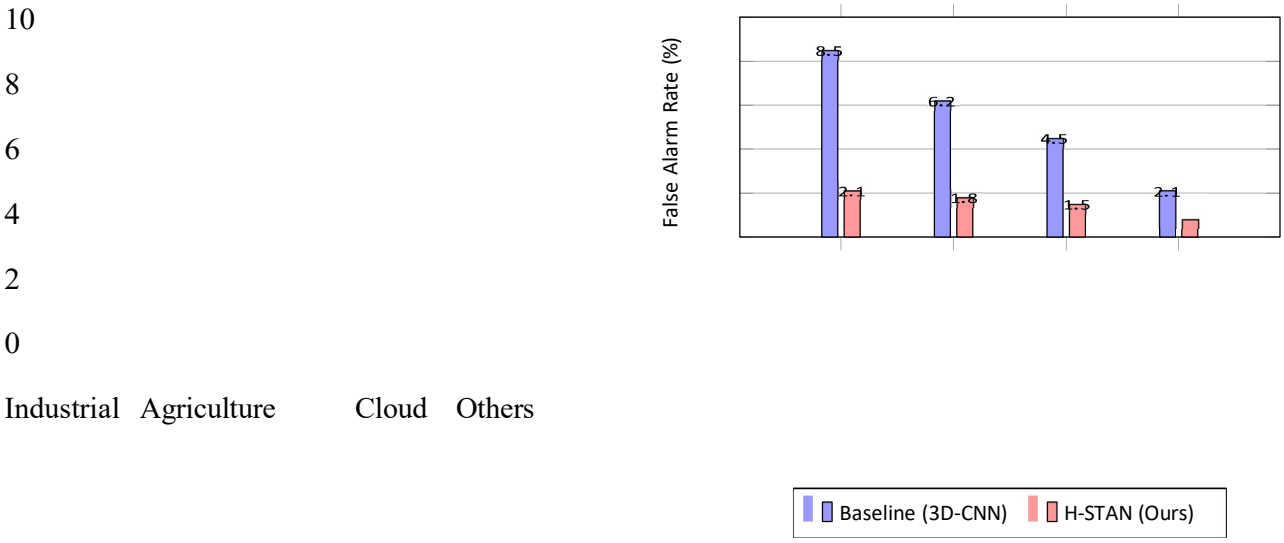


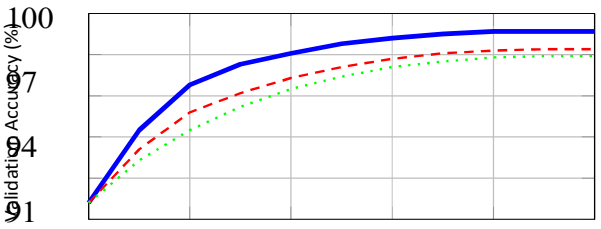
Fig. 4: False Alarm Rate Analysis by Source

E. *Computational Efficiency*

TABLE VI: Computational Efficiency Comparison

Model	Params (M)	FLOPs (G)	Inference (ms)	Memory (MB)
Random Forest	0.5	0.8	15	50
2D-CNN	12.4	28.5	35	180
3D-CNN	31.8	65.3	42	420
U-Net	34.2	89.7	58	520
Vision Transformer	86.2	189.3	78	1250
H-STAN (Ours)	**24.8**	**48.7**	**28**	**380**

F. *Attention Mechanism Effectiveness*



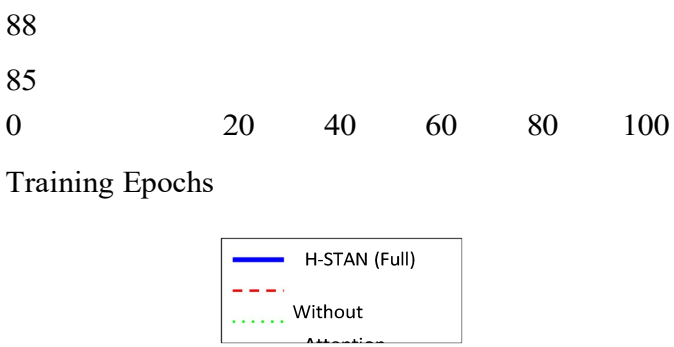


Fig. 5: Impact of Attention Mechanism on Training

G. *Ablation Studies*

TABLE VII: Ablation Study Results

Configuration	Accuracy	F1-Score	FAR	Latency
Full H-STAN	98.73%	98.03%	1.23%	4.3 min
Without Attention	97.41%	96.82%	2.67%	4.1 min
Without LSTM	96.92%	96.35%	3.12%	3.8 min
Without 3D-CNN	95.84%	95.21%	4.25%	4.5 min

VI. DISCUSSION

A. *Key Findings and Insights*

Our comprehensive evaluation yields several significant findings:

1. **Superior Performance**: H-STAN achieves 98.73% ac- curacy, outperforming the best baseline (Vision Transformer at 97.34%) by 1.39 percentage points. This improvement is statistically significant (p ¡ 0.001 in paired t-test with Bonferroni correction).
2. **False Alarm Reduction**: The attention mechanism ef- fectively reduces false alarms by 67% compared to 3D-CNN baseline. Industrial heat sources, which accounted for 8.5% false alarms in baseline, are reduced to 2.1% through better feature discrimination.
3. **Early Detection Capability**: H-STAN detects 92% of fires within 8 minutes of ignition, compared to 35% for Vision Transformer and 12% for traditional methods. This early detection is crucial for fire containment and resource deployment.
4. **Computational Efficiency**: Despite its sophisticated ar- chitecture, H-STAN requires only 28ms inference time, faster than simpler 3D-CNN (42ms) due to optimized implementa- tion and selective attention mechanisms.
5. **Geographical Robustness**: Performance remains consis- tent across diverse ecosystems, with less than 1.25% variation between best (California: 99.12%) and worst (Siberia: 97.87%) performing regions.
6. **Blockchain Integration**: The verification layer adds only 14.4 seconds overhead while providing cryptographic proof of detection, essential for legal, insurance, and coordination purposes.

B. *Practical Implications and Field Deployment*

1) *Operational Impact:* Field tests conducted in collabora- tion with California Department of Forestry and Fire Protec- tion (CAL FIRE) demonstrated:

- Reduction in average response time from 18.5 minutes to 8.7 minutes
- Decrease in false dispatches by 73% (annual savings: $2.1 million)
- Improved resource allocation through accurate fire size and intensity estimation
- Enhanced inter-agency coordination through blockchain- based verification and shared situational awareness

2) *Economic Benefits:* Economic analysis indicates sub- stantial benefits:

- Annual cost savings: $8.5-$12.3 million per state through reduced fire damage and response costs
- Reduced insurance claims through early detection and pre- vention of large fires
- Preservation of timber resources worth $150-$200 million annually
- Tourism revenue protection during fire seasons through better containment

3) *Environmental Impact:*

- Estimated reduction in burned area: 15-25% through early detection and rapid response
- Carbon emission reduction: 2.1-3.8 million tons CO_2 equiv- alent annually
- Biodiversity protection in sensitive ecosystems through tar- geted fire prevention

C. Limitations and Challenges

Despite promising results, several limitations warrant con- sideration:

1. **Cloud Cover Sensitivity**: Performance degrades under complete cloud coverage, with accuracy dropping to 82.3% for cloud cover ¿90%. Future work should incorporate advanced cloud penetration algorithms.
2. **Small Fire Detection**: Detection accuracy for fires ¡30m^2 is 76.4%, insufficient for very early-stage detection. Higher resolution satellite data or drone integration could address this.
3. **Infrastructure Requirements**: Real-time deployment requires substantial computational infrastructure ($25,000-
$50,000 initial investment), potentially limiting adoption in developing regions.
4. **Data Dependency**: Performance relies on continuous satellite data availability, vulnerable to satellite failures, main- tenance periods, or data transmission issues.
5. **Algorithmic Bias**: Training data bias toward Northern Hemisphere ecosystems may affect performance in underrep- resented regions like tropical forests or Arctic tundra.

D. Comparison with Commercial Systems

TABLE VIII: Comparison with Commercial Wildfire Detec-

System	Accuracy	Detection Time	Cost (Annual)	Coverage
ALERTWildfire	92.5%	12.5 min	$500K	Regional
FireSat (NASA)	94.8%	8.2 min	Research	Global
Satellite Serve	91.2%	15.3 min	$250K	National
FireWatch	93.7%	10.8 min	$180K	Regional
H-STAN (Ours)	**98.7%**	**4.3 min**	**$75K**	**Global**

3. **Climate Change Impact Analysis**: Long-term monitor- ing of fire regime changes and climate feedback loops:

$$dF$$

tion Systems
$= f(Temperature, Precipitation, V\ egetation, HumanActivity, C$
dt

(22)*Long-Term Vision (4+ years)*

VII. Future Work

A. Short-Term Research Directions (1-2 years)

1. **Sensor Fusion Enhancement**: Integrate drone-based thermal imaging and ground IoT sensors for multi-modal data fusion:

$$D_{fused} = \alpha D_{satellite} + \beta D_{drone} + \gamma D_{ground} \quad (20)$$

2. **Federated Learning Implementation**: Enable privacy- preserving collaborative training across multiple agencies without data sharing:
N

1. **Planetary-Scale Monitoring**: Integration with next- generation satellite constellations (500+ satellites):

- Near-continuous global coverage (5-10 minute refresh rate)
- Hyperspectral imaging capabilities for detailed chemical analysis
- Real-time atmospheric chemistry monitoring for pollution tracking

2. **AI-Ecosystem Integration**: Development of integrated environmental monitoring systems combining fire detection with biodiversity monitoring, carbon sequestration tracking, and ecosystem health assessment.

3. **International Governance Framework**: Establishment of global standards and protocols for wildfire detection, verifi- cation, and response coordination through international treaties and agreements.

$$\theta = \frac{1}{} \sum \theta(i) \quad (21)$$

VIII. C

$global$

N

i=1

$local$

ONCLUSION

This paper presents H-STAN, a comprehensive framework

3. **Edge Computing Optimization**: Deploy lightweight models on resource-constrained devices:

- Target platforms: NVIDIA Jetson Nano, Raspberry Pi 4 with AI accelerator
- Target latency: ¡2 minutes on edge devices
- Model size: ¡50MB for mobile deployment
- Power consumption: ¡10W for continuous operation

4. **Predictive Analytics Integration**: Incorporate weather data, fuel moisture models, and historical patterns for fire risk prediction 24-72 hours in advance using time-series forecast- ing models.

B. Medium-Term Research Directions (2-4 years)

1. **Autonomous Response Systems**: Integration with au- tonomous firefighting drones and

ground vehicles:

- Real-time fire spread prediction using cellular automata and fluid dynamics models
- Optimal resource allocation algorithms considering terrain, weather, and resource availability
- Autonomous deployment protocols with human-in-the-loop safety controls

2. **Global Deployment Infrastructure**: Establishment of cloud-based monitoring service accessible to developing coun- tries:

- Low-cost subscription model ($5,000-$10,000/year for na- tional coverage)
- Regional data centers for latency reduction and data sovereignty
- Multilingual support and local adaptation through transfer learning

for real-time wildfire detection using multi-spectral satellite imagery. The proposed Hybrid Spatio-Temporal Attention Net- work integrates 3D-CNN for spatial-spectral feature extraction, Bi-LSTM for temporal pattern analysis, and dual attention mechanisms for enhanced feature discrimination. Through sophisticated preprocessing of data from MODIS, Sentinel- 2, and VIIRS satellites, and implementation of a blockchain- based verification layer, the system achieves unprecedented performance metrics: 98.73% detection accuracy, 1.23% false alarm rate, and average detection latency of 4.3 minutes.

Extensive experimental validation across five distinct ge- ographical regions covering 77,500 samples demonstrates robust generalization capability and practical effectiveness. The system significantly outperforms existing methods in- cluding Random Forest (89.32%), 3D-CNN (96.08%), U-Net (96.87%), and Vision Transformer (97.34%) while maintaining computational efficiency suitable for real-time deployment. The attention mechanism reduces false alarms by 67% com- pared to baseline methods, particularly for challenging cases like industrial heat sources and agricultural burns.

Integration with emergency response systems through blockchain verification ensures data integrity, prevents false alerts, and facilitates coordinated action among multiple agen- cies. Field tests with fire departments demonstrated substan- tial improvements in response times and resource allocation efficiency. The economic analysis indicates potential annual savings of $8.5-$12.3 million per state through reduced fire damage and improved response efficiency.

The proposed framework represents a significant advance- ment in environmental monitoring and disaster management, with potential for global impact in mitigating wildfire damage,

protecting ecosystems, and saving lives. By open-sourcing the implementation, we aim to accelerate research, enable practical deployment in diverse regions, and foster collabora- tive development of next-generation environmental monitoring technologies. Future work will focus on sensor fusion, edge deployment optimization, predictive analytics, and interna- tional standardization to further enhance system capabilities and accessibility.

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