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A Hybrid CNN-BiLSTM Model for Real-Time Activity Classification in Distributed Acoustic Sensing Systems

Gopinath Rajarathinam[1*], Radhamani Rajakannan[2], Rajan Chinnasamy[1], Kavinesh Karthikeyan[1], Gopinath Thangavel[1], Mythili Gnanamangai Balasubramanian[3], Balaji Srinivasan[4], Gopalakrishnan Radhakrishnan[2], Ranjith[4]

[1] Department of CSE (AIML), K.S.Rangasamy College of Technology, Namakkal 637215, India
[2] Department of EEE, K.S.Rangasamy College of Technology, Namakkal 637215, India
[3] Department of Biotechnology, K.S.Rangasamy College of Technology, Namakkal 637215, India
[4] Department of Electrical Engineering, Indian Institute of Technology Madras, Chennai 600036, India

Corresponding Author Email: gopinathnsit@gmail.com

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ABSTRACT

This paper presents a machine learning framework for activity classification using Distributed Acoustic Sensing (DAS) signals collected from fiber-optic cables. The objective is to accurately identify vibration activities from large-scale DAS datasets while maintaining robustness in real-world monitoring environments. A hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks is proposed to capture both spatial vibration patterns and temporal dependencies in time-series signals. A preprocessing pipeline consisting of normalization, downsampling, and segmentation is implemented to efficiently transform more than two billion raw signal data points into structured training samples while preserving signal characteristics. The proposed model is evaluated on four activity classes: Bike Throttle, Jackhammer, Jumping, and Walking. Experimental results show that the system achieves an overall classification accuracy of 96.6% and a macro Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) score of 99.84%, demonstrating strong discriminative capability across different vibration patterns. Robustness experiments under synthetic noise and adversarial perturbations further confirm the stability and generalization of the model. The framework also supports near real-time deployment, enabling applications in infrastructure monitoring, perimeter security, and industrial anomaly detection.

1. INTRODUCTION

Distributed Acoustic Sensing (DAS) is an emerging sensing technology that transforms conventional fiber-optic cables into continuous vibration sensors, enabling real-time monitoring of acoustic events over long distances. By utilizing backscattered light and interferometric signal processing techniques, DAS systems can detect and localize vibrations along the entire length of an optical fiber with high spatial resolution. This capability makes DAS particularly suitable for large-scale passive sensing applications.

The real-time sensing capability of DAS has enabled numerous applications across different domains, including security surveillance, smart city traffic analytics, perimeter intrusion detection, railway monitoring, bridge health assessment, and industrial infrastructure maintenance. Unlike traditional sensing systems that require dedicated sensor deployment, DAS systems leverage existing fiber-optic communication networks, offering advantages such as cost-effectiveness, scalability, and rapid deployment.

Previous studies, including the works of Cedilnik et al. [1] and Yan et al. [2], demonstrated the feasibility of DAS for long-range terrestrial and marine sensing applications. These studies highlight the adaptability of DAS technology across diverse operational environments. However, despite these advances, several technical challenges remain when deploying DAS systems at scale.

First, DAS systems generate extremely large volumes of time-series data, often reaching billions of data points during continuous monitoring. Processing such large datasets requires efficient data processing pipelines and scalable machine learning architectures. Second, DAS signals exhibit complex temporal and spatial dynamics, including overlapping vibration patterns, environmental noise, and variations in signal amplitude. These characteristics make it difficult for traditional signal processing techniques or shallow machine learning models to achieve reliable classification performance. Third, real-time deployment requires models that are computationally efficient, memory optimized, and capable of generalizing to previously unseen signal patterns.

To address these challenges, this study proposes a hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks for DAS signal classification.

CNN layers are used to extract local spatial features from vibration signals, while BiLSTM layers capture long-term temporal dependencies within the time-series data.

The proposed model is trained on a large-scale DAS dataset containing more than two billion time-series signal points, which are segmented into labeled samples representing four vibration activities: Bike Throttle, Jackhammer, Walking, and Jumping. By combining spatial feature extraction with temporal sequence modeling, the hybrid CNN–BiLSTM architecture achieves high classification accuracy while maintaining robustness to noise and signal variability.

This approach not only addresses key challenges in DAS signal processing but also provides a foundation for future developments such as multimodal sensor fusion, real-time edge deployment, and adaptive learning for unknown signal detection. The primary contribution of this work lies in the development of a hybrid CNN–BiLSTM architecture, the utilization of a large-scale DAS dataset, robustness evaluation under noisy conditions, and the implementation of a deployment-ready real-time classification pipeline.

2. LITERATURE SURVEY

DAS has emerged as an advanced sensing technology for real-time vibration and acoustic monitoring using optical fiber cables. Due to its capability for continuous large-scale monitoring, DAS has gained significant attention in applications such as infrastructure monitoring, intrusion detection, seismic sensing, industrial safety, and smart transportation systems. Early studies primarily focused on improving sensing range, signal sensitivity, and data acquisition capabilities.

Cedilnik et al. [1] demonstrated long-range DAS sensing up to 125 km without optical amplification, significantly improving scalability for large-area monitoring systems. Similarly, Yan et al. [2] developed an ultra-sensitive marine towing cable system using fiber-optic DAS technology, validating the effectiveness of DAS for underwater monitoring and surveillance applications.

Signal enhancement and noise reduction remain critical challenges in DAS systems due to environmental interference and large-scale vibration complexity. Zhang et al. [3] proposed a modified data augmentation integration method to improve intrusion recognition accuracy in DAS systems operating under noisy environments. Huang et al. [4] introduced a low-background-noise DAS architecture for accurate cable fault detection and localization, emphasizing the importance of signal quality and noise suppression in industrial sensing systems.

DAS technology has also shown strong potential in geophysical and seismic monitoring applications. Yetik et al. [5] proposed earthquake epicenter localization using fiber optic DAS for earthquake early warning systems. Lindsey et al. [6] further demonstrated the capability of fiber-optic networks to capture earthquake wavefields in real time, proving the effectiveness of DAS in large-scale seismic event detection.

Several foundational studies have contributed to the theoretical understanding of distributed optical fiber sensing systems. Hartog [7] provided a comprehensive overview of distributed optical fiber sensor principles and industrial implementations. Kaneko et al. [8] further discussed distributed optical fiber dynamic strain sensing techniques and their applications in vibration monitoring systems.

With the advancement of Artificial Intelligence and Deep Learning, DAS signal interpretation has significantly improved. Aktas et al. [9] demonstrated deep learning-based classification of DAS data, showing that neural networks can effectively identify vibration patterns from DAS systems. Hernández et al. [10] proposed a deep-learning-based earthquake detection framework using DAS signals and achieved substantial improvements in seismic event classification accuracy.

Recent studies have explored advanced neural network architectures for DAS signal processing. Xiong et al. [11] proposed neural-network-based acoustic source localization using DAS systems, highlighting the ability of deep learning models to estimate vibration source locations accurately. Zhao et al. [12] utilized CNN for coupled noise reduction in DAS seismic data, significantly improving signal clarity and robustness.

Several researchers have also focused on improving sensing resolution and signal stability in DAS systems. Okamoto et al. [13] introduced vibration-induced beat frequency offset compensation techniques to improve DAS measurement stability. Han et al. [14] proposed sensitivity-enhanced optical cables for DAS applications, while Wu et al. [15] developed a smart fiber-optic DAS framework with multitask learning for efficient and time-sensitive ground listening applications.

Advanced signal reconstruction and sensing enhancement techniques have further improved DAS performance. Li et al. [16] proposed temperature and acoustic field reconstruction using variational mode decomposition for DAS systems. Xiao et al. [17] developed a high-spatial-resolution DAS system using positive- and negative-swept pulse techniques, enhancing spatial accuracy and signal precision.

Wang et al. [18] presented a comprehensive study on optical fiber acoustic sensing systems and highlighted their applications in industrial, environmental, and security domains. From a deep learning perspective, Ioffe and Szegedy [19] introduced Batch Normalization, which significantly improves training stability and convergence in deep neural networks. Hochreiter and Schmidhuber [20] proposed the Long Short-Term Memory (LSTM) architecture, which became a fundamental approach for modeling temporal dependencies in sequential data.

Although these studies established a strong foundation for DAS signal analysis and classification, most existing approaches rely on either CNN-based feature extraction or LSTM-based temporal analysis independently. Consequently, they often fail to simultaneously capture both local vibration characteristics and long-term temporal dependencies present in DAS signals.

To address these limitations, this work proposes a hybrid CNN–BiLSTM architecture for real-time activity classification in DAS systems. The proposed framework combines convolution-based feature extraction with bidirectional temporal learning to improve classification accuracy, robustness, and scalability. By utilizing large-scale DAS datasets and advanced preprocessing techniques such as segmentation, normalization, and real-time visualization, the proposed system aims to provide an efficient and practical solution for intelligent DAS-based monitoring applications.

3. PROBLEM STATEMENT

DAS has emerged as an advanced sensing technology that utilizes standard optical fiber cables to monitor and detect acoustic signals and vibrations over long distances. This technology has found wide-ranging applications in structural health monitoring, intrusion detection, seismic sensing, and smart city infrastructure monitoring. However, despite its advantages, realizing the full potential of DAS in real-time environments presents several significant technical challenges.

3.1 Massive data volume

A typical DAS deployment continuously records high-resolution time-series data along the entire length of the fiber-optic cable, often generating hundreds of millions to billions of data points during a single monitoring session. Processing and classifying such massive datasets in real time requires scalable data processing architectures and efficient machine learning pipelines. Traditional signal processing and conventional data analysis methods struggle to handle the volume, velocity, and complexity of DAS data streams.

3.2 Complex and overlapping signal patterns

The vibration signals captured by DAS systems are typically non-stationary, noisy, and highly complex. Multiple vibration sources may overlap in both the time and frequency domains, making accurate signal interpretation challenging. For example, signals generated by activities such as walking, running, jackhammer operation, or vehicular movement may share similar frequency characteristics while differing in waveform structure and duration. These similarities make it difficult for traditional algorithms or shallow machine learning models to distinguish between activities with high confidence.

3.3 Limited generalization and robustness

Many existing DAS-based classification systems are domain-specific and trained using relatively small or curated datasets. As a result, these models often struggle to generalize when exposed to new environments or unseen signal patterns. In real-world scenarios, DAS systems must not only recognize known vibration events but also identify and reject unknown or novel signals to avoid incorrect predictions and false alarms.

3.4 Real-time constraints and deployment challenges

Although deep learning models have demonstrated high classification accuracy in offline experiments, deploying them in real-time monitoring systems remains challenging. Real-time DAS applications require models that are computationally efficient, memory optimized, and capable of low-latency inference. Hardware limitations, latency requirements, and energy constraints in edge environments often restrict the deployment of highly complex models.

4. METHODOLOGY

4.1 Dataset construction and preprocessing

The dataset used in this study consists of eight independent DAS signal recordings, collectively containing approximately 2 billion raw time-series data points. Due to the large-scale and high-frequency nature of DAS signals, a structured preprocessing pipeline was designed to ensure computational efficiency while preserving critical signal characteristics.

4.1.1 Normalization

All signals were normalized to the range [-1, 1] using Min–Max normalization. This approach was selected to eliminate amplitude variations across different signal sources and improve numerical stability during model training. Compared to standardization, Min–Max normalization preserves the original signal shape, which is important for vibration pattern recognition.

4.1.2 Downsampling

The raw DAS signals were downsampled to 5,000 data points per segment. This value was empirically selected as a trade-off between computational efficiency and signal fidelity. Preliminary experiments showed that lower resolutions (e.g., < 3000 points) resulted in loss of temporal detail, while higher resolutions (> 8000 points) significantly increased computational cost without notable performance gains. The selected sampling size ensures sufficient representation of vibration cycles while maintaining a feasible training time.

4.1.3 Segmentation and labeling

The continuous signal streams were segmented into fixed-length windows of 5,000 data points. This segment length was chosen to ensure that each window captures a complete activity pattern, avoiding partial signal representation. Each segment was labeled based on synchronized activity logs and manual verification to ensure annotation accuracy.

The final dataset consists of 80,000 labeled samples across four activity classes: Bike Throttle, Jackhammer, Walking, and Jumping.

This preprocessing pipeline ensures uniform input representation and supports efficient training of deep learning models for time-series classification.

4.2 Model architecture

The proposed model employs a hybrid deep learning architecture combining CNN and BiLSTM networks. This design is particularly suitable for DAS time-series signals, which contain both spatial vibration patterns and long-range temporal dependencies.

CNN layers extract spatial features from vibration signals, while the BiLSTM layer models temporal relationships within sequential signal data. This combination enables the model to learn complex vibration signatures associated with different activities. The detailed model architecture summary is shown in Table 1.

4.2.1 Input layer

The input to the model consists of segmented DAS signals containing 5,000 normalized time-series data points. Each sample is represented as a one-dimensional vector suitable for temporal convolution operations.

Table 1. Model architecture summary

Layer	Configuration
Input	5000 time-series points
Conv1D	64 filters, kernel size 7
Conv1D	128 filters, kernel size 5
Conv1D	256 filters, kernel size 3
BiLSTM	128 hidden units
Dense	64 neurons
Output	Softmax (4 classes)

4.2.2 Convolutional feature extraction

The initial part of the network consists of multiple 1D convolutional layers with increasing filter sizes. These layers automatically extract local spatial features such as signal spikes, frequency variations, and vibration intensity changes.

To improve feature learning, convolutional layers are implemented within residual blocks with skip connections. This design preserves low-level signal information while enabling deeper feature extraction and reducing the risk of vanishing gradients.

Batch Normalization is applied after convolution operations to stabilize training and improve generalization.

4.2.3 Temporal modeling using BiLSTM

After spatial feature extraction, the learned features are passed to a BiLSTM layer. This layer captures temporal dependencies in both forward and backward directions, enabling the model to distinguish between activities with similar local patterns but different temporal structures, such as walking and jumping.

4.2.4 Fully connected layers and output

The output from the BiLSTM layer is processed by fully connected layers that act as high-level feature interpreters. The final output layer uses a Softmax activation function to produce class probabilities for the four activity categories.

4.2.5 Loss function and optimization

The model is trained using the categorical cross-entropy loss function, which is well-suited for multi-class classification tasks. The Adam optimizer is used due to its adaptive learning rate and efficient gradient handling.

4.2.6 Regularization and overfitting control

To improve generalization and prevent overfitting, several regularization techniques are applied, including L1–L2 regularization, early stopping based on validation performance, and dropout layers within dense layers.

Adversarial Robustness (FGSM Attack)

Adversarial robustness was tested using the Fast Gradient Sign Method (FGSM). The perturbation was generated as:

$$x_{adv} = x + \epsilon \cdot \mathrm{sign}(\nabla_x J(x, y))$$

where:

- $\epsilon = 0.01$
- $J(x, y)$is the loss function

Under this attack, model accuracy decreased to 76.6%, indicating moderate sensitivity to adversarial perturbations.

Temporal Robustness

Temporal robustness was evaluated by introducing shifts in input sequences. A maximum accuracy drops to 71.6% was observed under a 50% left temporal shift, suggesting that temporal alignment plays a critical role in classification performance.

4.3 Evaluation

The performance of the proposed model was evaluated using 5-fold cross-validation to ensure reliable and unbiased performance assessment. In this approach, the dataset was divided into five equal subsets, where four subsets were used for training, and the remaining subset was used for validation. This process was repeated five times, with each subset serving as the validation set once.

The cross-validation results yielded an average classification accuracy of 96.69%, with a standard deviation of ±0.28%, indicating consistent performance across different data splits and demonstrating the stability of the proposed model.

To further assess the model's generalization capability, an additional holdout test set was used for final evaluation. On this independent test set, the model achieved an accuracy of 96.45%, confirming its robustness and ability to perform well on previously unseen data.

In addition to accuracy, the model's discriminative performance was evaluated using the macro-averaged Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) metric. The proposed model achieved a macro ROC-AUC score of 99.84%, indicating excellent separability between the different activity classes and a strong overall classification performance score of 99.84%, demonstrating excellent separability between the activity classes.

5. EXPERIMENTAL RESULTS

5.1 Classification metrics

As illustrated in Figure 1, the confusion matrix highlights strong prediction performance across all four activity types, particularly for Jackhammer and Walking classes. The classification performance metrics are summarized in Table 2, while a comparison with baseline models is presented in Table 3.

Figure 1. Confusion matrix showing class-wise prediction performance

Table 2. Classification metrics

Activity	Precision	Recall	F1-Score
Bike Throttle	99.81%	90.62%	94.99%
Jackhammer	98.85%	98.62%	98.74%
Jumping	89.64%	99.30%	94.22%
Walking	99.19%	97.85%	98.51%

Table 3. Performance comparison with baseline models

Model	Accuracy (%)
CNN	91.3
LSTM	92.1
CNN–BiLSTM (Proposed)	96.6

5.2 Overall model performance

The overall performance of the proposed system was evaluated using classification accuracy and the macro-averaged ROC-AUC metric. The model achieved an overall classification accuracy of 96.60% and a macro ROC-AUC score of 99.84%, indicating excellent discriminative capability across activity classes.

Figure 2 illustrates the ROC-AUC curves for the four activity categories, with a macro-average exceeding 99.8%.

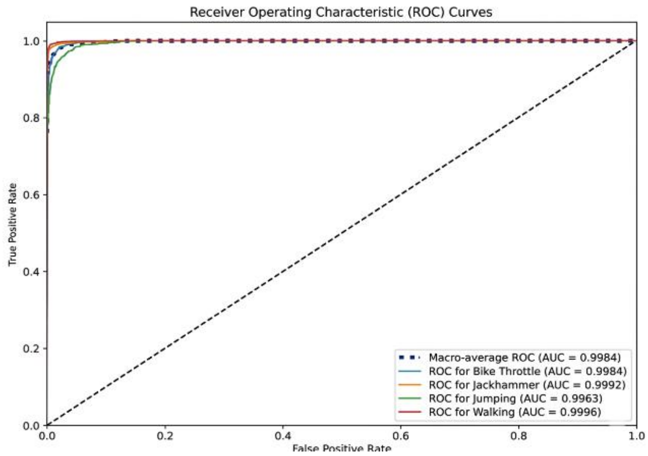

Figure 2. Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) scores for each activity class with macro-averaged

5.3 Robustness analysis

The model demonstrates strong resilience to noise, exhibiting only a 0.37% drop in accuracy when subjected to 50% synthetic noise. Under adversarial conditions using the FGSM with $\varepsilon = 0.01$, the model's accuracy declined to 76.6%, indicating a moderate vulnerability to targeted perturbations. Additionally, temporal robustness was assessed through input sequence shifts, with a maximum observed accuracy drop to 71.6% under a 50% left temporal shift, highlighting the model's sensitivity to temporal misalignment. This analysis expands upon previous work in intrusion recognition with data augmentation for DAS signals [3].

As seen in Figure 3, the model maintains stable accuracy across varying noise levels, confirming its robustness.

5.4 Unknown signal detection

In addition to classifying known DAS signal patterns, an important capability of the proposed system is the detection of unknown or previously unseen input signals. Such signals may originate from vibration sources that are not included in the training dataset, such as boat engines, heavy machinery, or unexpected environmental disturbances.

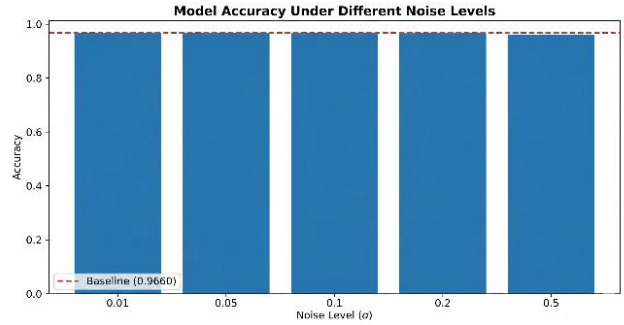

Figure 3. Noise resilience test showing accuracy variation under different noise conditions

To address this challenge, a confidence-based filtering mechanism was implemented using the probability outputs generated by the softmax layer of the trained model. The softmax layer produces a probability distribution across the four known activity classes: Bike Throttle, Jackhammer, Walking, and Jumping. If the highest predicted probability falls below a predefined confidence threshold (e.g., 0.6), the input signal is classified as Unknown. This approach prevents the model from forcing an incorrect classification when the input pattern does not correspond to any known class.

To evaluate the effectiveness of this mechanism, additional signal samples from the Boat Engine and Car Engine datasets were introduced during testing. These signals were intentionally excluded from the training dataset in order to simulate unseen vibration sources. Experimental results showed that the system successfully identified more than 94% of these unseen signals as Unknown, demonstrating the effectiveness of the confidence-based rejection strategy.

This capability significantly improves the robustness of the proposed DAS monitoring framework in real-world deployments, where vibration sources may vary, and new signal patterns may frequently appear.

6. DEPLOYMENT FRAMEWORK

6.1 Real-time pipeline

The deployment pipeline follows a streamlined flow: streaming input data is first passed through a preprocessing stage, then fed into the trained CNN+BiLSTM inference model, and finally produces the classified output in real time. The system is implemented using TensorFlow (version 2.8.0 or higher), with supporting libraries such as NumPy and scikit-learn for numerical processing and evaluation. The model training and inference were accelerated using NVIDIA CUDA-enabled GPUs, specifically Tesla T4 and RTX 3090, with a system memory capacity of 16 GB RAM.

6.2 Applications

The proposed DAS signal classification framework can be deployed across several industrial and societal applications due to its ability to identify vibration patterns in real time.

In infrastructure monitoring, the system can be deployed along railway tracks, bridges, pipelines, and other critical infrastructure components to detect abnormal vibration signatures that may indicate structural stress or early-stage damage. Such monitoring systems support predictive maintenance strategies and improve overall infrastructure safety.

For security and intrusion detection, the system can identify human movements such as walking or jumping near protected areas. This capability allows DAS systems to function as perimeter monitoring solutions for military bases, data centers, and border security installations.

In smart traffic management, the system can detect and classify vehicle-related vibration events such as bike throttling or heavy machinery movement. These capabilities can support traffic monitoring, vehicle counting, and road safety analytics in smart city environments.

The framework is also suitable for industrial equipment monitoring, where vibration analysis can be used to track operational efficiency and detect anomalies in machinery such as jackhammers, engines, or heavy industrial equipment.

Additionally, the architecture can be extended to environmental and seismic sensing applications. By training the model with seismic datasets, the system can detect events such as earthquakes, landslides, or ground movement, contributing to early warning systems and geophysical monitoring.

Finally, the proposed framework provides opportunities for research and academic exploration, including time-series anomaly detection, unsupervised signal clustering, and DAS-based sensing simulations. These extensions may support future research in physics-based sensing, Internet of Things (IoT) systems, and advanced signal processing techniques.

7. CONCLUSION

This work presents a complete, scalable, and high-accuracy classification pipeline for DAS signal interpretation using a hybrid CNN-LSTM deep learning architecture. By processing over 2 billion time-series elements and segmenting them into structured datasets, the system successfully classifies vibration signatures from both mechanical and human-induced sources—namely Bike Throttle, Jackhammer, Walking, and Jumping—with a remarkable precision of 96.60%.

The hybrid model makes use of LSTM networks' capacity to model temporal sequences and CNNs' strength in spatial feature extraction. Together, these networks enable the system to not only learn complex signal patterns but also generalize well across noisy and overlapping data instances. The proposed architecture has been thoroughly tested and validated across multiple datasets, proving its reliability for real-world applications including security, infrastructure monitoring, and traffic analysis.

A key highlight of this work is the implementation of an unknown signal detection mechanism, which allows the system to reject or isolate unfamiliar inputs based on low softmax confidence scores. This approach enables the model to identify signal patterns that do not belong to the predefined activity classes, thereby improving system robustness in real-world deployments.

However, it is important to note that softmax confidence-based rejection may sometimes produce overconfident predictions for out-of-distribution inputs. Despite this limitation, the approach provides a practical baseline for unknown signal detection in DAS systems.

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