BLE Channel Classification with Stability Encoding for Indoor Positioning

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Abstract

Bluetooth Low Energy (BLE) based indoor localization systems often face performance degradation when applied to new environments because signal patterns captured through the Received Signal Strength Indicator (RSSI) vary with obstacles, layouts, and device types. Models trained on one environment's data frequently fail to maintain accuracy on unseen data, due to unstable and fluctuating signal characteristics. To overcome these issues, this paper presents an enhanced multi-source domain generalized BLE channel classification framework by combining statistical feature encoding, attention-based pooling, and a variance-guided loss for stability-aware learning across multiple source domains. The experimental evaluation with multi-environment (room and corridors) BLE RSSI datasets shows that the proposed hybrid framework using LSTM achieves 90.6% accuracy in training and 78.5% in an unseen target domain, outperforming the baseline DANN model by approximately 17%. Furthermore, the CNN-BiLSTM variant further improves accuracy in the unseen target domain by 6.6% over the LSTM-based hybrid framework.

Keywords : Bluetooth Low Energy (BLE)| RSSI |domain generalization |Domain Adversarial Neural Network DANN | LOS/NLOS classification

I. INTRODUCTION

Indoor positioning has gained popularity in environments such as healthcare, smart buildings, and navigation systems, where global navigation satellite system (GNSS) signals are unreliable. Accurate localization relies heavily on correctly identifying wireless channel conditions, including Line-of-Sight (LOS), soft Non-Line-of-Sight (soft-NLOS), and hard Non-Line-of-Sight (hard-NLOS), which directly influence signal stability and distance estimation accuracy [1–3]. Among available technologies, Bluetooth Low Energy (BLE) offers a cost-effective and energy-efficient solution; however, its Received Signal Strength Indicator (RSSI) is highly sensitive to multipath fading and obstacles, leading to fluctuating values across different indoor layouts [4].

Consequently, a model trained in one environment often fails to maintain accuracy in unseen conditions [5].

Conventional BLE channel classification approaches relied on path-loss models [6] or statistical thresholds [7], which are simple but environment-dependent and ineffective without labeled data [8]. Deep learning approaches using CNNs and LSTMs [9, 10] better capture temporal RSSI patterns, but still suffer from domain shift due to differences in layout, beacon placement, and device hardware [11–13].

Recently, domain generalization (DG) methods employ adversarial learning, e.g., Gradient Reversal Layer (GRL) [14–16], to improve robustness by learning representations that remain stable across multiple source domains [17]. However, most methods do not model signal instability or variance, limiting their ability

to distinguish stable LOS from fluctuating hard-NLOS conditions in unseen areas. In RSSI-based localization and channel classification, higher RSSI values are often implicitly associated with closer proximity and higher reliability. Under NLOS conditions, however, multipath propagation and environmental reflections can produce unstable and temporarily high RSSI values that do not correspond to true distance. Such instability leads to biased feature representations and unreliable channel discrimination, particularly under domain shift, indicating that modeling signal stability is essential for robust generalization. In our earlier study on BLE -based indoor localization [18], we used relative signal ranking and LOS probability estimation to improve robustness under varying conditions. However, the model exhibited reduced accuracy when evaluated in unseen areas due to unaddressed domain shift. To address these challenges, this study proposes a multi-source domain generalized BLE channel classification framework to enhance performance across unseen environments. The main contributions of this study are:

1. Stability aware feature learning: The framework incorporates statistical stability features, and a variance-based loss computation to capture signal consistency, enabling differentiation between LOS and NLOS conditions. These features, along with RSSI enrich the feature space and encourage the model to differentiate stable LOS signals from fluctuating Soft-NLOS signals across domains.

2. Attention-based domain alignment: Instead of mean pooling, which gives equal weight to all anchors, an attention pooling mechanism is used during generalization that assigns dynamic weights to each anchor based on its relevance to the domain. This step enhances the cross-domain feature consistency and improves generalization. The remainder of the paper is organized as follows: Section II reviews related works; Section III describes the proposed framework; Section IV presents data collection, followed by experiments and results.

II. RELATED WORK

Early indoor localization methods, such as Weighted Centroid Localization (WCL) and RSSI averaging [19], are simple but prone to large errors under NLOS conditions. To improve robustness, deep learning models have been widely explored. DeepFi [20] utilized an autoencoder to learn CSI features, whereas DeepLoc [21] applied a fully connected layer (FC) with dropout for improved generalization. Hybrid CNN-LSTM models [8,9] further captured spatial and temporal RSSI dependencies but still failed under environmental changes.

To address domain shift, several domain adaptation (DA) frameworks were developed in wireless localization. DA approach aims to transfer knowledge from a labeled source domain to an unlabeled target domain by aligning their feature distributions. One popular approach is adversarial domain generalization, where a GRL is used to confuse a domain discriminator and encourage the model to learn domain-invariant features.

Fidora [14] employed adversarial DA for WiFi localization, and Zhang et al. [15] developed a graph-based DA model. In BLE and WiFi systems, AdaLOS [12] and AdaWiFi [13] applied feature alignment to enhance cross-environment performance.

However, most DA studies rely on access to target-domain data and are therefore not applicable to domain generalization (DG) settings. Recent DG approaches [22], [23] have been explored for time-series learning, such as invariant
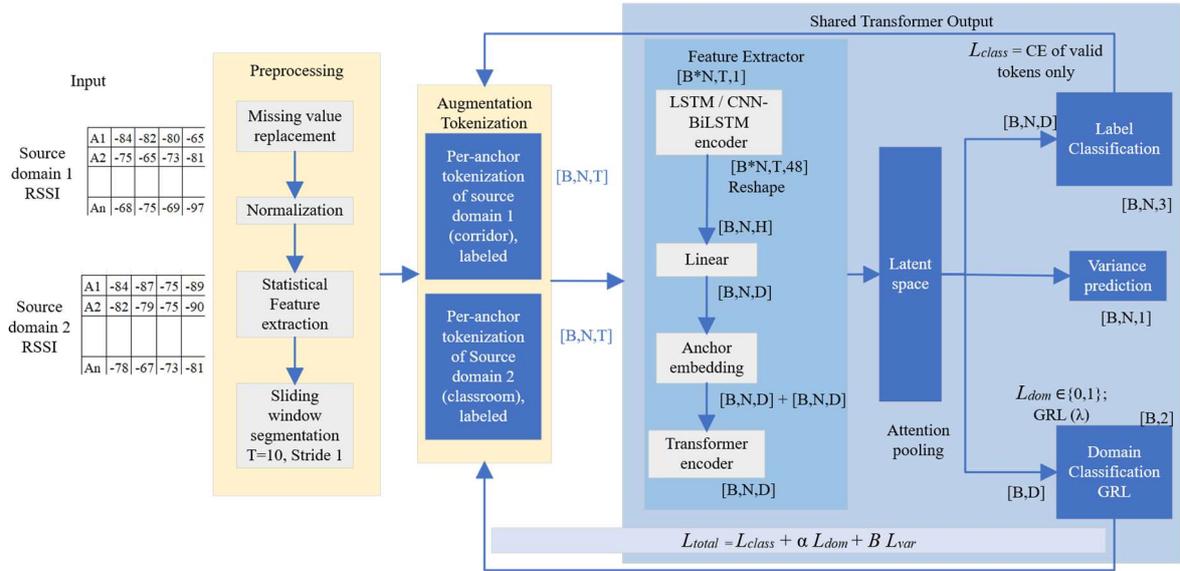
Fig.1. Complete workflow of the proposed domain adaptation based BLE channel classification.

risk minimization and domain-invariant representation learning for forecasting, aiming to extract representations that remain consistent across multiple source domains. These methods focus on learning domain-invariant representations and preserving temporal trends; however, they do not explicitly model signal instability or variance, which are critical factors for RSSI-based BLE channel classification.

III. PROPOSED METHOD

In Fig. 1, a multi-source domain generalized classification framework using LSTM or CNN-BiLSTM is designed to improve the reliability of BLE channel classification across unseen environments. The model integrates three main components: Statistical feature extraction combined with raw RSSI values to generate tokens.

  i.   Attention based domain-invariant pooling for multi-source representation learning.

  ii.   Variance prediction to enforce stability-aware learning.

All these modules capture both temporal signal dynamics and cross-domain variations across multiple source environments, enabling robust discrimination of hard-NLOS regions where RSSI patterns are unstable.

1.   Preprocessing

In the first stage, normalized RSSI sequences are segmented into short overlapping windows of length $T = 10$ to represent temporal signal behavior at each anchor. Let the raw RSSI window for the anchor i be:

$$\mathbf{x}_i = [r_1, r_2, \dots, r_T]. \tag{1}$$

From each window, three statistical descriptors are extracted:

$$\mu_i = \mathrm{mean}(\mathbf{x}_i), \sigma_i = \mathrm{std}(\mathbf{x}_i),$$
$$\Delta_i = r_T - r_{(T-1)}. \tag{2}$$

These represent the average strength, volatility, and first-order difference of the RSSI signal. They are concatenated with the raw RSSI sequence to form an enriched feature vector:

$$\mathbf{x}'_i = \left[\mathbf{x}_i, \mu_i, \sigma_i, \Delta_i\right]. \tag{3}$$

This process provides a richer input representation that captures both the statistical stability and temporal variations of the signal, allowing the model to recognize patterns that are often missed

when using raw RSSI data alone.

The preprocessing is performed independently for each source sub-domain to avoid any form of data leakage during normalization and statistical feature computation, and no target domain information is used during training.

2.   Tokenization

After preprocessing, each anchor i within a domain is represented as a token constructed from the normalized RSSI sequence $\mathbf{x}_i$ and its corresponding statistical descriptors $(\mu_i, \sigma_i, \Delta_i)$ calculated previously. Anchors with invalid or missing RSSI values are excluded, while the remaining anchors are organized as individual tokens preserving their anchor identifier, class label, and source domain index. Tokens are generated separately for each source sub-domain, ensuring that the learning process preserves multi-domain boundaries.

Table 2. Models Architecture and Hyperparameter Details

Component	LSTM/ CNN-BiLSTM
No of Layers	1 LSTM Layer in LSTM architecture/ 1 BiLSTM layer along 2 × Conv1D (channels = 16, kernel = 3), BatchNorm + ReLU
Hidden units	48
Token projection	Fully connected layer FC, output dimension d_{model}= 64
Anchor embedding	d_{model}= 64
Transformer encoder	1 layer, 4 attention heads, d_{model} = 64
Label classification	FC (64 → 64) + ReLU + FC (64 → 3)
Variance prediction	FC (64 → 64) + ReLU + FC (64 → 1)
Domain discriminator	GRL + FC (64 → 64) + ReLU + FC (64 → 2)
Optimizer	Adam
Batch size	64
Number of Epochs	50
Learning Rate	10^{-4}

The resulting set of tokens $\mathbf{x}'_i$ forms the input sequence for the next step of temporal modeling. To maintain consistent dimensionality across samples, anchors that are unavailable in each window are zero-padded, and their positions are flagged during training to prevent gradient updates. This representation ensures structural uniformity across domains and enables the shared LSTM or CNN–LSTM encoder to learn domain-invariant features from multiple source environments, supporting generalization to unseen target domains.

3.   Feature Extractor

Each encoded tokens are passed through the feature extraction network composed of an LSTM or CNN–BiLSTM encoder followed by a Transformer encoder, which models temporal dependencies and contextual relationships among anchors. Architecture details of both models are presented in Table 1. For each time step t:

$$h_t = \text{LSTM}(x'_t, h_{t-1}), \qquad (4)$$

where h_t denotes the hidden state summarizing temporal dynamics. In CNN–BiLSTM configuration, a convolutional layer is used to capture local variations before the bidirectional LSTM, which models both forward and backward temporal dependencies. The encoded outputs are further processed by a Transformer encoder, which applies attention to capture correlations among anchors within the same time window. The attention operation is:

$$\text{Attention} = \text{softmax}\left(\frac{S}{\sqrt{d}}\right)H. \qquad (5)$$

where S represents pairwise similarity scores, H the encoded features, and d is a scaling factor. This enables the model to learn whether an anchor's fluctuation pattern aligns with its neighbors, thereby improving contextual understanding across spatial regions.

The Transformer encoder layer consists of a multi-head self-attention mechanism with a feed-forward network, residual connections, and layer normalization. Since anchor tokens are unordered and

positional encoding is removed, which makes the model permutation invariant. Attention operation enables each token to adaptively assign weight to the information from other anchors based on similarity in signal patterns, while the feed-forward refines these context-aware embeddings into discriminative representations. This model structure allows the encoder to generalize cross-anchor dependencies without knowledge of spatial ordering, making it robust for different BLE anchor layouts.

4. Domain Generalization (DG)

To enhance domain generalization across multiple domains, the proposed DG module employs attention-based pooling instead of conventional mean pooling. Each token embedding h_t receives a learned attention weight:

$$a_t = \frac{\exp(\mathrm{w}^{\mathrm{T}} h_t)}{\sum_{j=1}^{\mathrm{T}} \exp(\mathrm{w}^{\mathrm{T}} h_t)} . \qquad (6)$$

The domain aware pooled feature is computed as:

$$f = \sum_{t=1}^{\mathrm{T}} a_t h_t. \qquad (7)$$

This adaptive weighting highlights tokens most responsible for inter-domain differences. The feature vector f is then passed through a GRL and a domain discriminator. During the forward pass, GRL performs nothing, while during backpropagation, the GRL multiplies the gradient by −1, forcing the encoder to learn domain-invariant and class discriminative features.

5. Variance Prediction

Although mean and variance features are provided as inputs, they alone may not sufficiently enable the network to capture signal stability. To address this limitation, a variance prediction module is added.

The model predicts the variance $\hat{\sigma}_i^2$, and minimizes the mean-squared error as:

$$L_{var} = \frac{1}{N} \sum_{i=1}^{N} (\hat{\sigma}_i^2 - \sigma_i^2)^2 . \qquad (8)$$

This variance branch acts as a regularizer for loss function Under Hard-NLOS conditions where RSSI fluctuates sharply despite moderate mean values this variance improves the model's ability to distinguish unstable signals from soft-NLOS and LOS cases.

6. Loss Optimization

The total loss function combines classification, domain generalization, and varian0ce prediction loss. The total loss is defined as:

$$L_{\mathrm{total}} = L_{\mathrm{class}} + \lambda_{\mathrm{dom}} L_{\mathrm{dom}} + \lambda_{\mathrm{var}} L_{\mathrm{var}}, \qquad (9)$$

where:
- L_{class} is the categorical cross-entropy loss for BLE channel classification,
- L_{dom} is the adversarial multi-source domain loss applied through the Gradient Reversal Layer (GRL), and
- L_{var} is the mean squared error (MSE) loss for variance prediction.

The weighting factors λ_{dom} and λ_{var} control the balance between classification accuracy, domain alignment, and stability regularization. This joint optimization framework ensures that the shared encoder produces embeddings that are simultaneously discriminative for channel types, invariant to environmental shifts, and sensitive to signal stability.

During inference, only the classification branch remains active, while the attention and variance modules contribute indirectly through the latent features learned during training. The target domain data is introduced only at test time.

For each anchor token, the classifier outputs a three-class probability vector:

$$p(y_t) = [p_{\mathrm{hard-NLOS}}, p_{\mathrm{soft-NLOS}}, p_{\mathrm{LOS}}] \qquad (10)$$

and the final channel *decision* for each RSSI window is obtained by averaging all token predictions:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} p(y_t), \qquad (11)$$

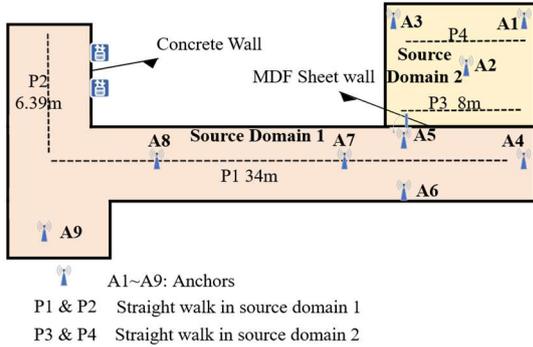where $\hat{y}$ is the classification results across different environments.

Fig. 2. Detailed floor plan and BLE anchor deployment in two source domain areas.
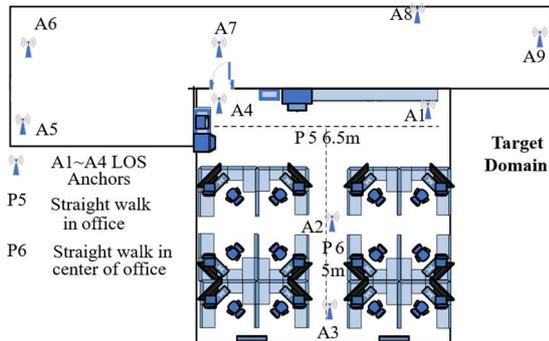

Fig. 3. Detailed floor plan and BLE anchor deployment in test/target domain.
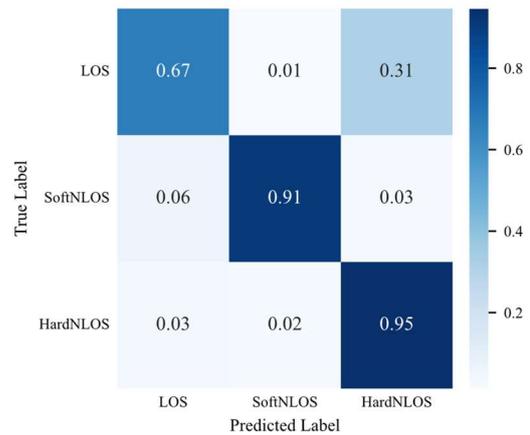
Table 2. Dataset Detail

|	Source domain 1		Source domain 2		Unseen Target Domain	
	P1	P2	P3	P4	P5	P6
Total	10827	2330	2238	2377	1226	1904
LOS	6254	1781	1297	1439	678	1157
Soft LOS	741	281	441	403	168	266
Hard NLOS	3832	268	500	535	380	481

IV. Dataset Description

The experiments were performed using a BLE RSSI dataset collected in three indoor environments of the Chosun University IT Building, South Korea, where each environment exhibits different spatial layouts and propagation conditions. As shown in Fig. 2, the source domain 1 includes path P1 in a 34 x 3m corridor and path P2 in 8 x 3.5 m corridor. The source domain 2 has paths P3 and P4 in an adjacent classroom of size 10 x 8m. The target domain Fig. 3 includes a separate office of size 10 x 8m with two paths P5 and P6, which is used for cross-domain validation.

Nine BLE beacons were deployed at a height of 1.5 m, spaced 3 to 4 m in the room and 7 to 8 m in the corridor to ensure that the BLE signals from anchors overlap for a seamless coverage.

(a)
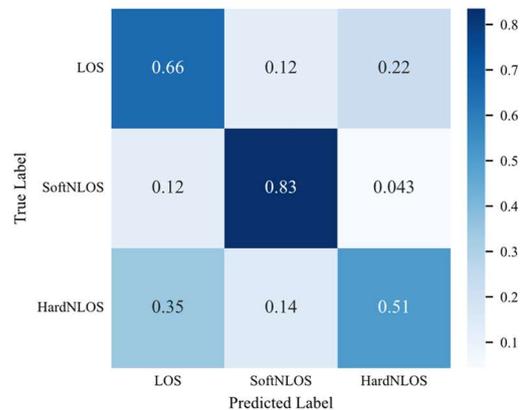
(b)

Fig. 4. Confusion Matrix of baseline DANN (a) Training (b) Test.

RSSI signals were collected at 1-second

intervals using two smartphones: Redmi Note 9S and Galaxy Note 8 to incorporate device variation. Dataset detail is outlined in Table 2. Ground truth labels were manually assigned as LOS, Soft-NLOS, or Hard- NLOS based on visual inspection. The collected samples were divided into training and validation sets using an 80-20. For domain generalization evaluation, the target environment was completely excluded from training validation and used only as unseen testing.

V. Experimental Results

The proposed DG framework was evaluated using BLE RSSI datasets obtained from three environments: two corridors (source domain 1), a classroom (source domain 2), and an office (unseen target domain).
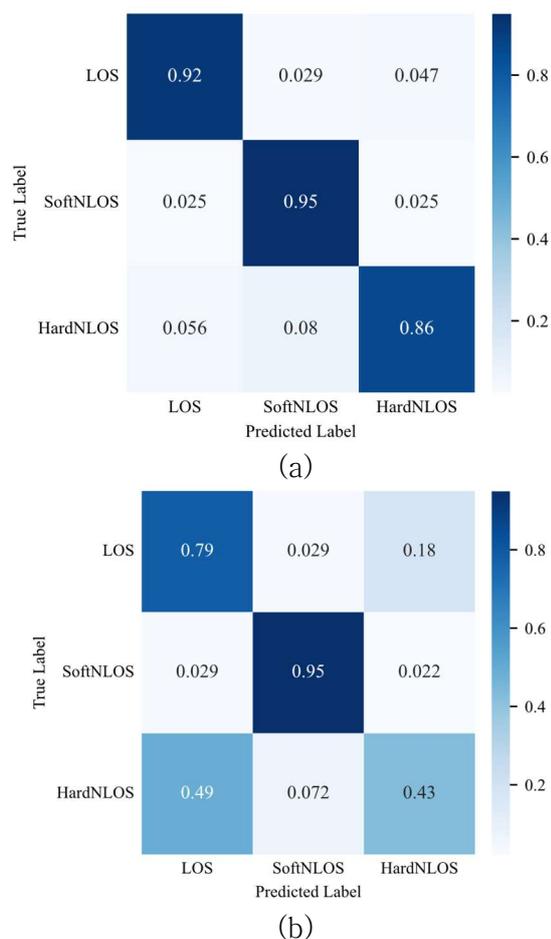

(a)

(b)

Fig. 5. Confusion Matrix of Hybrid LSTM DANN (a) Training (b) Test.

The baseline DANN model used GRL based source and target feature alignment but in this study, it serves only as a comparison point, as the proposed approach focuses on domain generalization.

The proposed LSTM and CNN-BiLSTM models extend baseline by integrating statistical features, attention pooling, and variance learning to enhance robustness across unseen environments.

All experiments were repeated five times with seed initializations. As shown in Table 3 and Fig. 5, the enhanced framework significantly improves cross-domain generalization.
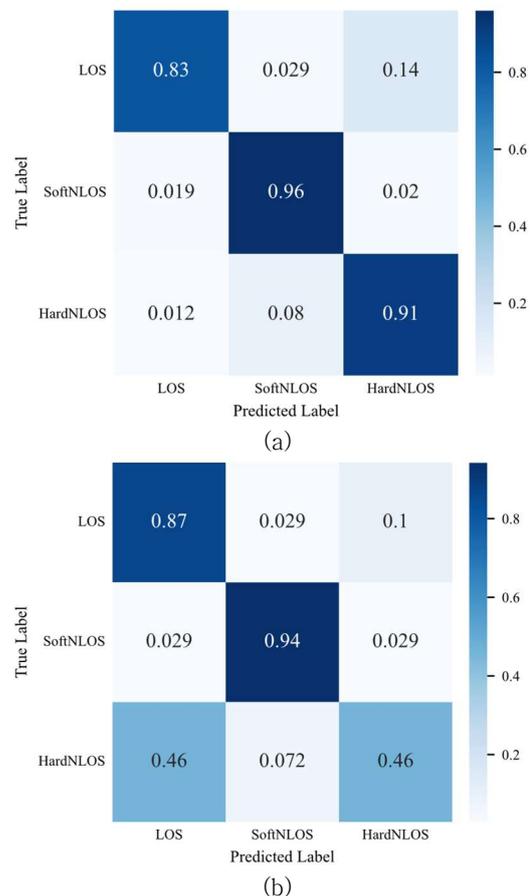

(a)

(b)

Fig. 6. Confusion Matrix of Hybrid CNN-BiLSTM DANN (a) Training (b) Test.

In Fig. 4 The baseline achieved 86% training accuracy and 67% on the target domain, while the CNN-BiLSTM model

Table 3. Cross-Domain BLE Channel Classification Results

Class Label	Metric	Baseline DANN		LSTM DANN		CNN-BiLSTM DANN	
		Train	Test	Train	Test	Train	Test
LOS	Precision	0.87	0.91	0.90	0.93	0.94	0.94
	Recall	0.67	**0.65**	0.92	**0.78**	0.92	**0.87**
	F1-score	0.76	0.76	0.91	0.85	0.93	0.90
Soft NLOS	Precision	0.95	**0.55**	0.86	**0.84**	0.87	**0.84**
	Recall	0.91	0.83	0.95	0.95	0.95	0.94
	F1-score	0.93	0.66	0.90	0.89	0.91	0.88
Hard NLOS	Precision	0.79	0.18	0.94	0.19	0.70	0.30
	Recall	0.95	0.50	0.86	0.43	0.52	0.44
	F1-score	0.86	0.26	0.90	0.26	0.60	0.36
Overall Accuracy		0.86	**0.67**	0.906	**0.785**	0.898	**0.851**

reached 90.6% and 78.5% respectively, a 17% relative gain in unseen target domain accuracy.

Confusion matrices shown in Fig. 5 and Fig. 6 confirm reduced misclassification between LOS, soft-NLOS, and hard-NLOS. Specifically, soft-NLOS recognition and hard-NLOS stability were improved notably by variance-guided learning.

To analyze temporal modeling effects, a CNN–BiLSTM variant replaced the LSTM encoder with a convolutional–bidirectional LSTM, capturing both local fluctuations and bidirectional dependencies. As shown in Table 3, this model achieved training accuracy of 89.8%, and 85.1% in unseen target domain, outperforming both baseline DANN and LSTM variants.

The confusion matrices indicate consistent Recall across all classes, demonstrating its stronger spatiotemporal learning and reduced domain shift.

Overall, the CNN–BiLSTM hybrid delivers the most generalizable performance, achieving the highest unseen target domain accuracy among all evaluated frameworks. In Table 3 all models accurately detect LOS conditions in unseen target domain with a high Precision of 0.90 to 0.94, and Recall 0.65 to 0.87, indicating that LOS patterns are easily separable under domain shift.

For Soft-NLOS, DA with temporal modeling improves Precision from 0,55 in Baseline to 0.84, reducing confusion with LOS samples. However, hard-NLOS conditions remain challenging as Precision and Recall drop sharply across all models due to severe signal blockage and non-stationary multipath effects. In such cases, anchors with similar instability features may be related to different physical obstructions and require spatial or geometry aware modeling.

Confusion matrices in Figs. 4, 5, and 6 collectively demonstrate that the proposed DG framework consistently enhances classification robustness across all models, achieving progressive improvement from baseline DANN to LSTM and CNN-BiLSTM variants.

VI. Conclusion

This study proposed a hybrid domain adaptive framework for BLE channel classification to enhance cross environment robustness. By integrating statistical tokenization, attention-based pooling, and variance loss in learning, the model achieved domain-invariance and stability awareness compared to the baseline DANN.

The experimental results demonstrated high accuracy in hard-NLOS recognition and other channel categories using LSTM. Furthermore, the CNN-BiLSTM yielded the highest unseen target domain accuracy by 6.6% over the LSTM based hybrid framework. Future work will be extending

this framework to various indoor environments and real time localization scenarios. Geometric information can also be considered to integrate to handle hard-NLOS cases.

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