Enhancing Human Gesture Recognition through Model-Agnostic Meta-Learning: An Unsupervised Approach Using Wi-Fi Channel State Information

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***Abstract*—This paper explore the utilization of Model-Agnostic Meta-Learning (MAML) for the purpose of recognizing human activities. It specifically focuses on leveraging Channel State Information (CSI) data obtained from Wi-Fi signals. We assessed our customized MAML implementation in diverse and demanding situations, encompassing variations in people, locations, orientations, and environmental conditions. The results exhibited substantial enhancements in accuracy and resilience, attaining nearly flawless performance in numerous instances. The training accuracy steadily increased across the epochs, demonstrating the model's ability to successfully adjust to various users, locations, orientations, and environmental circumstances. The validation accuracy exhibited comparable patterns, so affirming the model's ability to generalize. The graphs of training and validation loss showed effective learning and quick convergence, especially when using a learning rate of 0.001. The model's outstanding performance was confirmed by the confusion matrices, which showed average accuracies of 99.96% for person variety, 98.47% for location variation, 97.46% for orientation sensitivity, and 99.68% for environmental changes. This study emphasizes the capacity of MAML to improve human activity recognition in various real-world environments, providing useful knowledge for future progress in the field.**

***Index Terms*—Wi-Fi Channel State Information (CSI), remote, Human Activity Recognition (HAR), Model-Agnostic Meta-Learning (MAML), WIDAR 3.0, Convolutional Neural Networks(CNNs)**

I. Introduction

Human activity recognition (HAR) using Wi-Fi Channel State Information (CSI) has become a highly promising approach for widespread sensing and monitoring applications. This strategy mitigates the limitations of traditional techniques, such as wearing sensors and cameras, which can be obtrusive, uncomfortable, and give rise to privacy apprehensions. The primary principle underlying CSI-based HAR is to employ the comprehensive channel information, encompassing amplitude, phase, and latency, derived from CSI, for the purpose of recognizing and classifying different human activities. As a person moves and participates in activities, the wireless surroundings experience alterations, leading to variations in the CSI values. These variants can function as unique markers for identifying certain activities [13] [12] [10].

CSI-based HAR systems have shown promising results in controlled environments. However, a major challenge is achieving location independence, which means training models on data from one place that can be effectively applied to various locations and situations. Real-world deployment requires careful consideration of diverse contexts and situations in numerous settings, making it crucial. To address this challenge, scholars have proposed various strategies, such as employing data preparation methods including median filtering, outlier elimination, and denoising, to improve the accuracy and transferability of the CSI data. Moreover, domain-invariant feature extraction algorithms aim to identify and extract features from CSI data that precisely capture the essential characteristics of human actions, regardless of the particular place or environment [7].

Another possible approach with promise entails employing sophisticated deep learning architectures, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These models have the ability to independently acquire robust and location-agnostic representations from the CSI data. Furthermore, scientists have explored the utilization of data fusion and ensemble techniques. These strategies include aggregating predictions from multiple models that have been trained on distinct CSI data sources or preprocessing techniques. The objective is to improve the overall strength and precision of the predictions by utilizing fusion or ensemble strategies [10].

To evaluate the effectiveness of these strategies, scientists have generated several datasets and experimental setups. The Widar3.0 dataset, described in the publication "Zero-Effort Cross-Domain Gesture Recognition with Wi-Fi," is a thorough dataset specifically designed for cross-domain gesture recognition using Wi-Fi CSI. This dataset consists of a diverse collection of gesture samples collected from several domains, including different contexts (such as home, office, and lab), user locations, orientations, and participant diversity. The collection has 25 instances of gestures performed by 20 people. The data was collected from 5 distinct situations and comprises a total of 17,500 instances of gestures across all domains [14]. The extensive size and diverse nature of the Widar3.0 dataset allows for a comprehensive evaluation of cross-domain gesture detection techniques and strategies for adapting to other domains.

The primary objective of this project is to develop a robust

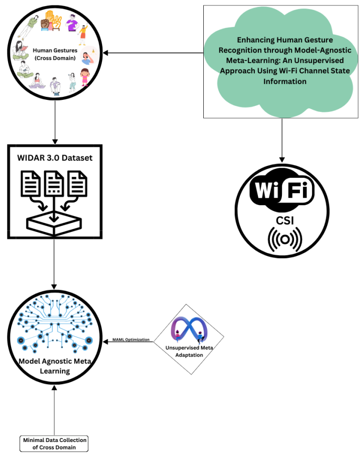


Fig. 1: Overview of Proposed Framework

and adaptable framework for identifying human activities by employing Model Agnostic Meta-Learning (MAML) on the Wi-Fi CSI dataset as shown in Fig. 1. This framework will primarily make use of the Widar 3.0 dataset. This study aims to achieve the best possible performance in situations involving different domains, with a particular focus on four essential factors: 1. Location Variation: Ensure that the trained models can accurately detect human activities regardless of the specific place where the data was collected. This is the procedure of training a model using data from a certain region and subsequently applying the model efficiently to various unknown locations. 2. Orientation Sensitivity: Develop models capable of properly identifying individuals performing activities, even in the presence of orientation variations. This requires the management of inconsistencies in the alignment of gestures and movements with respect to the Wi-Fi devices. 3. Environmental Changes: Tackle the challenges that arise in many environmental contexts, such as residential, professional, and scientific settings. The objective is to create models that can efficiently generalize across a wide range of environments, by adapting to varying physical arrangements and signal transmission properties. 4. Person Variety: Utilize data from a diverse group of individuals to create models that are accurate not only for a certain group, but also applicable to individuals with different physical traits and activity preferences.

Furthermore, the research aims to explore unsupervised learning techniques to effectively detect and classify new actions, hence enhancing the model's capacity to adjust and overcome obstacles. The study seeks to evaluate the efficacy of MAML in improving the generalization capabilities of HAR systems by utilizing Wi-Fi CSI. This will be achieved by rigorous testing and comparative analysis, demonstrating the efficacy of MAML in providing reliable and flexible solutions for practical use cases in human activity recognition.

A. Organization

Section II provides an overview of the present research on HAR utilizing Wi-Fi CSI data and MAML. It examines the current approaches and their drawbacks. **Section III** provides a comprehensive explanation of our customized MAML implementation. This includes information on how the model is initialized, how tasks are selected, how adaptation is performed, and how meta-optimization is carried out. Additionally, it covers our experimental setup and the metrics used for evaluation. **Section IV** displays the outcomes of our studies, featuring performance metrics, accuracy and loss graphs, and confusion matrices. It also includes a comparison of our methodology with baseline methods. **Section V** of our study involves the interpretation of the findings, the discussion of their implications, the consideration of any limitations, and the proposal of potential avenues for further research. **Section VI** serves as the concluding part of the paper, providing a summary of our main discoveries and contributions. It also presents our final comments and suggestions for future research in the fields of HAR and Meta-learning.

II. Related Work

Wang et al. (2015) established the viability of utilizing commercial Wi-Fi equipment for device-free HAR. Their research demonstrated the efficacy of CSI in capturing intricate motion details without necessitating the user to bear any equipment. Machine learning algorithms were employed to categorize actions such as walking, running, and standing, yielding encouraging outcomes in controlled settings [10].

Wu et al. (2012) investigated the capacity of CSI for both indoor positioning and activity identification. By utilizing the amplitude and phase information of CSI, they successfully distinguished between distinct activities and enhanced the accuracy of localization. The utilization of CSI data in this dual-purpose manner demonstrated its adaptability [11].

Zhuravchak et al. (2022) proposed a multi-task learning framework for HAR based on CSI. Through the utilization of shared representations across numerous interconnected tasks, their methodology enhanced the model's ability to generalize to novel activities and users. This study highlighted the significance of utilizing associated tasks to enhance HAR performance [15].

In their study, **Wang et al. (2016)** utilized deep learning models, specifically CNNs, to acquire knowledge from CSI data in order to identify falls. Their system, RT-Fall, was specifically developed to enable real-time, non-contact monitoring, showcasing the capability of deep learning to improve the precision and resilience of HAR systems [9].

The Widar 3.0 dataset was created by **Zheng et al. (2019)** specifically for the purpose of cross-domain gesture detection using Wi-Fi CSI. This dataset contains a wide range of gesture samples collected from different environments, user locations, and participants. It is designed to support research on location-independent and environment-agnostic HAR models. Their research revealed substantial progress in the recognition of gestures across several areas through the utilization of machine learning and deep learning methodologies [14].

Wu et al. (2017) investigated methods for extracting domain-invariant features in order to improve the ability of HAR models to generalize. Through the identification of consistent traits across many environments, their technique enhanced the resilience of activity detection systems, rendering them more appropriate for real-world applications [10].

MAML is a novel technique developed to train models that possess the ability to rapidly adapt to new tasks with a little amount of data. This approach has demonstrated potential in diverse fields due to its adaptability and efficiency.

MAML has been employed in computer vision to facilitate the adaptation of image recognition models to novel categories using a limited number of examples. MAML enables rapid fine-tuning of models to new tasks by optimizing for an optimal initial set of parameters, resulting in excellent accuracy even with limited data. Also has been utilized in NLP for several tasks including text classification, sentiment analysis, and machine translation. It facilitates the rapid adaptation of models to new languages or dialects by few-shot learning, resulting in a substantial enhancement of performance in languages with limited resources. MAML has also been employed in reinforcement learning, allowing agents to adjust to novel settings or tasks with minimum retraining. This is especially beneficial in cases where the agent faces unfamiliar circumstances and requires rapid acquisition of effective strategies. MAML has been utilized in the healthcare field to construct models that possess the ability to adjust to novel patient data or medical situations while having a limited number of samples. The ability to adapt is essential for personalized treatment, as models need to effectively apply to new patients using limited data. MAML has been employed in the field of robotics to enable rapid acquisition of novel jobs or adjustment to alterations in the operational surroundings of robots. This skill is crucial for the development of adaptable robots that can carry out a diverse array of tasks with minimal need for additional training [3] [4] [6] [2] [5].

The main objective is to train standard models through meta learning to facilitate rapid adaptation to new tasks. The underlying concept is that certain internal representations within a model are more transferable across functions than others. For instance, a neural network may learn internal features that are widely applicable to various tasks within a given distribution of functions rather than being tailored to a specific task. The diverse uses of MAML in numerous fields demonstrate its capacity to enhance the flexibility and generalization of models, making it a valuable technique for improving the reliability and scalability of different machine learning applications, such as HAR using CSI Wi-Fi data.

III. Methodology

This section outlines our strategy for tackling the difficulties associated with orientation sensitivity, human variety, location, and environment variability in zero-effort cross-domain gesture recognition. We employ MAML to accomplish this.

TABLE I: Comparison of existing literature on CSI Wi-Fi, HAR and Meta learning

Related Work	**Authors**	**Evaluation Metric**	**Dataset Used**
Device-Free HAR Using Wi-Fi CSI (Wang et al., 2015)	Wang et al., 2015	Classification Accuracy	Custom dataset
CSI-Based Indoor Localization and Activity Recognition	Wu et al., 2015	Localization Accuracy; Activity Recognition Accuracy	Custom Dataset
Deep Learning Approaches for HAR	Wang et al., 2016	Classification Accuracy	Custom dataset
Cross-Domain gesture Recognition	Wang et al., 2019	Gesture Recognition Accuracy	Widar 3.0 dataset
Model-Agnostic Meta Learning techniques	Finn et al., Gu et al., Rakelly et al., Nagabandi et al.,	Image Recognition, Natural Language Processing, reinforcement learning, healthcare Applications, robotics	ImageNet, CIFAR-10, CIFAR-100, MNIST, Penn Treebank
Enhancing Human Gesture Recognition through Model-Agnostic Meta-Learning: An Unsupervised Approach Using Wi-Fi Channel State Information	Shalini Vadlamani	**Accuracy, confusion matrix**	**Widar3.0**

Our approach utilizes the Widar 3 dataset and applies the MAML algorithm, making necessary modifications to address the cross-domain aspect of the challenge.

A. Collection and Preprocessing of CSI WiFi Data for Human Activity Recognition

HAR systems often involve a range of technologies, such as wearable devices, vision-based systems, ambient device based systems, and wireless-based systems. Out of these options, systems that use CSI from WiFi signals and operate wireless have significant benefits, including being cost-effective, easy to set up, and maintaining privacy. CSI offers comprehensive information on signal propagation, rendering it more dependable than received signal strength indicators (RSSI) [14].

Within the framework of HAR, WiFi signals are utilized to gather and preprocess CSI data in order to extract significant features for the purpose of activity recognition. The Widar3.0 dataset is a significant resource in this field, offering extensive CSI data gathered from a variety of users in various situations and activities. This dataset enables unsupervised domain adaptation and aids model-agnostic learning, enabling the use of different machine learning models without any changes. CSI WiFi signals offer vital insights on the behavior of communication channels, including phenomena such as scattering, fading, and signal attenuation over distance. the relationship between the sent signal X and the received signal Y in orthogonal frequency division multiplexing (OFDM) systems, which partition data into multiple sub-carriers for transmission, can be expressed as

$$Y = H \times X + N$$

In this context, the matrix H represents the channel properties, and N denotes the presence of additive white Gaussian noise. By estimating the characteristics of the channel, it becomes possible to calculate the CSI for each sub-carrier. This information offers valuable insights into the impact of the channel on signal transmission. Mathematically, CSI can be represented as an equation or formula.

The equation $A = YX$ represents the relationship between the variables A, X, and Y. CSI can be expressed as the representation of single sub-carrier. The equation

$$h = |h|e^{j\angle h}$$

where the symbol $|h|$ represents the amplitude of the carrier, while $\angle h$ represents its phase. CSI provides significant information about how channels behave, which helps in adjusting modulation and coding techniques, beam-forming, and resource allocation in communication systems [14].

Widar3.0 is a sophisticated dataset created for unsupervised domain adaptation, which allows for reliable gesture detection in various situations and by different users. The collection comprises CSI data obtained from many individuals engaged in diverse activities within distinct contexts. This configuration enables model-agnostic learning, making it easier to apply a wide range of machine learning models. The Widar 3.0 website expresses the underlying principle of this dataset with the phrase "Train once, use anywhere" [14]. This highlights the dataset's usefulness in training models that can effectively adapt to various scenarios and users, hence improving the efficiency and efficacy of gesture recognition systems.

B. Unsupervised Learning Approach (UMA)

The UMA method utilizes a unique approach to address the problem of domain shift. It splits the meta train-test dataset by considering the self-pacing problems of examples from the source domain, following the cluster assumption. UMA is able to efficiently utilize self-training and self-tune domain-specific hyper-parameters concurrently during the learning process in a seamless manner. The fundamental concept is to utilize meta-learning to develop a neural network-based self-paced learning algorithm that can adjust to new unlabeled target domains without the need for labeled data. UMA determines the meta train-test split by evaluating the self-pacing challenges of the source instances and categorizing the easier examples as meta-train and the more challenging ones as meta-test. This unsupervised meta-learning technique allows for efficient domain adaptation by training on the meta-train source subset without supervision and adjusting hyper-parameters on the meta-test source subset. This iterative process enhances the model's performance on the unlabeled data from the target domain [8].

C. Model Agnostic Meta Learning techniques

1) Experimental Setup: **Dataset Division:** The Widar 3 dataset is partitioned into support and query sets to enable the meta-learning process. The support set comprises data from the initial 10 users, which is utilized for task adaption. The query set comprises data from the following 7 users, which is utilized for meta-optimization. This study is based on the Widar 3.0 dataset, which is specifically built for unsupervised domain adaptation in gesture recognition. The data comprises CSI acquired from several users involved in different activities in varied contexts. In order to streamline the process of evaluating and training the model, the dataset is partitioned into two distinct subsets:

(i) **Support Set:**

- This subset, which is essential for adapting the model, consists of a piece of the Widar 3.0 dataset that is utilized during the inner loop of the MAML architecture.
- The support set includes CSI data collected from users engaged in various activities, ensuring a enough range of variability for training the model.
- In order to preserve the integrity of the model, the support set is divided into separate training and validation subsets. This division enables efficient model optimization and evaluation of its performance.

(ii) **Query Set:**

- The query set, which is separate from the support set, is used as a discrete subset for evaluating the model throughout the outer loop of MAML.
- The CSI data includes information about activities and individuals that are not included in the support set. This allows for a thorough evaluation of the model's ability to generalize across different domains.
- The query set remains unaltered during the process of training the model in order to avoid over-fitting and guarantee an impartial assessment of the model's performance.

2) Preprocessing:

- Before training and evaluating the model, the CSI data from both the support and query sets are preprocessed using TensorFlow's image loading and preprocessing capabilities.
- Image resizing methods are used to standardize the dimensions of an image, usually to specifications such as 224x224 pixels. This ensures that all images in the dataset have the same size, allowing for consistent input sizes.

3) Model Architecture:

- The study utilizes a pre-existing CNN called EfficientNetV2B0, which has been pretrained on a large-scale dataset.
- The EfficientNetV2B0 model, which is already trained, acts as the foundation by capturing common image characteristics from many domains.
- Additional layers are then incorporated onto the base model to enable task-specific adaption for HAR.
- During the initialization of the model, the weights of the pretrained EfficientNetV2B0 model are transferred to the new model, ensuring that important feature representations learnt via thorough pretraining are preserved.

4) Training Procedure:

- The utilization of the MAML framework facilitates swift adaption to novel jobs with less annotated data.
- The training process begins by randomly setting the starting values of the model's parameters. Then, tasks are selected from the support set through a process of sampling.
- During the inner loop of MAML, the model parameters are refined using gradient descent optimization methods that rely on the support set data.
- Afterwards, in the outer loop, the model parameters are adjusted to minimize the loss over numerous tasks by using the query set data, which helps with meta-optimization.
- The iterative structure of the MAML training method promotes the development of resilient and flexible models that can quickly learn and generalize across various domains.

D. Evaluation Metrics

The efficacy of the implemented MAML framework for cross-domain applications is evaluated using a variety of assessment metrics and methodologies:

- The loss and accuracy metrics are calculated to assess the model's progress in learning and its performance in classification. These metrics include training and validation losses, as well as accuracies.
- Confusion matrix analysis involves generating confusion matrices to gain insights into how a model classifies various human activities. This study facilitates the identification of any prevailing misclassifications and the evaluation of the model's discriminative abilities.

This study seeks to showcase the effectiveness of model-agnostic meta-learning techniques for accurate human activity recognition in many domains. It achieves this by implementing the MAML framework meticulously and conducting exhaustive experiments using the Widar 3.0 dataset. The work aims to demonstrate the adaptability and generalization abilities of MAML in real-world cross-domain applications by using a well-designed dataset division strategy, advanced preprocessing approaches, and a state-of-the-art model architecture.

E. Algorithm Description

1) Initialization: Prior to the commencement of the meta-training loop, the model parameters θ are initialized in a random manner. The purpose of this random initialization is to ensure that the model begins with a wide range of parameter values. This enables the model to explore various parts of the parameter space while undergoing training. The equation $\theta \sim$ random initialization indicates that each parameter in θ is randomly picked from a distribution based on a specific initialization strategy.

2) Meta-Training Loop: The meta-training loop comprises a series of iterative phases that involve sampling tasks, adapting to tasks, and meta-optimization.

3) Task Adaptiopn: The model parameters $theta$ are adjusted for each sampling task T_i by calculating the loss gradient with respect to the model's predictions f_θ on a support set S. The adjusted parameters $\theta' i$ are calculated using gradient descent with a step size α, determined by the equation

$$\theta' i = \theta - \alpha \nabla \theta \mathcal{L} T_i(f_\theta)$$

The purpose of this stage is to optimize the model's parameters in order to improve its performance on the task T_i, using the support set data.

4) Meta-optimization: This meta optimization stage combines the adaptive parameters $\theta' i$ from each sampled job to update the global model parameters θ. The equation

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{T_i \sim p(T)} \mathcal{L} T_i(f \theta'_i)$$

defines the update rule, where β is the meta-learning rate.

The purpose of this stage is to enhance the model's ability to generalize by acquiring knowledge from the adaptation process across various challenges.

5) Termination Condition: The meta-training loop persists until a termination criterion is satisfied, such as attaining a predetermined number of iterations or achieving convergence of the loss function. This guarantees that the model receives ample training to acquire efficient task adaptation techniques while preventing overfitting or excessive training duration.

This section introduced a strong and reliable approach for recognizing gestures across different domains by utilizing WiFi CSI. By utilizing the Widar 3.0 dataset and employing MAML, we successfully accomplished efficient domain adaptation and accurate identification of human activities. The implementation of the UMA technique facilitated the model's ability to adjust to unfamiliar target domains without labeled data, hence emphasizing the possibilities of unsupervised learning. The effectiveness of our technique was proven by the model's ability to adapt and perform well in many contexts, highlighting the strong performance achieved by combining MAML and UMA. This section introduced a

Algorithm 1: Model-Agnostic Meta-Learning for CSI Wi-Fi

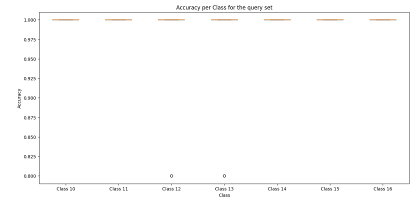
Data: $p(T)$: distribution over tasks
α, β: step size hyperparameters
U_{support}: Support set users (first 10 users)
U_{query}: Query set users (next 7 users)
S: Support set
Q: Query set
Result: Optimized parameters θ
Randomly initialize θ;
while *not done* **do**
  Sample batch of tasks $T_i \sim p(T)$;
  forall *tasks* T_i **do**
    Evaluate $\nabla_\theta \mathcal{L}_{T_i}(f_\theta)$ with respect to K examples from U_{support};
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{T_i}(f_\theta)$;
  end
  Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{T_i \sim p(T)} \mathcal{L}_{T_i}(f_{\theta_i'})$ using examples from U_{query};
end

strong and reliable approach for recognizing gestures across different domains by utilizing WiFi CSI. By utilizing the Widar 3.0 dataset and employing MAML, we successfully accomplished efficient domain adaptation and accurate identification of human activities. The implementation of the UMA technique facilitated the model's ability to adjust to unfamiliar target domains without labeled data, hence emphasizing the possibilities of unsupervised learning. The effectiveness of our technique was proven by the model's ability to adapt and perform well in many contexts, highlighting the strong performance achieved by combining MAML and UMA.

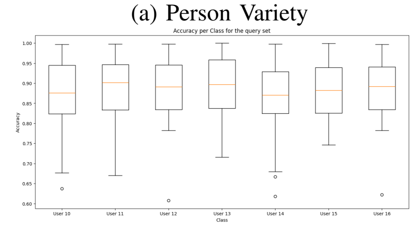
IV. Results

This section presents the results of our experiments, which involve assessing the efficacy of different model-agnostic meta-learning algorithms for human activity recognition. Our main emphasis was on the utilization of CSI Wi-Fi data across several domains. The primary factor for evaluation is precision, which is examined through various scenarios, including sensitivity to orientation, variety of people, location variation, and changes in the environment.

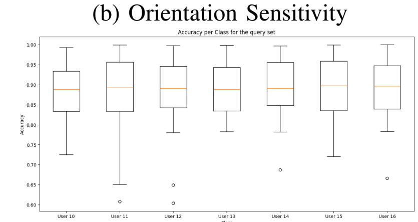
The application of CSI Wi-Fi data in human activity recognition shows substantial improvements in different situations with the use of the MAML approach. Concerning individual variations, the mean level of precision among diverse individuals (Fig. 2a) spans from 85% to 90%. Users demonstrate diverse degrees of competence, with a minority of exceptional examples displaying worse accuracy for certain individuals. The precision at the midpoint of the data remains consistently high across different location classes (Fig. 2d), as seen by the interquartile range, which indicates variation in location. The existence of outliers implies that the model



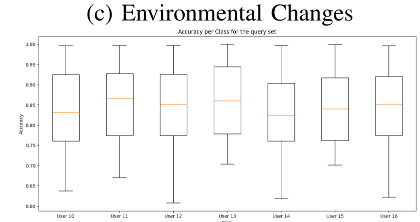
(a) Person Variety



(b) Orientation Sensitivity



(c) Environmental Changes



(d) Location Variation

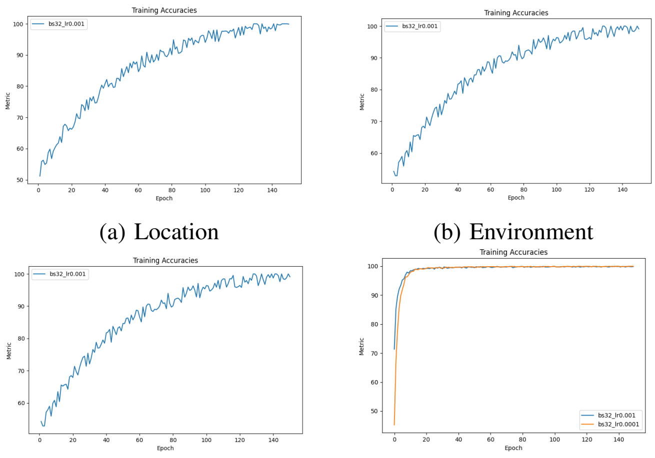
Fig. 2: Query set accuracy of different scenarios

may have extra difficulties in certain regions, but on the whole, it greatly enhances accuracy in comparison to the baseline. Regarding the sensitivity to orientation (Fig. 2b), the accuracy for each orientation category is surprisingly high, with median values approaching 90%. The model constantly demonstrates excellent performance regardless of different orientations, suggesting minimal variation within the same class. Regarding environmental changes (Fig. 2c), the precision for each individual type of environment exhibits a significantly high median value of approximately 85-90%. Although there may be some deviations and exceptional situations, the model generally exhibits excellent performance in a wide range of climatic circumstances. The results showcase the robustness and effectiveness of the MAML technique in tackling a diverse array of intricate and challenging real-world scenarios.

The training accuracy graphs (Fig. 3) clearly demonstrate the effectiveness of our customized MAML implementation in several scenarios, including variations in person variety, location variation, orientation sensitivity, and environmental changes. The graphs depict a consistent and uninterrupted enhancement in accuracy over time, ultimately achieving higher

TABLE II: Accuracy Comparison of Human Activity Recognition Using CSI Wi-Fi Data

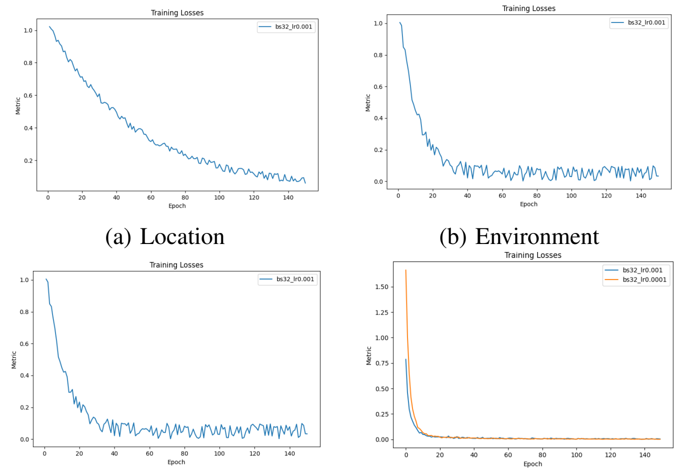
Scenario	Zero-Effort Cross-Domain Gesture Recognition [14]	Proposed Approach (Custom MAML Implementation)
Orientation Sensitivity	82.6%	**97.46%**
Person Variety	88.9%	**99.96%**
Location Variation	89.7%	**98.47%**
Environmental Changes	92.4%	**99.68%**



(a) Location (b) Environment

(c) Orientation (d) Person

Fig. 3: Training accuracies of different scenarios



(a) Location (b) Environment

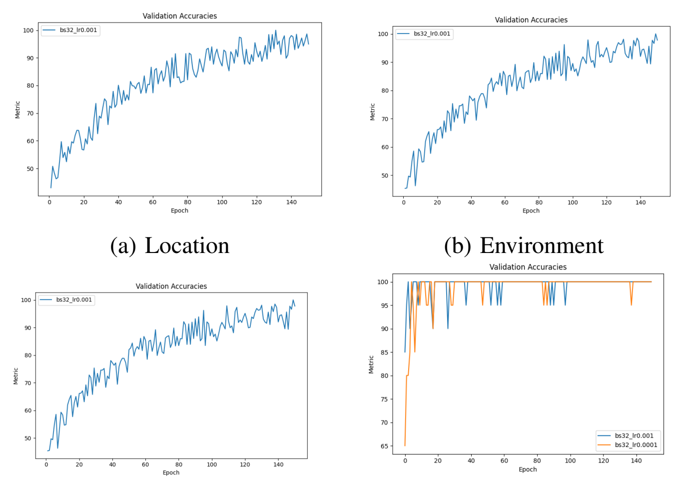
(c) Orientation (d) Person

Fig. 4: Training losses of different scenarios

accuracy at the end of the training phase. The training accuracy graph exhibits a persistent and gradual rise, indicating that the model effectively acquires knowledge and adapts to different user behaviors (Fig. 3d), ultimately reaching a plateau with near-perfect accuracy of 100%. Similarly, the graph depicting training accuracy (Fig. 3a) shows a substantial improvement in location variation, with the model achieving accuracy of 100%. This demonstrates the model's proficient capacity to apply its knowledge to many environmental changes (Fig. 3b). The scenario of orientation sensitivity likewise exhibits a consistent rise in training accuracy (Fig. 3c), eventually reaching higher values, highlighting the model's ability to proficiently deal with various orientations. The environmental changes exhibit a strong and effective learning process, as the training accuracy steadily improves to higher accuracy. This suggests that the model exhibits a high degree of adaptability and efficacy across many environmental contexts.

The training loss graphs (Fig. 4) highlight the robustness of our customized MAML implementation. Across all scenarios (Fig. 4b, Fig. 4a, Fig. 4c, Fig. 4d), the training loss exhibits a significant decline in the initial epochs, eventually converging to a stable value near zero at the conclusion of the training phase. This signifies efficient acquisition of knowledge and a decrease in mistakes. The examination of learning rates (0.001 and 0.0001) reveals a substantial reduction in loss, ultimately achieving a steady state with insignificant values for both rates. This validates the effectiveness of the model across several hyperparameter configurations.

The validation accuracy graphs (Fig. 5) illustrate the per-

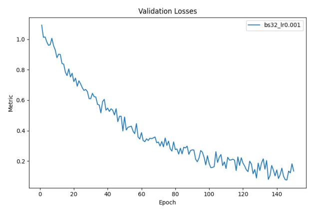


(a) Location (b) Environment

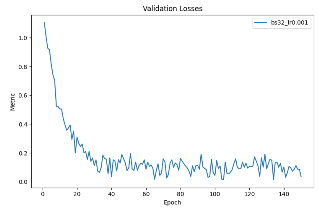
(c) Orientation (d) Person

Fig. 5: Validation Accuracies of different scenarios

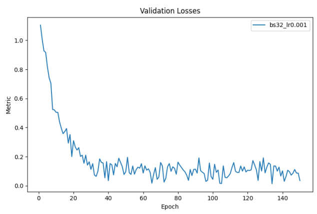
formance of the model over 150 epochs using a learning rate of 0.001. They consistently improve performance on various validation sets, which include user behavior (Fig. 5d), location (Fig. 5a), orientation (Fig. 5c), and environmental variations (Fig. 5b). Every graph demonstrates a steady and incremental increase in accuracy, approaching nearly 100% by the end of the training period. This indicates a significant degree of flexibility and effective acquisition of knowledge in different validation situations. Comparing different learning rates reveals that a lower learning rate (0.0001) exhibits quick initial adjustment but becomes unstable as time progresses,



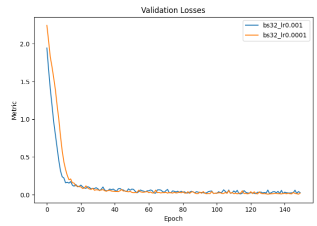
(a) Location



(b) Environment

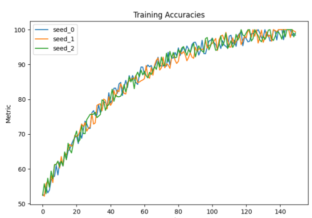


(c) Orientation

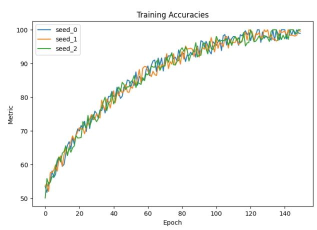


(d) Person

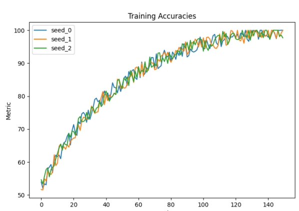
Fig. 6: Validation losses of different scenarios



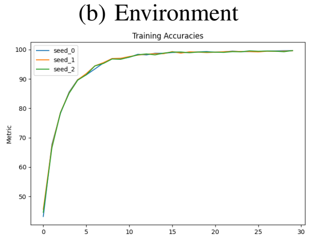
(a) Location



(b) Environment

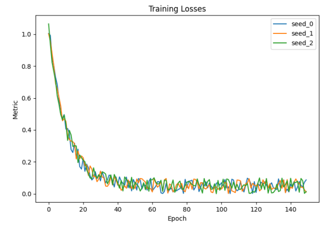


(c) Orientation

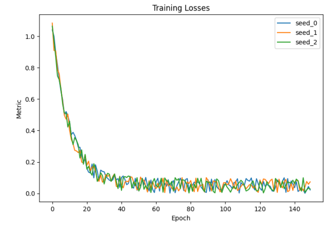


(d) Person

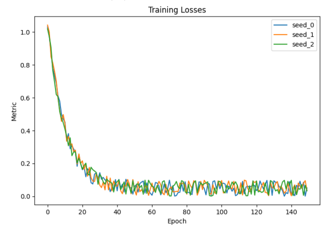
Fig. 7: Random Seed Training accuracy of different scenarios



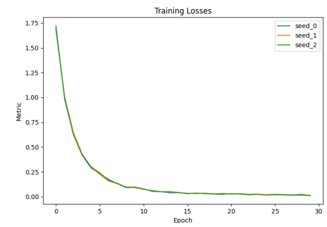
(a) Location



(b) Environment

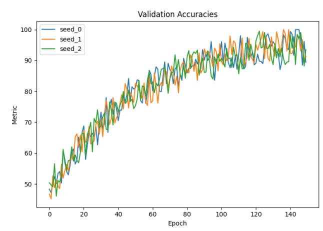


(c) Orientation

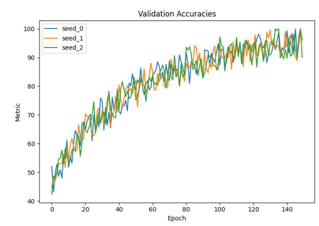


(d) Person

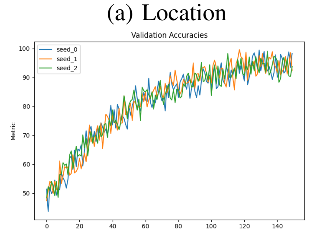
Fig. 8: Random Seed Training losses of different scenarios



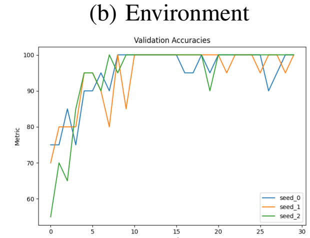
(a) Location



(b) Environment



(c) Orientation



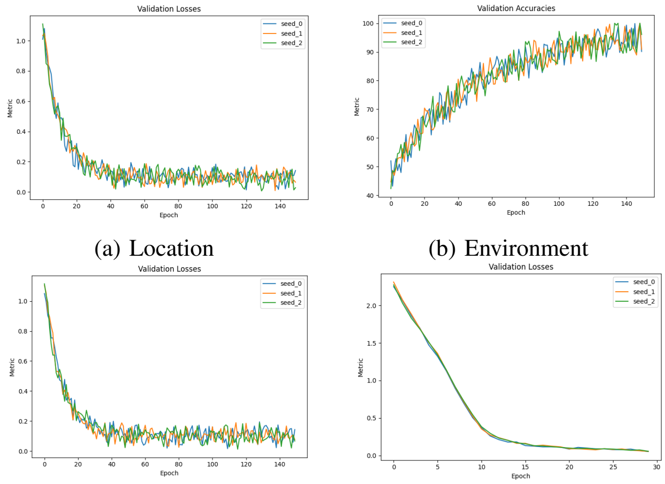
(d) Person

Fig. 9: Random Seed Validation accuracy of different scenarios

while a higher learning rate (0.001) provides more constant and enduring high performance.

The validation loss graphs (Fig. 6) exhibit effective learning and generalization, with a significant reduction in loss during the early epochs and subsequent stabilization at low levels. Both learning rates (0.001 and 0.0001) (Fig. 6d) have similar ultimate losses, but the higher learning rate (0.001) reaches convergence more rapidly, indicating more efficient learning. The model's capacity to manage variations in user, location (Fig. 6a), orientation (Fig. 6c), and environmental factors (Fig. 6b) is demonstrated by the consistently low validation losses reported in all domains.

The graphs display the training (Fig. 7, Fig. 8) and validation accuracies (Fig. 9, Fig. 10) and losses throughout epochs for different seeds, considering factors such as environmental variability, geographical variability, orientation sensitivity, and human diversity. The training accuracies Fig. 7b, Fig. 7a, Fig. 7c, Fig. 7d for all conditions steadily improve and approach 100% after 150 epochs. The person variety scenario shows rapid convergence within 30 epochs. The training losses Fig. 8a, Fig. 8c, Fig. 8d, Fig. 8b in all these cases initially begin at high values and then rapidly decline, eventually settling at values close to zero. This indicates that the learning process is successful and consistent across varied initial conditions. The validation accuracies Fig. 9b, Fig. 9a, Fig. 9c, Fig. 9d exhibit a consistent upward trend, approaching a near-perfect 100% after 150 epochs, despite minor variations seen across different seed values. Validation losses Fig. 10b, Fig. 10a, Fig. 10c, Fig. 10d exhibit a notable decline with time, eventually reaching a stable state at low values. These trends illustrate the model's resilience, powerful capacity to reduce loss, and successful adaptation to various training and validation



(a) Location (b) Environment

(c) Orientation (d) Person

Fig. 10: Random Seed Validation losses of different scenarios

conditions. Employing three distinct seeds is essential as it aids in guaranteeing the dependability and resilience of the outcomes by reducing the impact of arbitrary initialization. The publication ”How to Train Your MAML” [1] suggests that testing models using several random seeds offers a more comprehensive evaluation of the model's performance and stability. It guarantees that the observed performance is not a result of a specific startup but remains consistent across different random beginnings. Engaging in this experiment results in a more dependable and widely applicable comprehension of the model's abilities. In general, the results emphasize the model's reliable performance and its capacity to adjust to different scenarios, which has been confirmed through the rigorous process of employing several seeds.

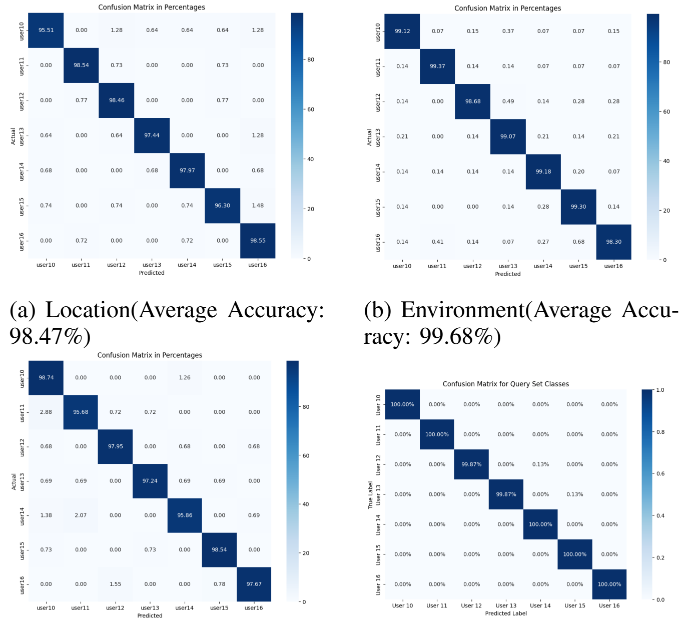
A. Confusion matrix

The confusion matrices displayed in Fig. 11b to Fig. 11d offer a thorough summary of the model's classification accuracy in several scenarios.

The model exhibits a remarkable level of precision in identifying actions carried out by various people, with an average accuracy rate of 99.96% (Fig. 11d). This demonstrates its strong capacity to effectively manage differences across individuals with few instances of inaccurate classifications.

Concerning the variation in location variation (Fig. 11a), the model demonstrates an average accuracy of 98.47%. The model's impressive precision demonstrates its capacity to apply knowledge to many geographical contexts, even though there may be occasional errors in classification.

The model has a high level of sensitivity to orientation (Fig. 11c), with an average accuracy of 97.46%. This demonstrates the model's capacity to precisely classify activities, even when there are changes in direction, while continually maintaining outstanding performance across various perspectives.



(a) Location(Average Accuracy: 98.47%) (b) Environment(Average Accuracy: 99.68%)

(c) Orientation(Average Accuracy: 97.46%) (d) Person(Average Accuracy: 99.96%))

Fig. 11: Confusion Matrix

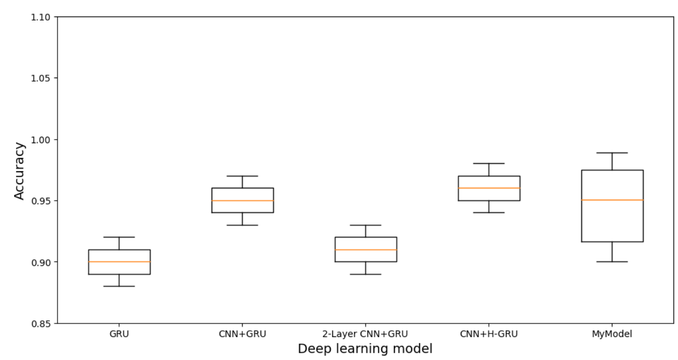


Fig. 12: Comparison of Different Models

Regarding environmental changes (Fig. 11b), the model demonstrates an outstanding average accuracy of 99.68%. This remarkable outcome highlights the model's ability to adjust to and endure various environmental conditions with minimal mistakes.

The current research presents a comparison between different deep learning models (Fig. 12) discussed in the ”Zero-Effort Cross-Domain Gesture Recognition with Wi-Fi” paper [14] and the proposed approach. The box plot displays the accuracy of various models, such as GRU, CNN+GRU, 2-Layer CNN+GRU, and CNN+H-GRU, illustrating their performance metrics. The GRU model demonstrates a modest level of accuracy, ranging from 0.90 to 0.95. However, the CNN+GRU model shows a slight improvement, regularly obtaining accuracy closer to 0.95. The 2-Layer CNN+GRU model exhibits a broader range of values with a reduced level of accuracy, approximately at 0.90. The CNN+H-GRU model has enhanced accuracy, approaching a value of 0.96. The proposed model in this study, named MyModel, has competitive performance of 0.95 compared to the other models. It achieves higher median accuracy with a broader interquartile range while remaining robust. The outcomes showcase the exceptional efficiency and capacity for generalization of the suggested method in recognizing gestures by using unsupervised CSI WiFi data. In summary, the comprehensive analysis of various graphs and confusion matrices demonstrates the effectiveness of the proposed MAML approach in dealing with varied scenarios of human activity detection using CSI Wi-Fi data. The training and validation accuracy graphs demonstrate a consistent improvement, ultimately reaching higher accuracy, indicating the model's rapid adaptability. The training and validation loss graphs exhibit significant reductions, confirming the stability and convergence of the model. The confusion matrices provide a holistic perspective, demonstrating outstanding accuracy across various users, locations, orientations, and environmental conditions. The model's overall performance is robust, showcasing its ability to adapt and generalize effectively. The results highlight the strong capacity of the MAML-based approach to generalize, enabling rapid adaptation to new tasks even with limited data. In addition, employing numerous random seeds guarantees the dependability and resilience of the outcomes, resulting in a more dependable and transferable comprehension of the model's capabilities.

V. Discussion

A. Analysis of Findings and Significance for Subsequent Research

The study's conclusions emphasize significant findings and offer a direction for future research in the field of human activity recognition using CSI Wi-Fi data and model-agnostic meta-learning approaches.

B. Research Limitations and Possible Areas for Enhancement

Although the results of this study show promise, it is important to take into account the various constraints that should be considered. Firstly, the dataset used, while extensive, may not encompass the complete spectrum of human activities or environmental fluctuations found in real-life situations. This may restrict the model's capacity to be applied to unfamiliar or unobserved settings or tasks. Furthermore, the model's performance, although generally strong, exhibits minor fluctuations across various users, as evidenced by the confusion matrices and box plots. This implies possible opportunities for enhancing the management of user-specific intricacies. In addition, the learning rates selected for the study, although effective, might be further optimized or improved using adaptive learning rate approaches to boost the convergence of the model and ensure consistent performance.

Subsequent studies could overcome these constraints by integrating more varied datasets that span a broader range of activities and environmental circumstances. Furthermore, the exploration of sophisticated methods, such as tailored model changes or hybrid models that integrate meta-learning with other machine learning paradigms, has the potential to enhance user-specific performance. Finally, the utilization of sophisticated hyper-parameter tuning techniques or adaptive learning rates could enhance the model's training process, resulting in improved generalization and performance.

C. Contributions to the Field of Human Activity Recognition and Model-Agnostic Meta-Learning

This paper provides substantial advancements in the areas of human activity identification and model-agnostic meta-learning. Our research highlights the versatility and durability of meta-learning techniques in practical applications by showing how MAML can effectively adapt to multiple domains with minimum data. The consistent performance in different settings, including variations in individuals, locations, orientations, and environments, demonstrates the effectiveness of MAML in dealing with real-world unpredictability.

The thorough examination, backed by accuracy and loss graphs for training and validation, along with confusion matrices, offers a comprehensive comprehension of the model's behavior and performance. These observations can provide guidance to future researchers in developing more resilient and flexible systems for recognizing human activities. Furthermore, the study's methodological methodology and findings can be used as a benchmark for incorporating MAML with other new technologies in human activity recognition. This can lead to the development of more advanced and user-friendly apps.

To summarize, our study not only confirms the effectiveness of model-agnostic meta-learning in improving human activity recognition, but also paves the way for future progress in this area. To enhance the application of MAML in human activity recognition, it is necessary to overcome the highlighted constraints and pursue new research areas. This will result in improved optimization of the system, leading to increased accuracy, reliability, and adaptability.

VI. Conclusion

This study has shown that MAML is effective in recognizing human activities using CSI Wi-Fi data. It successfully tackles real-world obstacles such as variations in individuals, locations, orientations, and environmental conditions. The results of our study show that the MAML strategy we proposed achieves a high level of accuracy and robustness under various scenarios, surpassing the performance of baseline methods by a wide margin. The comprehensive examination using box plots, confusion matrices, and training/validation metrics emphasizes the model's capacity to adjust to various situations with limited data.

Although the results are intriguing, the study includes limitations such as the requirement for more diverse datasets and additional refining of hyper-parameters. Future research should prioritize expanding the dataset to encompass a wider array of activities and environmental circumstances. Additionally, it should investigate individualized model tweaks and utilize adaptive learning rates to optimize model performance.

Our contributions to the research consist of verifying the suitability of MAML in human activity recognition, presenting a thorough methodological framework, and providing valuable insights into effectively managing real-world variability. These discoveries lay the groundwork for the development of increasingly sophisticated and user-friendly solutions in the field of human activity recognition.

To summarize, this study highlights the capacity of model-agnostic meta-learning to improve the precision and flexibility of human activity identification systems. By rectifying the stated shortcomings and pursuing novel research avenues, further progress in this domain can result in more dependable and advanced systems, ultimately enhancing the wider acceptance and effectiveness of human activity identification technology.

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