Human Activity Recognition Using Ensemble Neural Networks and The Analysis of Multi-Environment Sensor Data Within Smart Environments

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Abstract

The significant focus and potential value of Human Activity Recognition (HAR) technologies based on non-invasive ambient sensors have been attributed to the advancement of Artificial Intelligence (AI) and the widespread adoption of sensors. Due to the proactive engagement of human activities and the utilization of Machine Learning (ML) techniques that depend on domain expertise, developing a standardized model for comprehending the everyday actions of diverse individuals has significant challenges. A technique for recognizing the user's everyday activities in multi-tenant intelligent environments has been developed. This methodology considers data feature limits and recognition approaches and is designed to limit sensor noise during human activities. This work aims at enhancing the quality of a publicly accessible HAR dataset to facilitate data-driven HAR.Additionally, the paper proposes a novel ensemble of neural networks (NN) as a data-driven HAR classifier. A Spatial Proximity Matrix (SPM)uses ambient sensors to facilitate contextawareness and mitigate data noise. The proposed method, named Homogeneous Ensemble Neural Network and Multi-environment Sensor Data (HENN-MSD), leverages a combination of a homogeneous ensemble NN and multi-environment sensor data to identify what individuals do in daily life accurately. The study featured the generation and integration of four fundamental models using the support-function fusion approach. This method included the computation of an output decision score for each basis classifier. The analysis of a comparative experiment conducted on the CASAS dataset indicates that the proposed HENN-MSD technique exhibits superior performance compared to the state-of-the-art methods in terms of accuracy (96.57%) in HAR.

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1 Introduction

The World Report on Ageing and Health (World Health Organization, 2015) indicates that there has been a significant rise in life expectancy over the past few decades. Nevertheless, the extended lifespan frequently entails the occurrence of many ailments, necessitating continuous monitoring of symptoms to avert deterioration of the clinical condition. Examples of such diseases are neurological conditions and non-communicable diseases. Consequently, the demographic shift towards an older population leads to a rise in hospital admittance and an increased need for care resources, such as rehabilitation services. However, the viability of relying only on human-based monitoring is diminishing due to a significant decline in the ratio between the old and working-age populations.

Implementing an automated and distant monitoring system for human behaviorcan potentially address the issue of population aging (Alshamrani, M., 2022). This technology offers significant benefits, including a notable reduction in healthcare expenses and an enhancement in the standard of existence and autonomy of patients. Nevertheless, converting a monitoring system that relies on human intervention to an automated human activity identification system is complex. Identifying an action or comprehending a scenario is relatively straightforward for humans. Still, it presents significant challenges for computers due to the need for advanced approaches in data pretreatment and analysis.

Human activity recognition (HAR) is the automated identification and classification of human actions (Beddiar, D.R., 2020). This field of study, which has gained increasing attention from scholars, is driven by notable technical advancements. Over the years, several approaches have been established in the HAR field to enhance care competence and efficiency. These methods have shown significant promise in enhancing illness prevention, facilitating remote surveillance, and enabling intelligent diagnosis for the aged population.

Ambient and wearable gadgets significantly impact these methodologies (Uddin, M.Z., 2021). Nevertheless, due to the inherent constraints of environmental sensors, such as their invasive nature, high prices, and limited applicability to instrumented surroundings, scholarly investigations are increasingly focusing on utilizing wearable devices outfitted with inertial sensors. In recent times, there has been a growing fascination with smartphones. These devices are equipped with various sensors that can capture a range of attributes such as movement, location, temperature, and ECG. Moreover, smartphones have seamlessly integrated into people's daily lives, requiring no alteration in their behavior.

Additionally, smartphones have achieved widespread global adoption and can be utilized in outdoor and indoor circumstances (Sesyuk, A., 2022).In addition to the benefits mentioned above, smartphones' appeal lies in their growing computational capabilities, which render them nearly equivalent to laptops. Smartphones can collect, archive, transmit, and process substantial volumes of data within brief timeframes, all while conserving energy resources.

Initially, conventional ML methods were employed for sensor-based HAR (Garcia, F.A., 2019). The approaches that were most often employed in the study were Discriminative Analysis (DA), Naive Bayes (NB), Support Vector Machine (SVM), Hidden Markov Models (HMM), Joint Boosting (JB), AdaBoost, and k-Nearest Neighbors (k-NN) (Nafea, O., 2021). Conventional ML techniques are characterized by their relatively modest resource requirements regarding time, data, and complexity. Nevertheless, relying on specialized expertise throughout extracting features frequently results in the creation of costly models (requiring an expert's involvement) and is challenging to compare (Zhu, R., 2019).

This work aims to enhance the sophistication of ML models, specifically Ensemble Neural Networks (ENN), to achieve precise identification and categorization of human behaviors inside intelligent settings. The process entails gathering data from diverse sensors deployed across multiple environments and utilizing this information to train and enhance the ENN. The resultant system can be employed practicallyto monitor, comprehend, and address human behaviors, hence finding utility in intelligent settings.

2 Related Works

The topic of HAR inside smart environments is rapidly growing and holds significant practical implications. The primary aim of this study field is to advance intelligent systems that can effectively recognize and categorize human activities and behaviors. This is achieved by analyzing data from a range of sensors strategically placed inside smart settings. The fundamental components of this study field are utilizing ENNs and examining sensor data across several environments.

A survey of DL for sensor-based activity recognition is presented by Wang et al. (2019). Reviewing and summarizing deep learning-based studies in activity identification is the recommended methodology (Wang, J., 2019). As part of implementation, findings from diverse investigations are synthesized and categorized using DL techniques. The output values include a thorough analysis of DL techniques, their uses, and their performance in sensor-based activity identification. Benefits include comprehensively reviewing cutting-edge methodologies, which helps researchers and practitioners choose the best ones.

For activity detection in smart homes, Sukor et al. (2019) suggest a hybrid method that blends knowledge-driven and data-driven reasoning (Sukor, A.S.A., 2019). The technique entails combining data-driven ML algorithms with knowledge-based rules.The hybrid method, its usefulness in identifying activities, and insights into the interplay between knowledge-driven and data-driven reasoning are all included in the output values. The capacity to handle complicated scenarios and enhanced activity identification accuracy are positives; on the other hand, the requirement for specialist knowledge to construct knowledge-based rules and potential difficulties with rule maintenance are negatives.

Poli et al. (2020) aim to enhance dataset quality to recognize human activities (Poli, A., 2020). The suggested technique entails evaluating the datasets' suitability for activity detection and suggesting ways to improve data gathering and preparation. As part of the implementation, current datasets are subjected to data quality enhancement approaches, and their effects on the precision of activity recognition are assessed. The output values include suggestions for improving dataset quality and understanding why accurate activity detection depends on high-quality data.

An overview of data fusion methods for Internet of Things (IoT)-enabled physical activity detection and measurement is given by Qi et al. (2020). Reviewing and classifying data fusion methods used in IoT-based activity recognition systems is part of the suggested approach. Implementation involves presenting the benefits and drawbacks of various fusion techniques and summarizing research findings (Qi, J., 2020). The output values include a summary of data fusion techniques and how they may be used to recognize physical activity using IoT.

ML-based multi-sensor information fusion for practical applications in HAR is the main topic of Qiu et al.'s (2022) research. The suggested technique involves applying ML algorithms to investigate data integration from several sensors. The implementation process includes testing the effectiveness of multi-sensor fusion algorithms in situations of actual HAR (Qiu, S., 2022). The output values include knowledge of cutting-edge multi-sensor fusion techniques, their benefits, and research obstacles. While downsides may include greater system complexity and difficulties integrating data, positives include improved identification accuracy and resistance to sensor fluctuation.

ENNis suggested by Irvine et al. (2019) for sensor-based HAR in intelligent settings (Irvine, N., 2019). The technique entails building ENNs to increase the precision of activity recognition models. Training, deploying, and assessing the performance of ensemble models in intelligent settings are all parts of the implementation. The ensemble models' proven ability to improve activity identification is included in the output values. While downsides may include higher computing needs and model complexity, positives include enhanced recognition accuracy and model resilience.

Li et al. (2023) concentrate on identifying human activities using data from many sensor environments (Li, Y., 2023). The suggested approach uses sensor data from multiple surroundings to identify human activity. The implementation process includes creating flexible activity recognition models and assessing their effectiveness. The output values include adaptive HAR models and knowledge about their performance in various contexts. While downsides might include the complexity of adjusting models to multiple locations and potential difficulties in data collecting across different settings, pros include the capacity to distinguish activities in various circumstances.

In summary, the HAR using ENNs and the analysis of multi-environment sensor data within smart environments signifies an emerging area of study that has promise for significant impact across several domains of human existence. Integrating ML, sensor technology, and smart environment synergistically enables the development of systems that augment convenience, safety, and efficiency in many situations and applications.

3 Homogeneous Ensemble Neural Network and Multi-environment Sensor Data (HENN-MSD)

Identifying and understanding human behaviors inside intelligent systems is an emerging area of study with significant practical implications. This study domain's primary aim is to advance intelligent systems that can effectively discern and categorize human activities and behaviors. This is achieved by analyzing data from diverse sensors strategically placed inside smart settings (Liloja, 2023). The fundamental components of this study field are the utilization of ensemble neural networks and the examination of sensor data collected from several environments.

The architectural structure of HENN-MSDis seen in Figure 1. The procedure consists of three phases: sensor assortment, data preprocessing, and activity categorization. The collected data originates from multiple environmental sensors, encompassing natural fluctuations in the domestic environment and alterations induced by living beings.

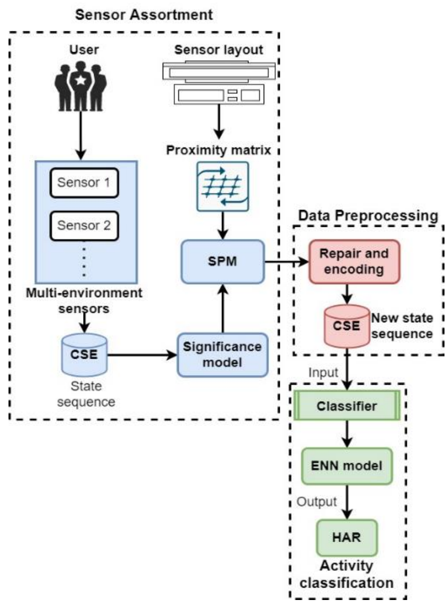

Figure 1: HENN-MSD Framework

The data preprocessing phase mitigates the influence of extraneous data in activity recognition. One crucial concern is the proficient adaptation of the new dataset to ensure its compatibility with the classification algorithm in diverse data fusions. The paper employs the Contribution Significance Evaluation (CSE) approach to evaluate the significance of different sensor data to facilitate identifying appropriate sensor types for HAR. Furthermore, anSPM is built based on the coherence features of the house layout and human activities. To generate a new feature set for classification, the state sequence of the object to be recognized is refined by removing any irrelevant data. Subsequently, the sensor data series undergoes restoration and encoding. The present study employs the binary encoding method evenly to decrease the data encoding volume. Finally, an activity recognition model based on HENN is developed.

CSE

The proper sensor data selection is crucial to obtain enough quality and prevent redundancy. Various home environment sensors are already accessible, including motion, door, temperature, power consumption, burner, item, hot water, and cold water sensors. In general, each action is correlated with distinct categories of sensors. Three primary factors contribute to the challenges associated with obtaining activity characteristics. This study examines three key factors: (1) the various types of sensors used, (2) the positioning of these sensors within a home setting, and (3) the variations in sensor state changes across persons engaged in similar activities, influenced by their unique living patterns. Hence, regarding the selection of features, we have introduced a method for analyzing the saliency of sensor categories. This method relies on the self-information quantity and universality of the fusion sensor.

The utilization of Term Frequency-Inverse Document Frequency (TF-IDF) is prevalent in the fields of information extraction and data analytics. The utilization of TF-IDF is applicable for the extraction of keywords from publications. Moreover, it is frequently employed in the industrial sector for preliminary text data cleansing. Claude Shannon, the seminal figure in the development of contemporary information theory, provided a comprehensive description of information, established a quantifiable measure for its magnitude, and introduced the fundamental idea of entropy within the framework of information theory. Motivated by the approaches mentioned above, we have introduced the CSE methodology for quantifying the influence of a certain sensor type on the detection of a particular behavior.

Consequently, we have successfully identified the sensor category that significantly affects the recognition of activities. The CSE relies on frequency measurement to gather sensor feature data for activity detection. The process of data reduction is facilitated by the exclusion of data that does not undergo any alteration in its original value, hence enhancing the identification of more unique data points.

SPM

This section comprehensively explains the methodology employed to construct the SPM for context awareness. The approach involves strategically positioning environment sensors to effectively capture contextual information while mitigating the adverse effects of Multi-person Cross Actions (MCA) on data noise. In the field of HAR, three common scenarios often result in a misinterpretation of sensor data:

1) System error is a type of error that is not random and is induced by the measuring technique.2) Unintentional mistakes arise due to several factors, such as data exclusions and storing errors, which can be attributed to researchers' lack of concentration during data calibration or statistical procedures.3) Error in behavioral perplexity.

In the experiment, a public dataset has been used, which unfortunately does not allow for eliminatingerrors 1 and 2. In the third scenario, the implementation of environmental sensors enables range-wide monitoring. Consequently, it becomes unfeasible to directly ascertain the specific trigger reason alone based on the sensor sequence. For instance, the sensors activated by an individual engaged in culinary activities within the kitchen are often situated close to such kitchen area. Nevertheless, if the state value of the bedroom sensor undergoes a nearly simultaneous alteration, the presence of a pet or another individual has probably instigated this alteration. The initiation of sensor state changes by the same individual is not feasible due to their lack of alignment with the progressive temporal and spatial variations in human activities. As a result, it was determined that the subject's disorganized data should be restricted.

The distance matrix is a two-dimensional square matrix with extensive application in mathematics, computer science, and graph theory. The determination of the distance component inside the distance matrix is contingent upon the range of the sensor's monitoring capabilities. The distance matrix, specifically the diagonal array, is employed to quantify the distance between environmental sensors inside a residential setting. Considering this, the sensor data-context perceptual proximity matrix is constructed.

Based on the temporal characteristics of the trigger reaction, sensors may be categorized into two groups: real-time sensors and delay sensors. The real-time sensor provides an immediate and direct indication of the trigger's location. Hence, the distance is determined by directly measuring the physical separation of the real-time sensor. On the other hand, the time-delay sensor has a substantial detection range and cannot directly ascertain the precise location of the triggering item. However, it does possess the capability to indicate alterations in the user's state of being indirect. As an illustration, the act of cooking has the potential to induce a gradual alteration in the ambient temperature within an enclosed space. Following this regulation, we have developed a matrix that imposes proximity constraints.

The proximity matrix $P(P\epsilon R^{n*n})$, representing the distances between sensors in a house. The distance element$P(s_i, s_j)$is computed using Equation (1).n is the number of sensors.

The proximity function $P(s_i, s_j)$is defined as follows:

$$P(s_i, s_j) = \begin{cases} |s_i, s_j|_{spatial,} s_i, s_j \in \text{ Straight Detection} \\ 1, otherwise \end{cases} \quad (1)$$

where $|s_i, s_j|_{spatial,}$represents the spatial distance between two instant sensors. The calculation technique for $|s_i, s_j|_{spatial,}$ is based on the minimal number of instant sensors that need to be traversed to link $s_i, and\ s_j$, which is known as the Manhattan distance. In light of the hysteresis phenomenon seen in the delay sensor's state transition, the relevant distance is 1. The delayed sensor examines data considered non-noise data and has a substantial contribution.

HENN Model

In recent times, there has been a growing interest in the investigation of ensemble techniques for classification. This interest stems from recognizing their potential to enhance resilience, performance, and generalization capacities compared to approaches that rely on a single model. The proposed methodology involves the utilization of four Multi-Layer Perceptrons (MLPs) as foundational classifiers to construct a uniform ensemble technique. A model is developed for each time routine, namely Morning, Afternoon, and Evening, due to certain activities exclusively associated with distinct routines. Moreover, a mixed model is formulated to account for events that transpire randomly throughout the day. Fig. 2 displays four base classifiers, with the variable "n" representing the number of classes in each model. MG, AN, and EG represent the Morning, Afternoon, and Evening models. MI represents the Mixed model.

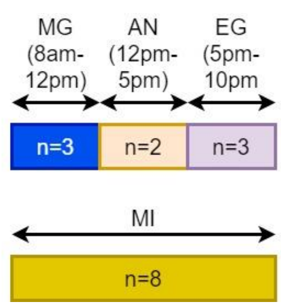

Figure 2: Four Fundamental Classifiers for Time Instances

Fig. 3 illustrates the structure of the homogeneous ensemble technique that has been developed, highlighting the comparison of conflict resolution options. The input feature vector for each base model comprises data generated by 5 binary sensors (Movement Sensor (MS), Door Sensor (DS), Heat Sensor (HS), Item sensor (IS), Temperature Sensor (TS)) and an extra time routine feature, resulting in a combined total of 11actions (0-other, 1-hygiene, 2-medication, 3-sleep, 4-work, 5-leave house, 6-relaxation, 7-entering home, 8-cooking, 9-Eating, 10-Bath). The output forecasts of every foundational model are generated based on the estimated probability of each class. These predictions are then integrated using the support function fusion method during the ensemble inclusion phase. As a result of the absence of overlapping classes in each model, it is necessary to train each model with a complement class. This complement class should include meaningful activity samples from each primary class in the other models.

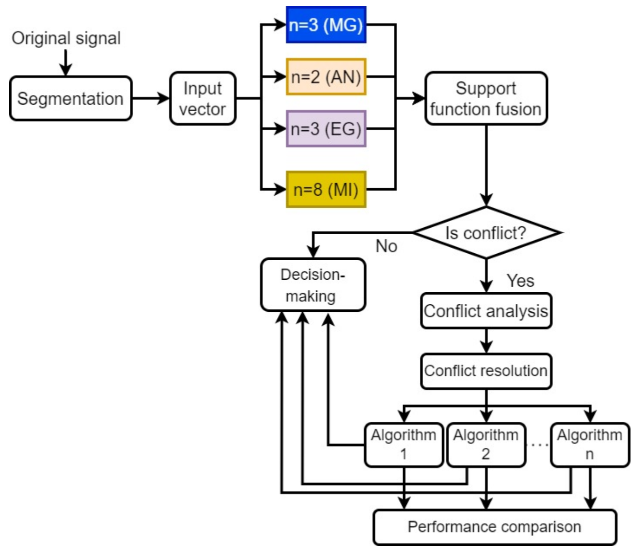

Figure 3: Framework of HENN

The objective of this study is to enable each model to accurately determine whether new instances of activity belong to that particular model. Consequently, when a model encounters an unfamiliar input of an activity class present in its counterpart, it should correctly identify that the activity does not serve as a primary class in the model. As a result, the model should exclude itself from the decision-making process. For instance, when the morning model is confronted with an activity instance that is encapsulated within the C1 class (with MS, DS, HS, and TS),it ought to acknowledge that 'Action 4' is a member of the complement class and, as a result, should refrain from including itself in the deliberation procedure.

4 Results and Discussion

The dataset utilized in this experiment is the CASAS dataset (Cook, D.J., 2012), which the University of Washington gathered. It consists of data obtained via the implantation of environmental sensors in the residences of individuals with varying lifestyles. It candepict individuals' authentic daily activity data accurately. The composition of households varies in terms of the number of family members and the arrangement of living spaces.Table 1 displays the dataset's name, family member composition, duration of statistical data, MSD count, data items, presence of visitors, and categories of activities.

Table 1: Dataset Description

Name of dataset	Family Members	Observed days	Size of the data	Number of actions
Cairo	Adult couple	58	725535	12
Milan	Woman and dog	73	434675	14
Kyoto 7	Two residents	45	138798	13
Kyoto 11	Three residents	231	2810814	24

Every dataset is linked to a particular home or environment, and the table provides essential information such as the count of family members, the time of data collection (in days), the size of the dataset (measured in data points), and the number of individual acts documented. The dataset known as "Cairo" is of particular significance as it encompasses 58 days during which an adult couple was observed. This dataset is notable for its extensive size, consisting of 725,535 data points, effectively capturing 12 distinct acts. On the other hand, the dataset known as "Milan" encompasses a female subject and a canine companion, spanning 73 days. This dataset has 434,675 data points, each linked to one of 14 unique activities. The dataset known as "Kyoto 7" captures two individuals' behavioral patterns over 45 days. It has a total of 138,798 data points, encompassing 13 distinct behaviors. The dataset known as "Kyoto 11" consists of three inhabitants and provides a thorough collection of data spanning 231 days. This dataset has 2,810,814 data points, encompassing 24 distinct activities. The dataset descriptions play a crucial role in enabling researchers to comprehend the extent and attributes of the data they are analyzing and in aiding them in selecting suitable datasets for their particular studies on HAR.

Table 2: Contribution Significance Evaluation (CSE)of Multi-environment Sensorsand Corresponding Actions

Data type		**Actions**										
Name of dataset	**Sensor type**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Cairo	**TS**	0.98	0	1	1	0.81	0.1	0	0	0	1	0
	MS	0.65	0	0.99	0.61	0.81	1	0	0	0	0.33	0
Milan	**TS**	0.54	0	0	1	0.73	0.05	1	0	0.48	0.42	0.23
	MS	0.91	0	0.6	0.51	1	0.83	0.51	0	1	1	1
	DS	0	0	1	0	0	1	0	0	0.3	0.04	0
Kyoto 7	**HS**	0	0.02	0	0	0.01	0	0.37	0	1	0	0
	MS	1	0	0	1	1	0	1	0	0.69	0	0
	DS	0	0	0	0	0	0	0.05	0	0.27	0	0
	IS	0	0	0	0	0	0	0.16	0	0	0	0
Kyoto 11	**TS**	0.13	0	0	0.06	0.15	0	0	0	0	0	0.02
	MS	0.65	0.68	0	0.9	0.47	0.69	0.59	0.7	0.54	0.65	1
	DS	0.02	0.06	0	0.01	0.06	1	0	1	0.02	0	0

Table 2 represents multi-environment sensors' Contribution Significance Evaluation (CSE) and corresponding actions.The numbers presented in the table denote the scores of contribution importance, wherein higher values signify a more pronounced impact of a certain sensor type in detecting a particular activity.The Cairo dataset shows that the TS exhibits a significant contribution significance score of 0.98 for Action 0. This finding suggests that the TS sensor type plays a large role in recognizing Action 0 within the context. In contrast, the contribution scores for Action 1 in the Cairo dataset indicate that the MS and DS have substantial values of 0.99 and 0.61, respectively.The MS demonstrates notable CSE scores for various activities in the Milan dataset. For instance, Action 0 has a score of 0.91, whereas Action 4 has a value of 1. In the Kyoto 7 dataset, the HS has a strong statistical significance concerning Action 8, as shown by a score of 1.

Conversely, in the Kyoto 11 dataset, the MS assumes a prominent function in identifying several actions.The significance scores of these contributions play a crucial role in comprehending the informative nature of different sensor types in recognizing particular activities within each dataset. This aids researchers in making informed decisions about sensor selection and designing efficient human activity identification systems in smart settings.

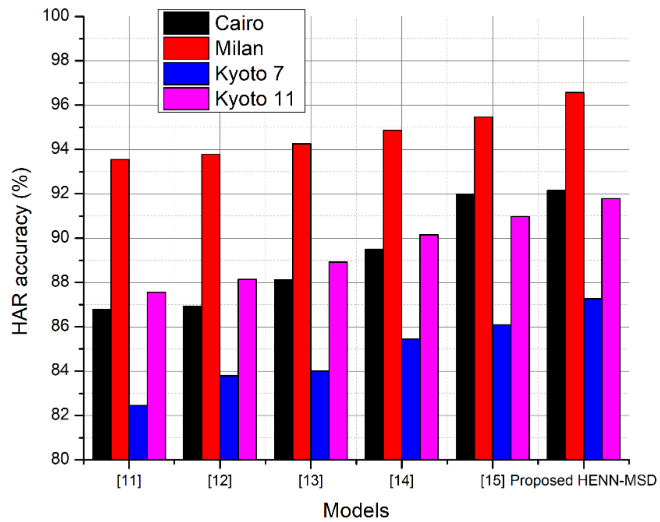

Figure 4: HAR Accuracy of Various Models for Different Datasets

Fig. 4 shows the HAR accuracy of various models for different datasets. The table presents data on the efficacy of different models in accurately detecting and categorizing human actions in smart environments.It is worth mentioning that the accuracy values exhibit a consistent upward trend across all datasets as we advance from reference models (Poli, A., 2020) (Qi, J., 2020) (Qiu, S., 2022) (Irvine, N., 2019) (Li, Y., 2023). This trend suggests a notable enhancement in HAR performance with each subsequent model. Nevertheless, the HENN-MSD model demonstrates exceptional performance in terms of accuracy scores across all datasets, hence highlighting its supremacy in HAR. The HENN-MSD model has a notable accuracy rate of 92.15% in the Cairo dataset.

Similarly, this model gets an impressive accuracy rate of 96.57% in the Milan dataset. Likewise, the HENN-MSD model demonstrates accuracy ratings of 87.26% and 91.78% in the Kyoto 7 and Kyoto 11 datasets, respectively. The findings of this study indicate that the suggested model exhibits exceptional performance in improving the precision of human activity identification across various smart settings. The results highlight the potential of the HENN-MSD for practical implementation and deployment.

5 Conclusion

The primary purpose of this study is to improve the overall quality of a publicly available Human Activity Recognition (HAR) dataset. The ultimate goal is to make this dataset more suitable for data-driven HAR applications. Furthermore, the research study presents an innovative combination of NN to serve as a data-centric classifier for HAR. Constructing a Spatial Proximity Matrix (SPM) involves positioning ambient sensors to enhance contextawareness and reduce the impact of data noise. The approach developed in this study, called HENN-MSD, utilizes a fusion of a homogeneous ensemble neural network and multi-environment sensor data to discern people's everyday activities with high precision effectively. The research conducted in this study focused on developing and incorporating four essential models through the use of the support-function fusion technique. The approach involved calculating an output decision score for each basis classifier. The results obtained from a comparison experiment on the CASAS dataset suggest that the HENN-MSD strategy outperforms existing methods in the field of HAR in terms of accuracy, achieving a rate of 96.57%.

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