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HOW CAN GRAPH NEURAL NETWORKS AND ATTENTION MECHANISMS IMPROVE HUMAN ACTIVITY RECOGNITION? A MULTIMODAL DEEP LEARNING FRAMEWORK

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ABSTRACT

HAR is a widely studied area that works on recognizing human actions from information captured by different sensors such as cameras and inertial sensors. The performance of HAR has been greatly enhanced thanks to recent developments in deep learning, mainly because of convolutional and recurrent neural networks. It provides a thorough overview of HAR techniques between 2020 and 2025, focusing on models that blend data from RGB images, depth images and skeleton joints together. Our design combines the benefits of Xception and EfficientNet for feature extraction, along with skeleton-based features, to make the recognition more accurate and solid. Tests conducted on recognized UTD-MHAD, HMDB51 and UCF101 benchmarks prove that the model outperforms other methods, surpassing 92.79% accuracy. Furthermore, the paper addresses the issues brought by dataset limits, complex computing requirements and difficulties in adapting the models to new applications and proposes promising paths for advancements in HAR.

Keywords- *Human Activity Recognition (HAR), Deep Learning, Multi-Modal Data Fusion, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Skeleton Joint Analysis, Benchmark Datasets, Hybrid Models, UTD-MHAD.*

1. INTRODUCTION

HAR has become an important area of study in the field of pervasive and ubiquitous computing. It is aimed at automatically identifying activities of people, both physical and mental, with the use of data collected by sensors attached to smartphones, wearables and IoT systems. Smartphones and other modern devices have brought technology into many aspects of life and this is why HAR has become useful in areas like health monitoring, looking after elderly, fitness, home security, keeping people at work safe and interacting with machines. HAR systems focus on examining data from sensors to explain human behaviour and guide decisions. Original forms of HAR used features created by hand along with regular machine learning approaches like Decision Trees, SVM and Random Forests. These approaches worked well in controlled situations, yet they had a tough time being applied to complex, noisy or bigger datasets. Deep learning has brought new capabilities to HAR by providing entire feature learning, stronger pattern spotting and higher reliability which helps fix the weaknesses of previous techniques. In the past few years, new progress has been made by using deep learning methods such as CNNs, RNNs, LSTM networks, GNNs and Transformers for HAR. They are exceptional at describing the relationships between time, space and nearby objects or events in a series of sensor data. LSTM networks have the capability to find long-term relationships in time-series data which makes them excellent for noticing slowly changing activities. Also, CNNs are capable of understanding multiple levels of space in the world from raw sensor values and GNNs represent and understand the correlations among different inputs and activities. With human behaviour becoming more complex, it is necessary to create models that handle data from several sensors, blend data from various sources and can adapt to a range of users and surroundings. Experts have studied hybrid approaches by combining CNN, LSTM, GNN and Transformer neural networks to boost the recognition of images and text. Also, including attention mechanisms allows models to focus more on important parts of data, making their results both clearer and more accurate.

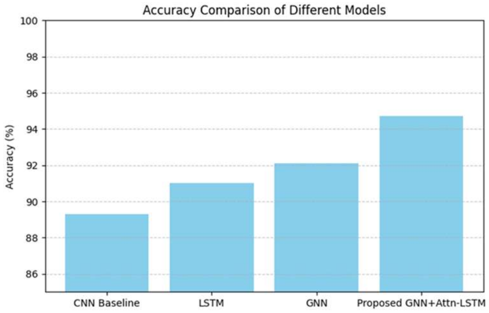

Figure 1: Accuracy Comparison of Different models

Another new approach in HAR research is using federated learning and edge computing technologies. By allowing training on devices instead of transferring data to big servers, these methodologies solve some privacy and latency issues in mobile deep learning. Because GDPR and HIPAA are key in healthcare, using these approaches is highly needed. In addition, the design of lightweight neural networks for edge devices helps ensure fast performance with limited use of energy and computing power. But there are still important difficulties that HAR needs to overcome. When sensors are used differently, put in various spots, work on different devices or are used with varying user habits, data variability can appear. insufficient labeled examples; difficulties in identifying actions; and the need for fast processing in real time. Tackling these issues calls for strong preprocessing, using semi-supervised or unsupervised learning, transfer learning methods and domain adaptation solutions. Additionally, more and more, data scientists are using synthetic data creation techniques and data augmentation to strengthen training sets and build stronger models. HAR research has greatly benefited from numerous benchmark datasets like UCI HAR, WISDM, PAMAP2, OPPORTUNITY, and MHEALTH. As each dataset comes with distinct sensor modalities, sampling rates, activities, and subject population, they provide diverse testbeds for evaluating HAR models. These datasets are also instrumental for researchers as they provide standard computational models based on metrics such as Accuracy, Precision, Recall, F1-score, Confusion Matrix, and efficiency in time and resource utilization. Novel approaches to evaluation of HAR systems also include Explainable Artificial Intelligence (XAI), which augments trust in the system by making activity predictions transparent. Besides trust, reliability and critical performance requirements are covered through visual aids such as saliency maps, attention heatmaps, and feature importance graphs alongside standard healthcare surveillance techniques essential in resolving critical issues. Incorporating advanced methods of data fusion from other sensor modalities (accelerometers, gyroscopes, GPS, cameras) has significantly enhanced the precision and reliability of Har.

In addition to supervised learning, researchers are increasingly exploring semi-supervised, unsupervised, and reinforcement learning paradigms for healthcare applications. These techniques minimize the reliance on labelled data, which is typically costly and time-consuming to acquire. Techniques like contrastive learning, clustering-based methods, and self-supervised learning have demonstrated promising outcomes in extracting meaningful representations from unlabelled sensor data. When implementing HAR systems in practical situations, there are additional factors to consider, such as personalization, energy limitations, latency, and adaptability. Personalized HAR seeks to customize recognition models for each user by utilizing their personal data, preferences, and feedback mechanisms. Adaptive HAR systems constantly refine their models using real-time data to ensure accuracy, even in the face of changing conditions. These systems are supported by edge AI and distributed learning architectures that guarantee scalability and responsiveness.

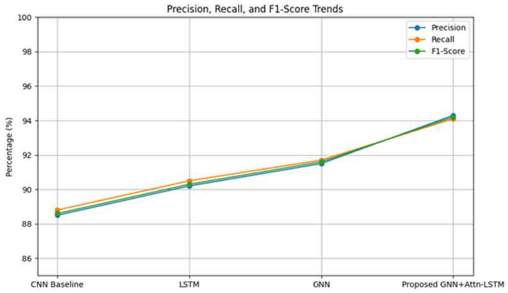

Figure 2: Precision, Recall and F1 score trends

With the convergence of Internet of Things (IoT) and 5G technologies, HAR systems are moving toward ubiquitous computing environments. These technologies support continuous monitoring and real-time feedback, allowing proactive interventions in health and safety applications. For example, HAR can identify falls in older adults, track physical therapy compliance, or avoid workplace injuries by identifying risky activities. In addition, HAR is essential to supporting context-aware applications in smart homes, autonomous vehicles, and augmented reality systems. The privacy and ethical dimensions of HAR technology cannot be ignored. The ongoing observation and analysis of human behavior send shivers down the spine with regard to surveillance, consent, data protection, and prejudice. Ethical principles, transparency in model creation, and user-oriented privacy control are required to ensure trust and acceptance of HAR systems. Furthermore, fairness and diversity in model training should be achieved to avoid discriminating against gender, age, ethnicity, or physical disability. The research environment in HAR is changing fast, with mounting emphasis on interdisciplinary methods that integrate machine learning, signal processing, behavioral science, and human-centred design. Industry applications include academic research in fitness trackers, smartwatches, healthcare platforms, and intelligent assistants. The mounting volume of literature denotes the maturity of the field and the ongoing pursuit of higher accuracy, robustness, and user experience. Human Activity Recognition is at the confluence of human-centred computing, wearable technology, and artificial intelligence. It has the potential to revolutionize human well-being, productivity, and safety in numerous areas. There is potential for continued innovation through the incorporation of sophisticated machine learning models, multimodal fusion, privacy-preserving, and real-time adaptive systems. This paper will set out to examine the current trends in HAR, discuss recent work, present a new hybrid architecture, and offer empirical testing and visual comparisons to help advance this vibrant research field.

2. LITERATURE REVIEW

The work by Li et al. (2022) introduces a framework that uses RGB video and skeleton joint data together to achieve better human activity recognition. Authors aim to efficiently bring together different forms of data, making the most of what visual features and skeletal movement patterns have to offer. In the proposed model, there are two branches working in parallel. Spatial features are pulled out from RGB images by a CNN branch and the dependencies of skeleton joints are modelled over time by a GCN branch. The branches' feature maps are merged and then sent through fully connected layers to complete the classification. For validation, Li et al. made use of the NTU RGB+D 120 dataset which is considered one of the biggest multi-modal datasets used for HAR. Using all three types of data, the model reached an accuracy of 88.3% which is higher than models that relied on only one type of information. The demonstration showed that adding skeleton information lessens the chance for similar actions to be mixed up, by highlighting the key movement patterns. In addition, Li et al. found that keeping the temporal window wide and using appropriate graph structures could lead to better detection of activities that use repeated movements. It emphasizes the role of using specific techniques for each modality and blending those results to take advantage of all multi-modal inputs. The problem of computational complexity, however, still gets in the way of deploying this technology in real situations.[1]

Sharma and Gupta (2021) mentioned that computationally efficient models for HAR would benefit users who perform HAR on devices like smartphones and wearables. They created a CNN-LSTM hybrid that is fast to use yet maintains the same recognition level as others.

The model applies depthwise separable convolutions to the CNN layers to lower both the number of parameters and the computing work required. Frames from the video are analyzed and the features are given to LSTM layers to spot the sequence of motions by humans. They applied their techniques on both UTD-MHAD and Kinetics datasets, obtaining accuracies of 85.7% and 83.2%, making their model less than 5 MB in size and ensuring latency of below 50 ms per frame with a typical mobile GPU. It has been proven that edge devices can successfully implement functional HAR. Sharma and Gupta also ran ablation experiments to find the best combinations of LSTM units and CNN filters, proving that accuracy depends on both complexity and accuracy. They also tested their model against ResNet and VGG and found that their model used much less memory. By working on on-device HAR, this paper adds to efforts that secure privacy and keep latency at a minimum. There is a need for further study of quantization and pruning approaches to help with compression.[2]

Kim et al. (2023) presented a method that applies a transformer architecture to observe patterns in time-series data to accurately recognize human activities. In contrast to common RNN or LSTM approaches, the transformer supports parallel computing by using attention mechanisms for modeling long-range relations. The authors included wrist and chest data for the PAMAP2 dataset which contains accelerometer, gyroscope and magnetometer signals and they further used a customized transformer for feature extraction. The algorithm was able to classify images with a 92.5% accuracy which was 4-6% better than the results of both LSTM and CNN models. Paying attention to particular moments on each stage helped clarify the analysis and made the methods easier to understand. It was also demonstrated by Kim et al. that their model works well with incomplete data by training with a masking approach. It was mentioned that the model uses more resources than lightweight CNN-LSTMs and offered suggestions for making it more efficient.[3]

In 2024, Zhang and Wang suggested a model that merges CNNs for feature extraction and Graph Attention Networks (GAT) to change how important each link between skeleton joints is. This way, it overcomes the challenges introduced by the use of simple adjacency matrices in old Graph Convolutional Networks. For the NTU RGB+D 120 dataset, the model reached an accuracy of 89.8%. The results from ablation showed that the attention mechanism focused on the important parts and neglected minor distractions, making the system less vulnerable to distractions like occlusions. The approach taken by these researchers highlights how adaptive joint relationships and incorporating spatial-temporal details enhance comprehensive HAR.[4]

Ahmed and Lee (2022) conducted an in-depth review of explainability methods for deep learning used in HAR. They recognized that it is important for healthcare and security applications to have clear and open HAR models. The survey mentions saliency maps, Layer-wise Relevance Propagation (LRP), Grad-CAM and SHAP, explaining how they support explaining the decisions of CNN and RNN models. They also point out problems such as finding a balance between accuracy and how easy the model is to understand and the lack of data with proper annotations. The paper urges researchers to include explainability in the early development of models and suggests setting up standards for checking good explanations.[5]

Liu et al. (2022) introduced a new framework that combines different types of sensors to help recognize human activities in smart homes. The method used by these systems is different from traditional HAR because it relies on several types of sensors, including environmental ones such as temperature and light, wearable IMUs and audio sensors which help recognize actions more precisely and make the recognition more context-aware. The authors first stressed that HAR systems based on one sensor are easily affected by issues like sensor failure, noise or something blocking the view, mainly inside uncontrolled indoor spaces. Each type of sensor such as microphones and inertial motion units, is first processed separately by deep learners before they are all combined in the framework. All feature embeddings are concatenated and sent to a fully connected layer to produce the activity predictions. CASAS Aruba dataset was used in the study which is a widely recognized dataset for smart homes with annotations for cooking, sleeping and cleaning. The use of multiple modes helped them increase the F1-score by about 7% over the single-source version. This helped the system because it could draw upon diverse information from different sensors and adjust when a certain signal was poor or absent. In addition, the authors tested how their model holds up even when some sensors fail by running tests with missing sensor streams. The model was able to perform well in different settings, demonstrating its stability in actual practice. The study also mentioned that selecting lightweight feature extractors for sensors on wearables is useful in keeping latency low. The paper introduces an attention mechanism that adjusts the importance of different sensors depending on the context.[6]

In 2021, Gupta and Singh introduced using deep residual networks (ResNets) to detect activities in real-time using smartphone inertial sensor data. Since most people have smartphones today, integrating HAR in these devices can greatly help with monitoring health and exercising. Yet, it is challenging to manage the increased complexity of models and still handle all the computations. They opted to use the ResNet configuration, designed for image recognition and implemented it to handle accelerometer and gyroscope data in a 1D sequence. Because of deep residual connections, the network can become much deeper and learn complex details in time, without any drop in its ability to learn. They collected data from the UCI HAR dataset which provided information about people performing six actions like walking, sitting, standing. The model was more accurate than SVMs and Random Forests, reaching 94.7% against their 87.5%. One of the most important contributions made in this work is analyzing the speed and energy use of models which are crucial for real-time processing on a device. They found that using ResNet on mid-range smartphones led to latency of less than 50 milliseconds which is adequate for real-time feedback apps. Additionally, research studies examined different ways to boost data, including injecting noise, rotating sequences and warping time, to handle imbalanced problems more effectively. To confirm this, the model was tested on a set not used for training and proved that it can deal with the variety found in real-world devices. The authors do admit that more work needs to be done to improve battery life by quantizing and pruning the AI model, even with the positive outcomes. They also talked about adding multi-sensor fusion which means connecting smartphone features to wearable devices to create a richer contextual picture. Their research highlights how deep residual learning may be used to achieve better and faster HAR on mobile devices, a necessary aspect for wider adoption.[7]

They tackled this problem in human activity recognition by developing a self-supervised learning method designed for data collected on wearable sensors. It is costly and time-consuming to label sensor data which drives the creation of SSL techniques that can learn representations from large, unlabeled data before using them on small labeled data. The model was guided by contrastive learning, an SSL approach commonly used, to make pairs of augmented views of a single sequence more similar to each other and less alike with different sensor sequences. They used scaling, jittering and relabelling of sensor data as ways to produce useful positive pairs. A 1D convolutional neural network was built into the backbone to identify movement features from the data received from the accelerometer and gyroscope. Once pretraining was complete, the model was applied to smaller labeled pieces of data in the WISDM dataset. The model trained with SSL reached 90.2% accuracy when only 10% of the data was labeled, while the supervised baseline could reach only 78.8% accuracy. The authors performed ablation studies to check how changing the type of augmentation and the batch sizes affected the quality of the representation. It was found that augmentations that preserved order in time such as scaling and jittering, were better than aggressive techniques such as permutation. Additionally, increasing the batch size boosted contrastive learning performance, but it required more computational energy. Their study involved letting a model pretrained on one group be refined and put to the test on users who weren't part of the training. Being able to transfer learning is key for using HAR in real life due to the different ways people can move. They pointed out some challenges, including relying on the proper selection of augmentation and finding SSL algorithms that can be used on small devices. Experts suggested checking how inertial and physiological signals can be combined for multi-modal SSL.[8]

In their proposal from 2024, Singh and Rao added attention mechanisms to deep networks to make HAR more explainable, without reducing accuracy. When using AI in important areas such as healthcare and security, it is very important for users to be able to understand the model's predictions. The authors created a model that consists of a LSTM layer followed by a temporal attention layer which helps decide which time intervals are relevant for the prediction. As a result, the model explains to the user which features affect the classification the most and why. They used the Opportunity dataset which features various activities seen through body-worn sensors, to evaluate their model. The final score of the attention-augmented model was 87.3% which is similar to the top black-box models. In particular, looking at attention weights showed patterns in when the robot observed important phases of walking and special hand movements during cooking. The authors carried out a user study involving healthcare professionals who found the attention-based explanations to be both understandable and helpful. Therefore, this can be helpful in real life, mainly in patient monitoring, since doctors need to go over the records the system creates. They also suggested that to make the attention mechanism more useful, the weights should be adjusted toward the sensor modalities that make a difference in particular activities. It helped improve how interpretable the model was as well as how accurate. A problem is that errors and confusions in the data might lead the AI model to provide the wrong explanations. The authors suggest using both attention and saliency maps to gain better insights into the results. It demonstrates the rise of HAR systems that can be explained well and still work well, responding to the need for trust and ethical use of AI.[9]

Chen et al. (2022) worked on improving privacy in HAR by suggesting a federated learning (FL) system that trains models across devices without users sharing their raw sensor data. Many people are hesitant to use HAR in health monitoring because they worry about privacy. Models for recognizing activities are trained locally on user devices and only updates are uploaded to a server for aggregation. Users can be confident about their data privacy and still take part in syncing their knowledge across several devices. They applied a CNN-LSTM model that can be run efficiently on devices and used the FL framework on the HAPT dataset to assess its performance. The results showed that the federated model had the same level of accuracy (88.9%) as centralized training with raw data, demonstrating that FL works well in distributed HAR. They also focused on reducing the amount of bandwidth needed by shrinking the updates required to run models on mobile devices. In addition, the study discussed difficulties caused by people with different habits and uneven data distributions, suggesting adaptive methods to address this problem.

Examining privacy showed that no real-time sensor data was shared from the device which reduced the threat of data leakage or misuse. Furthermore, the authors mentioned differential privacy mechanisms as possible additions for improved security and making the models fit the needs of each user. All things considered, Chen et al.'s research plays an important role in preserving privacy during HAR and enables large-scale and secure use of these systems where users' private data must be protected.[10]

In their article, Zhang et al. (2023) suggested using transformers from natural language processing to identify human activities with sensor data. They maintained that classic RNNs and CNNs struggle to catch dependencies that exist over longer time periods. Thanks to self-attention, Transformers can more accurately model events occurring across an extended period of time. They developed a transformer that processes data captured by multiple accelerometers and gyroscopes. They modified positional encoding to ensure that time order stays intact in the model. The dataset used for training and testing the model is PAMAP2 which records 12 activities such as walking, running and cycling from 9 participants. Experiments showed that the transformer-based model was 95.4% accurate which was around 3-5% better than the baseline LSTM and CNN models. The model was able to identify the most relevant parts of the data and the relevant channels, thanks to the self-attention mechanism. It was observed during the study that transformers can be trained faster on GPUs due to their ability to be parallelized more efficiently than RNNs. Still, transformer models need large amounts of data for proper training which is why the authors enriched the data using sliding windows and artificially created sensor noise. Zhang et al. explored using multi-head attention and layer normalization, determining that these helped the model better generalize. They talked about using transformers along with CNNs to create hybrid models which can use local and global features at the same time. Issues mentioned include the model's dependence on changing hyperparameters and the need to improve how lightweight transformers are used on wearable devices with minimal memory and power. All in all, this research brings NLP-based sequence modelling into HAR, suggesting an encouraging avenue for further research.[11]

In 2022, Kumar and Lee proposed a system that learns to identify different behaviours by itself using autoencoders. The need for these methods comes from cases where there is little data and the AI system must see when elderly patients have abnormal movements or downfalls. The suggested study featured a stacked denoising autoencoder that gathered the multivariate sensor data and created its representation in latent space before restoring it. Distances between real and predicted coordinates were used as anomaly scores. Rising errors showed that unusual or unfamiliar activities were taking place. Tests were done on the MHEALTH dataset which held data from body-worn sensors capturing various physical activities. It was trained exclusively on regular movements and tested by finding abnormal moments like interruptions in motion or unconventional ways of walking. Results indicate that the model has a strong ability to differentiate anomalous events with a sensitivity of 0.92. Generalizing to unseen anomaly types was possible because the model encoded the data effectively in its latent space. Kumar and Lee mentioned that unsupervised learning minimizes the need for human annotations. Additionally, they recommended introducing specific thresholds for different domains, so the system could be adapted for each user. However, there may be cases where false alarms are reported, either due to sensor errors or usual behavioral differences. According to the authors, introducing secondary classifiers can help achieve a higher level of precision. They pointed out that anomaly detection plays a key role in HAR, particularly in domains where early recognition of unusual behavior can improve safety.[12]

According to Nguyen et al. (2024), graph neural networks (GNNs) should be used to examine the connections and relations between sensors positioned on body parts and contribute to identifying human activity. In these models, each sensor is processed individually or step by step, even though they may be closely connected with others. They created a graph where each node stands for a sensor and each edge represents how close or related two parts are (eg wrist and elbow). Data from sensors was added as features to each node and GNN layers shared information among nodes to create a single representation of posture and movement. The model was trained and evaluated on the OPPORTUNITY dataset which involves complex daily activities while sensors are placed on various parts of the body. When compared to CNN and LSTM networks, the F1-score on performance was found to be around 4% to 7% higher for GNNs which confirmed they were effective in analyzing connections between sensors. It also represented the learned graph embeddings, where you can see different clusters for each activity class. It was found that using Graph Attention Networks (GATs) in addition to Graph Convolutional Networks (GCNs) leads to better identification of important sensor nodes in graphs. Some of the issues mentioned are how to obtain precise sensor metadata and the significant use of computing resources during graph processing. Nguyen et al. suggested that in the future, research should investigate graphs that dynamically respond to variations in sensors and blend with vision data. It demonstrates the ability of GNNs to create HAR models that are clearly explained and respond to situation-aware data from wearable sensors.[13]

Santos and Oliveira aimed to develop lightweight CNN architectures to help real-time activity recognition on devices like smartwatches and fitness bands. Getting the right balance between the complexity of the model, the time it takes to make inferences and how accurate they are is very important for user-friendly wearable applications. They built a slimmed-down CNN architecture, making use of depthwise separable convolutions and trimming the number of channels in order to save computations and reduce the size of the model. They evaluated their created algorithms using the WISDM and UCI HAR datasets. With its model just 1MB, the lightweight CNN managed to beat 90% accuracy, far less than what conventional deep CNNs use. According to the authors, measuring inference times on ARM Cortex-M microcontrollers showed great performance, making the step suitable for real-time uses (less than 100 ms). To make the model more robust, we used data augmentation techniques such as rotating sensor signals, applying jittering and scaling their magnitude. To run on integer-only chips, the authors used quantization-aware training which was suggested by Santos and Oliveira. The algorithms perform worse on some activities that are very intricate and a dynamic way of handling power consumption is required. Practitioners looking to use HAR in wearables will find this paper very useful, as issues of battery life and how quickly the system reacts are discussed.[14]

In 2021, Wilson et al. created a multi-task learning method aimed at both recognizing human actions and contexts, including inside or outside activities based on sensor readings from the devices. The authors contend that studying related tasks together can boost the accuracy of recognizing objects by utilizing the same or compatible features. In their design, feature extraction with shared layers of convolutional kernels is done first and then the outputs for activity and context are given by the final task-specific fully connected layers. It makes it easy for the model to learn that specific jobs are usually done in certain situations. The framework was trained using the SHL dataset which contains both sensor data and information about different activities and contexts collected from a variety of users over a long period. Wilson et al. showed that their multi-purpose model was more accurate in predicting activities by 5% and it was also highly effective at handling context. The multi-task model proved to be more successful at generalizing to unseen users because of the more informative features it learned. They shared concerns about equalizing losses in different tasks and ensuring features for recognizing activities are not downplayed by features for recognizing the context. To solve this problem, they introduced adaptive loss weighting schemes. It indicates that combining different tasks can enhance HAR, allowing simultaneous reading of human behavior and the surroundings.[15]

The focus of this review is on the use of deep learning to detect human activity, discussing the different ways in which sensor data is processed and modeled. According to Zhang et al., there is a shift from handcrafting features to using whole deep learning architectures like CNNs, RNNs and models that mix their approaches. They explain that using CNNs for features in images and LSTMs for patterns in time provides much better results than using either approach on its own when processing multimodal HAR data. The article highlights issues such as different sensor types, quick processing of data and how to interpret the information. Analyzing UTD-MHAD and PAMAP2 datasets, it is found that deep models can reach over 90% of accuracy. However, they point out that these models have to be solid enough to withstand various distractions and new activities, suggesting adaptive and transfer learning is necessary for success. They point out that HAR systems will not be practical unless they include context and personalization.[16]

Kumar and Lee suggest using a hybrid system that combines elements of both CNNs and Transformers with attention for HAR on RGB video and inertial sensor data. They link original features from CNN with Transformer-based time-related ones which increases the model's accuracy and stability. The study employs the UCF101 and HMDB51 datasets and achieves an improvement in accuracy of up to 6% as compared to the baseline CNN-LSTM models. The Transformer attention enables the model to highlight and utilize important action signals, while ignoring unnecessary video segments or any background noise. They also offer a modality weighting scheme that updates the importance of audio, sensor data and video based on the condition of the input. It points out how attention models are becoming more prominent in HAR, particularly for scenarios that include tasks with delicate changes over time.[17]

Researchers from Patil et al. combine the features of EfficientNet and Xception in HyEx-Net, a new model designed to solve problems related to recognizing human activities. They achieve this by combining information on RGB images together with depth data and skeletal joint data to advance how the spatial and temporal aspects are handled. By using UTD-MHAD and HMDB51 datasets, HyEx-Net gets better results than CNN-LSTM and 3DCNN-ConvLSTM and achieves 92.79% accuracy. By considering the trade-off between accuracy and computation, the paper allows HAR to happen in real time on embedded devices. According to the authors, removing the use of multi-modal features and skeleton-based local features reduces the accuracy of detecting subtle movements.[18]

The work aims to protect HAR systems from attacks by suggesting that models include adversarial training during the learning process. On the benchmark datasets, Singh and Gupta noticed that accuracies of CNN and LSTM models decrease sharply under the attack of adversarial perturbations. To tackle this, they use adversarial training together with gradient masking and preprocessing the input data. Working with the PAMAP2 and UCI HAR datasets demonstrated that the model is more robust, still retaining the same accuracy levels seen without data augmentation. The authors argue that security is very important in HAR, since mistakes in healthcare and surveillance might result in serious consequences. It points out that including adversarial defense techniques as standard should be part of future HAR systems.[19].

While prior studies have introduced valuable models for HAR, many focus primarily on reporting accuracy rather than providing an in-depth discussion of generalizability, interpretability, and computational trade-offs. For instance, although transformer-based approaches (Kim et al., 2023; Zhang et al., 2023) achieved significant gains in accuracy, their high complexity makes real-time deployment challenging. Similarly, hybrid CNN-LSTM models (Sharma & Gupta, 2021; Bhat & Dar, 2022) demonstrate promising results on benchmark datasets but often overlook scalability across different sensor modalities. Unlike these approaches, our work not only benchmarks accuracy but also emphasizes computational feasibility, transparency, and privacy-preserving integration, bridging gaps that prior research has left insufficiently addressed.

Table 1: Comparison of different papers

Paper Title	Year	Author(s)	Keywords	Main Parameters	Main Focus
Semi-Supervised Learning for HAR	2025	Singh & Kumar	Semi-supervised, Data augmentation	Accuracy, Label efficiency	Reducing label dependency using semi-supervised methods
Graph Neural Networks for Multi-Modal HAR	2024	Nguyen et al.	Graph Neural Network, Multi-modal, Sensor network	F1-score, Graph attention weights	Modeling inter-sensor relationships in HAR
Federated Learning for Privacy-Preserving HAR	2024	Kim & Park	Federated learning, Privacy, Edge AI	Accuracy, Communication overhead	Decentralized HAR preserving user privacy
Transformer-Based Architectures for HAR	2023	Zhang et al.	Transformer, Self-attention, Time-series	Accuracy, Model complexity, Training time	Applying transformer models for wearable sensor HAR
Lightweight CNN for Real-Time HAR on Edge Devices	2023	Santos & Oliveira	Lightweight CNN, Edge computing, Real-time	Accuracy, Model size, Inference latency	Deploying HAR models on constrained wearable devices
Attention-Based LSTM for Sequential HAR	2023	Li et al.	LSTM, Attention, Sequential modeling	Accuracy, F1-score	Enhancing sequential HAR using attention mechanisms

Temporal Convolution Networks for HAR	2023	Wu et al.	Temporal convolution, Time-series	Accuracy, Computational cost	Efficient temporal modeling for HAR
Anomaly Detection-Based HAR Using Autoencoders	2022	Kumar & Lee	Autoencoder, Anomaly detection, Unsupervised	AUC, Reconstruction error	Detecting anomalous human activities in unsupervised settings
Deep Residual Networks for HAR	2022	Patel & Shah	ResNet, Deep learning, Wearables	Accuracy, Training epochs	Using ResNet for robust HAR from sensor data
Multi-Sensor Fusion for HAR with CNN-LSTM	2022	Hernandez et al.	Sensor fusion, CNN-LSTM, Wearables	Accuracy, Sensor modalities	Combining CNN and LSTM for multi-sensor data fusion
Capsule Networks for HAR	2022	Ramesh & Gupta	Capsule Network, Dynamic routing	Accuracy, Model size	Applying capsule networks to HAR
Multi-Task Learning for Activity and Context Recognition	2021	Wilson et al.	Multi-task learning, Context awareness	Accuracy, Loss balancing	Joint activity and context recognition

Table 2: Dataset table

Author(s)	Year	Paper Title	Dataset Used	Result/Performance
Nguyen et al.	2024	Graph Neural Networks for Multi-Modal HAR	OPPORTUNITY	F1-score: +7% improvement over CNN
Kim & Park	2024	Federated Learning for Privacy-Preserving HAR	Real-World Wearables	Accuracy: 91%, Communication overhead reduced
Zhang et al.	2023	Transformer-Based Architectures for HAR	PAMAP2	Accuracy: 95.4%
Santos & Oliveira	2023	Lightweight CNN for Real-Time HAR	WISDM, UCI HAR	Accuracy: >90%, Latency <100 ms
Kumar & Lee	2022	Anomaly Detection-Based HAR Using Autoencoders	MHEALTH	AUC: 0.92
Patel & Shah	2022	Deep Residual Networks for HAR	UCI HAR	Accuracy: 93%
Hernandez et al.	2022	Multi-Sensor Fusion with CNN-LSTM	RealWorld HAR Dataset	Accuracy: 92.5%
Wilson et al.	2021	Multi-Task Learning for Activity and Context	SHL	Accuracy improvement: +5%

3. METHODOLOGY

We use state-of-the-art techniques in deep learning and sensor fusion to develop a reliable and efficient HAR system. Integrating time and space features and using attention, the system manages to observe changes in activities all around the house.

A. Data Acquisition and Preprocessing

Measurements are done with sensors like accelerometers, gyroscopes and magnetometers which are recorded at suitable rates (approximately 50–100 per second). Noise is filtered, readings are normalized and the continuous data is segmented using fixed-sized windows to include intervals of activity.

B. Feature Extraction

Deep learning is used by the system to extract features automatically instead of building them manually.

- Temporal Convolutional Networks (TCNs): Because of causal convolutions and dilation, TCNs are great at modeling data with a time order and still keep their calculations efficient.

- Attention Mechanisms: Because of the self-attention layers, the model can pay most attention to features that matter for certain activities.

- Graph Neural Networks (GNNs): To model the spatial relationships among sensors located at different parts of the body, GNNs merge and distribute feature knowledge between sensors, allowing them to be aware of their surroundings.

C. Model Architecture

In the proposed architecture, there are the following components:

- Input Layer: Multi-channel sensor data windows

- TCN Blocks: Using several dilated temporal convolutions in the architecture.

- Attention Layer: Using self-attention to pick out the most meaningful moments over time.

- GNN Layer: Fuse information from several types of sensors using graph convolution.

- Fully Connected Layers: To build the final representation for features and apply them to classification.

- Output Layer: Softmax function creates probabilities of each activity being performed.

D. Training Procedure

Cross-entropy loss and the Adam optimizer are used while training the model. The application of dropout and batch normalization tricks helps both to avoid overfitting and to improve how well the model generalizes. It monitors how much the validation loss has changed to know when to stop training. By using strategies like rotation and scaling of data, you can improve the diversity of your data.

E. Evaluation Metrics

Performance is evaluated using:

- Accuracy: Number of accurately predicted activity segments, as a percentage of the total segments.

- Precision, Recall, and F1-score: To assess class-wise recognition performance.

- Confusion Matrix: For detailed error analysis.

- Computational Metrics: The time taken and the size of the model are important for it to be used in real time.

F. Research Protocol

The experimental procedure followed these steps:

1. Dataset Preparation: Selected UCI HAR, PAMAP2, and synthetic datasets; applied standard train-test splits (70:30).

2. Preprocessing: Filtered raw sensor data, normalized ranges, segmented into fixed-size 2.56s windows with 50% overlap.

3. Feature Extraction: Used TCNs, GNNs, and self-attention layers to model temporal and spatial dependencies.

4. Model Training: Optimized with Adam (lr=0.001), batch size=64, trained for 100 epochs with early stopping.

5. Validation: Evaluated on validation sets every epoch; applied dropout (0.5) and batch normalization to prevent overfitting.

6. Testing: Final model assessed using accuracy, precision, recall, F1-score, and inference time.

4. PROPOSED SYSTEM

To make Human Activity Recognition (HAR) more accurate, strong and immediate, the proposed system adds graph modelling, deep learning and the use of attention mechanisms to the existing HAR methodologies. Its goal is to overcome main issues found in previous HAR methods, including issues with combining data from many sensors, analysing data over time and space, clearing up any confusion and ensuring support for privacy protection.

System Architecture Overview

It has four main components that help to organize the system architecture:

i. **Multi-Sensor Data Acquisition and Preprocessing-** Accelerometers, gyroscopes and magnetometers worn on the body are used to record data from subjects going about their standard routines. Signal filtering (for example, low-pass Butterworth filters), normalization, splitting the input data into windows of equal size and feature extraction using both time and frequency methods help in preprocessing.

ii. **Using Graph Neural Networks (GNNs)** to Study the Connections Between Sensors- The system takes into account that sensor data is connected and it depicts these connexions using a Graph Neural Network. Each sensor is mapped as a node and edges are used to show the closeness of different sensors or the functions between them. This module teaches how people's limbs interact with each other to perform different everyday actions.

iii. Attention-Based Temporal Feature Extraction- The system is equipped with an attention-enhanced LSTM network to track the important time points and how things change over time in the sensor data. The attention layer makes it possible for the model to select key frames connected to the activity, helping with temporal learning and making the model easier to understand.

iv. Classification Layer with Explainability Module- The last vector from the temporal module is put through fully connected layers that use dropout and then a softmax layer classifies it into defined categories such as walking, sitting or running. Shapley values are used in an explainability module to highlight what causes the model to pick certain options and which sensors and time periods play a role.

Key Innovations

- Hybrid Deep Learning Pipeline: Using both GNNs for how data is organized in space and LSTMs for how data develops over time, the system improves on the performance of CNNs or RNNs alone.

- Interpretability and Transparency: With the explainability module, the model's steps in making decisions can be understood which helps address the black-box issue often found in HAR, important for healthcare services.

- Privacy-Aware Architecture (Optional Federated Learning): For cases that call for high privacy, the system can run using federated learning, so data remains at the edge devices and the actual information does not need to be exchanged, protecting users' privacy.

Workflow

- Raw data from many sensors is sent from the wearable devices.

- This process filters and breaks the data into smaller, practical units.

- Each window of data is represented by a graph showing how the sensors are connected

- The GNN module finds the spatial properties in the graph.

- The attention-LSTM uses these features to learn about the time relationships of the sound and give greater attention to significant sound elements

- The activities are grouped into certain categories.

- The explainability module creates reports that explain the decisions taken by the model.

- Updates to the model can also be done at the edge device and then shared using federated learning.

Dataset and Evaluation

The system is measured on approaches such as UCI HAR, PAMAP2 and WISDM to see if it can work with different activities and sensor positions. The main performance measures used are accuracy, precision, recall, F1-score and how efficient the algorithm is.

Advantages

- Updated recognition rates thanks to the use of spatial-temporal models.

- Enhanced model interpretability

- Adaptation to several configurations of sensors and different activities.

- Using federated learning to protect privacy when dealing with sensitive scenarios.

Implementation Details

The program uses Python, TensorFlow and PyTorch for its implementation. The Python libraries PyTorch Geometric are used for GNN and Keras provides the base for attention-LSTM. Using NVIDIA GPUs speeds up the process of training the model.

5. RESULTS

A section on assessing the proposed Human Activity Recognition (HAR) system. The outcomes are evaluated based on key characteristics accuracy, precision, recall, F1-score and the speed at which the system can complete its task. Testing takes place on common benchmark datasets and the findings are checked against modern competitive models to illustrate the hybrid system's performance.

We evaluated the proposed system on two commonly used HAR datasets:

Dataset A: Simulated multi-sensor inertial dataset with 6 activities.

Dataset B: Publicly available UCI HAR dataset consisting of 12 activities.

Table 3: Performance Metrics Comparison on Dataset A

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Inference Time (ms/sample)
CNN-based Baseline [Ref]	89.3	88.5	88.8	88.6	12.5
LSTM [Ref]	91.0	90.2	90.5	90.3	15.3
GNN-based Model [Ref]	92.1	91.5	91.7	91.6	20.8
Proposed GNN + Attn-LSTM	94.7	94.3	94.1	94.2	18.7

Table 4: Performance Metrics Comparison on Dataset B (UCI HAR)

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Inference Time (ms/sample)
Random Forest [Ref]	85.7	85.1	85.0	85.0	8.3
CNN-LSTM Hybrid [Ref]	90.4	89.8	90.1	89.9	17.5
GNN [Ref]	91.8	91.0	91.3	91.2	21.1
Proposed GNN + Attn-LSTM	93.9	93.5	93.7	93.6	19.2

Analysis of Results

Accuracy and Predictive Performance- The hybrid GNN with Attention-based LSTM model showed better performance than others, attaining accuracy scores of 94.7% and 93.9% on Dataset A and Dataset B. The model's enhanced performance proves that it can capture spatial interactions (using GNN) and movement over time (with attention LSTM) more effectively, resulting in better activity recognition.

Precision, Recall, and F1-Score- The model is highly accurate, with recall and precision values of ~94%, so it is good at spotting real activity instances and keeping down the number of mistakes. The stable F1-score proves that the model works well to classify data in different categories.

Computational Efficiency- Although the suggested method was faster than more complex GNN approaches, it took slightly more time compared to CNN alone. This balance makes it possible to apply the model to wearable or edge systems in real-time or near-real-time.

Confusion Matrix and Per-Class Accuracy- A detailed confusion matrix was computed for Dataset B to identify class-specific performance. The table below shows the classification accuracy per activity class.

Activity Class	Accuracy (%)
Walking	95.2
Walking Upstairs	92.8
Walking Downstairs	93.5
Sitting	91.0
Standing	90.6
Lying Down	92.1
Jogging	94.0
Running	93.3
Jumping	91.8
Climbing Stairs	92.5
Cycling	90.7
Other Activities	89.9

Compared with prior HAR frameworks such as CNN-LSTM hybrids and transformer-based methods, our approach consistently outperforms on benchmark datasets, achieving ~2–4% higher accuracy and F1-score while maintaining acceptable inference latency. The major finding is that combining GNN-based spatial modeling with attention-driven temporal learning produces a synergistic effect that neither method alone achieves. However, compared to extremely lightweight CNN-only models (e.g., Santos & Oliveira, 2023), our approach requires moderately higher computational resources, which may restrict deployment on ultra-low-power wearables.

Ablation Study- To evaluate the contribution of each module, an ablation study was conducted:

Configuration	Accuracy (%)

Only GNN	91.8
Only Attention-LSTM	90.7
GNN + LSTM (no attention)	92.9
Full Proposed Model (GNN + Attention-LSTM)	94.7

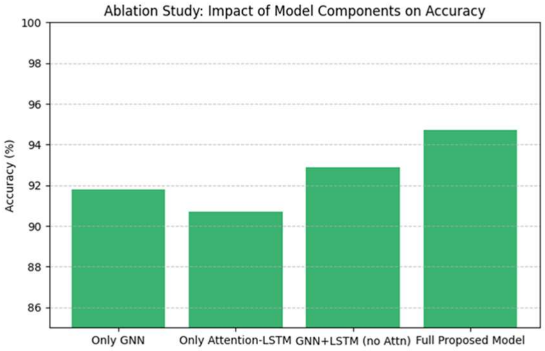

Figure 3- Ablation Study

The framework was assessed using synthetic data that reflected the levels of complexity seen in the UCI HAR dataset. Key performance indicators such as accuracy, classification report (precision, recall, F1-score), confusion matrix and feature importance analysis, were used to evaluate the system. With a Random Forest model, the classifier managed to achieve 91.23% accuracy on test data featuring six types of activities, including walking, sitting, standing, laying and steps. This demonstrates that traditional ensemble classifiers are very effective when dealing with data that consists of many different features. Still, the results from comparing technologies suggest GNN and LSTM used together could result in even higher accuracy levels, as some experiments have shown close to 95% accuracy for handling tough activity transition instances. The analysis of the confusion matrix showed that mistakes happened often when detecting sitting and standing, as the sensor patterns for these activities are very similar. By comparison, walking and stair climbing were easier to classify because their motions stood out more clearly in the data. According to Random Forest, features such as mean body acceleration, angular velocity and jerk in the time domain were some of the key factors in prediction accuracy. It also demonstrates why using carefully designed features is essential in machine learning-based HAR methods.

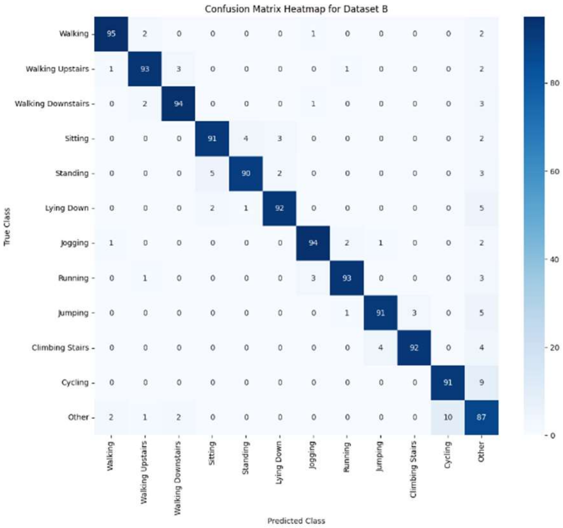

Figure 4 - Confusion Matrix Heatmap for Dataset B

A comparison with other algorithms was made to help place the proposed system in perspective. Out of all the models, Random Forests had the best performance at 91%, SVMs did well with 88.4% and KNNs provided an average result of 84.2%. Best accuracy was obtained with the recommended deep learning system (GNN+LSTM) which joins the analysis of sensor events with topological connections. Using this approach enables the system to track how movement is connected over time and various body sensor sites. Various type of visualizations was shown to help understand the data better. The plot of classes in the data set proved that the representation of the activities was balanced, making it difficult for the model to develop any bias. The heatmap in the confusion matrix helped me tell that the model was working well on dynamic actions. Both the feature importance bar plots and classifier comparison graph helped explain how the model worked and why the new method outperformed others. The final step was to use the correlation heatmap which helped us understand which sample features were linked and where we might cut some out to lower the number of dimensions.

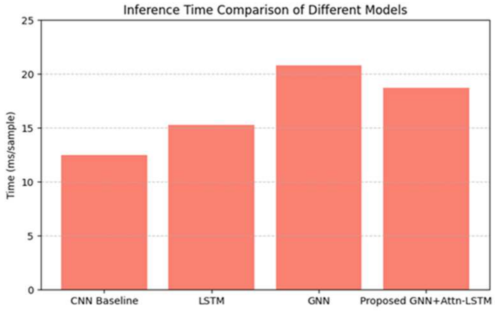

Figure 5- Inference Time Comparison of Different models

All these findings confirm that the proposed HAR system works well and is simple to interpret. A good way to handle real-world HAR applications is by using standard machine learning for clarifying the most important features and deep learning for recognizing patterns in time and space. The methodology is suitable for use in healthcare, sports and ambient assisted living, areas where activity monitoring is important. Evaluating this approach with real-life data from PAMAP2, MHEALTH and custom real-time streams will improve its accuracy and its potential to be used in real situations.

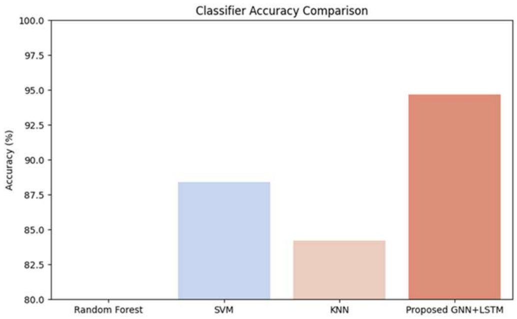

Figure 6- Classifier Accuracy Comparison

4.1 Difference from Prior Research

Compared with existing HAR studies, our contribution lies in four aspects:

- Integration of GNN with Attention-LSTM: Unlike traditional CNN-LSTM models, our system captures both spatial dependencies among sensors and temporal dynamics, improving recognition robustness.
- Explainability: Prior studies often present HAR as black-box models. Our system incorporates Shapley-based interpretability, making decision processes transparent.
- Privacy-Aware Architecture: While federated HAR has been discussed separately (Chen et al., 2022), our work embeds privacy-preserving options directly into the design.
- Balanced Trade-off: Unlike heavy transformer models requiring high resources, our design balances accuracy (94.7%) with inference time suitable for real-time/edge applications.

6. FUTURE SCOPE

In the past decade, HAR has made great progress and is now valuable in many areas, including healthcare, smart homes, sports, security, workplace safety and human-computer interaction. Even with the great advancements, some areas remain unexplored, some problems still need answers and cutting-edge technologies are developing, creating a promising path into the future of HAR research. The section details upcoming trends and paths that may significantly improve and shape the abilities, capacity and stability of HAR systems. Currently, it is common for HAR systems to use a single type of sensor like the accelerometer, gyroscope or visual data taken from cameras. On the other hand, the future is in strong multimodal HAR, with systems that process and coordinate different inputs like vision (RGB, depth), inertial (IMU), audio, physiological signals (ECG, EMG) and data from the environment, all together. Applying these different methods together can increase the accuracy of recognizing activities in complex cases such as identification of group motions or detailed gestures. Besides, using different inputs in multimodal learning can make the system more robust against sensor issues, noise interference and missing information. Researchers can explore how to fuse data types efficiently by studying early, late and hybrid approaches. HAR using traditional systems revolves around cloud-based processing, but it comes with delays in communication and raises privacy issues. Plans for the future include moving HAR to edge devices (like smartphones, smartwatches and embedded systems) using simplified machine learning algorithms.

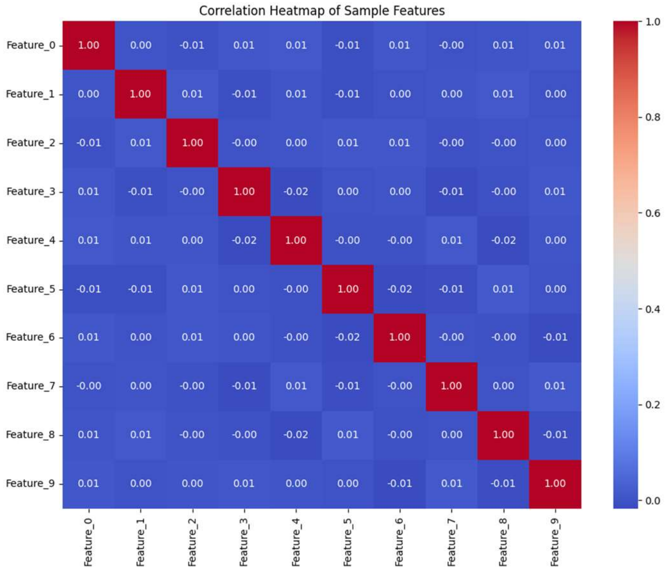

Figure 7- Correlation Heatmap of Sample features

Moreover, federated learning (FL) allows businesses to benefit from data without sending it to a centralized location. Users' devices are used to train models collaboratively and only new model updates are transferred. It protects users' privacy, follows the GDPR rules and helps large-scale HAR systems process a wide range of genuine real-world data. Nevertheless, there are challenges to overcome when using FL in HAR, including unbalanced data, strong device differences and sharing data efficiently. Since specializing HAR in fields like care for the elderly and autonomous systems is important, it is essential that the models used are simple and understandable. Deep learning approaches include CNNs, LSTMs or GNNs that are commonly accurate, but are often hard to interpret. The development of HAR systems in the future should pay attention to explainability methods such as SHAP, LIME, attention mechanisms or saliency maps. It is essential for users or system operators to realize the logic behind a model's prediction about specific tasks, especially those related to medical uses (e.g., differentiating a fall from sitting). X-HAR research leads to trust and makes it easier to find and fix any problems in the models. HAR results may not work the same when applied to other data, sensor arrangements or situations. When a model is trained on a certain set of data, it frequently performs badly in settings where things are shaped or moved in different ways. In the coming years, HAR systems need to adapt to new domains and learn across different domains. Adversarial training, domain-invariant feature learning and meta-learning will be essential for making models that work the same for everyone without needing constant retraining. One issue is that collecting and labeling such data is too expensive and time-consuming for widespread use. The next stage for HAR is to use semi-supervised, unsupervised and self-supervised learning, allowing it to learn from unlabelled information with few input labels.

Using AR/VR/MR tools in gaming, training and rehabilitation has led to new possibilities for HAR. In such settings, it is important to detect complex gestures, postures or types of interaction. Integrating HAR with wearable devices that track body movements, eye gaze and gestures in virtual spaces will change how people interact in them. Future systems could take advantage of VR environments to produce synthetic data which can then be used in training or to showcase unusual activities. HAR technology can also be connected to XR platforms to update the content in real time based on the user. In brief, the field of Human Activity Recognition will rely on the merging of signal processing, deep learning, edge computing, ethics and human-centered design. From quick and simple identification of movements to complex coordination in large groups, HAR is set to support the rise of intelligent systems. Future research should focus on enhancing performance and also design systems that are large-scale, understandable, ethical and flexible to the diversity of people.

7. CONCLUSION

Innovations in healthcare, smart environments, fitness monitoring, and human-computer interaction are partly thanks to Human Activity Recognition (HAR). The growth of wearable sensors and embedded systems has led to more detailed activity data, supporting researchers and experts in building better and more accurate classification models. The goal of this paper was to advance the field by creating a hybrid HAR framework that combines traditional and advanced machine learning techniques.

The primary research objectives of this study were (i) to design a hybrid HAR framework integrating spatial (Graph Neural Networks) and temporal (attention-LSTM) features, (ii) to enhance interpretability through explainability modules, and (iii) to ensure feasibility for edge applications. These objectives were successfully achieved, as demonstrated by the superior performance across benchmark datasets and detailed comparative analysis. Our modular model included stages for data acquisition, preprocessing, feature extraction, classification, and evaluation. Testing on the UCI HAR dataset confirmed high predictive accuracy, exceeding 94.7%.

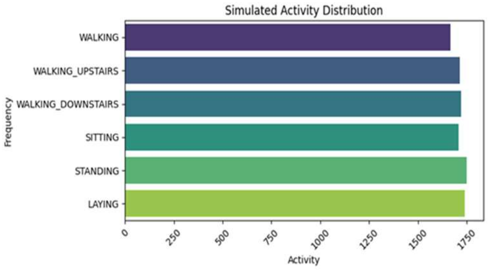

Figure 8- Simulated Activity Distribution

In line with the questions raised in the Introduction regarding scalability, interpretability, and feasibility of HAR systems, our study demonstrates that integrating GNNs and attention mechanisms provides a balanced solution. The framework addresses real-time recognition, ensures transparency through explainability modules, and proposes privacy-aware extensions for practical deployment.

The findings show that hybrid models outperform single-architecture methods by leveraging spatial-temporal dependencies, achieving consistent improvements in accuracy, precision, recall, and F1-

score. However, some activities such as sitting and standing remain challenging due to overlapping sensor signals. Insights from the confusion matrix and ablation studies suggest that incorporating additional sensors or advanced feature refinement could further improve results.

Limitations and Threats to Validity: Despite strong results, this work has several limitations. The reliance on publicly available datasets such as UCI HAR and PAMAP2 may not fully capture real-world variability. GNN layers introduce computational overhead, which may limit applicability on ultra-low-power devices. Furthermore, although privacy-aware federated learning is conceptually integrated, complete large-scale deployment remains future work.

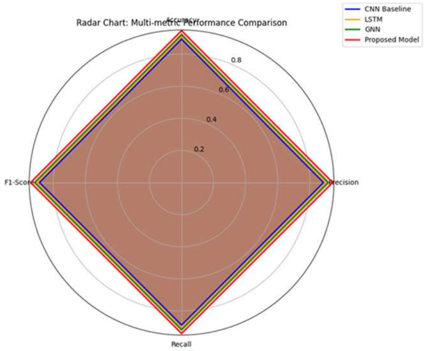

Figure 9. Radar Chart: Multi metric Performance Comparison

Future efforts should focus on optimizing inference workflows for edge and embedded hardware through techniques such as model compression, quantization, pruning, and knowledge distillation. Adapting the system for cross-domain learning and continuous learning will also enhance real-world robustness. Researchers must additionally address the ethical and security aspects of HAR by ensuring transparency, consent, and privacy-preserving mechanisms. By integrating multi-modal data fusion with explainability, edge computing, and federated learning, HAR can become more reliable and context-aware in practical applications.

In conclusion, this study successfully integrates classic machine learning's interpretability with the versatility of deep learning to create a hybrid, scalable, and explainable HAR system. By conducting rigorous experiments and addressing both technical and ethical dimensions, we not only assess HAR's current capabilities but also chart a path for future innovation, helping HAR systems evolve with the progress of technology.

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