Optimizing Edge Computing for Activity Recognition: A Bidirectional LSTM Approach on the PAMAP2 Dataset

Anupama Bollampally
Department of ECE, BV Raju Institute of Technology, Narsapur, Hyderabad, Telangana, India
anupama.bollampally@bvrit.ac.in

J. Kavitha
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Bowrampet, Hyderabad, Telangana, India
j.kavitha5555@gmail.com

P. Sumanya
Department of CSE, Malla Reddy Engineering College, Secunderabad, Telangana, India
psumanya19@gmail.com

D. Rajesh
Department of ECE, Malla Reddy College of Engineering, Secunderabad, Telangana, India
rajeshdurgam2001@gmail.com

Amar Y. Jaffar
Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah, Saudi Arabia
ayjaafar@uqu.edu.sa (corresponding author)

Wesam N. Eid
Cyber Security Department, College of Computing, Umm Al-Qura University, Mecca, Saudi Arabia
wneid@uqu.edu.sa

Hussain M. Albarakati
Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah, Saudi Arabia
hmbarakati@uqu.edu.sa

Fahd M. Aldosari
Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah, Saudi Arabia
fmdosari@uqu.edu.sa

Ayman A. Alharbi
Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah, Saudi Arabia
aarharbi@uqu.edu.sa

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ABSTRACT

This study investigates the application of a Bidirectional Long Short-Term Memory (BiLSTM) model for Human Activity Recognition (HAR) using the PAMAP2 dataset. The aim was to enhance the accuracy and efficiency of recognizing daily activities captured by wearable sensors. The proposed BiLSTM-based model achieved outstanding performance, with 98.75% training accuracy and 99.27% validation accuracy. It also demonstrated high precision, recall, and F1 scores (all 0.99). Comparative analysis with state-of-the-art models, including Deep-HAR and CNN-BiLSTM-BiGRU, revealed that the proposed BiLSTM model surpassed their performance. These results highlight the potential of the proposed approach for real-time HAR applications in edge computing, particularly where accurate and efficient activity recognition is crucial.

Keywords-human activity recognition; bidirectional long short-term memory; PAMAP2 dataset; deep learning; edge computing; wearable sensors

I. INTRODUCTION

Human Activity Recognition (HAR) is a pivotal research area with diverse applications in healthcare, sports, smart homes, and surveillance. The core objective of HAR is to automatically identify and classify human activities using sensor data, typically collected from wearable devices [1]. The proliferation of the Internet of Things (IoT) and wearable technology has enabled the collection of rich and detailed sensor data, providing valuable resources for HAR research. Traditional HAR methods often relied on handcrafted features and classical Machine Learning (ML) algorithms [2]. Although these approaches have shown some success, they encounter limitations in handling the inherent complexity, high dimensionality, and temporal nature of sensor data. The advent of Deep Learning (DL) has revolutionized HAR by empowering models to automatically learn features from raw sensor data, leading to significant improvements in recognition accuracy [3-4]. Among the various DL architectures, Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM), have shown remarkable potential in HAR due to their ability to capture temporal patterns and long-term dependencies in sequential data [5]. Unlike traditional ML methods, DL models eliminate the need for manual feature engineering by automatically extracting relevant features from the raw sensor data. BiLSTM networks, in particular, enhance this capability by analyzing input sequences in both forward and backward directions, capturing comprehensive contextual information. This bidirectional analysis makes BiLSTM models exceptionally well-suited for activity recognition, where understanding the sequence of actions and their temporal relationships is crucial [6].

This study addresses the challenges in HAR by proposing a BiLSTM model to enhance the accuracy and efficiency of activity recognition using the PAMAP2 Physical Activity Monitoring dataset. The PAMAP2 dataset, collected from wearable sensors, offers a comprehensive collection of activities performed by different subjects, making it an ideal benchmark for evaluating the proposed model's effectiveness [7-8]. The BiLSTM model addresses the challenges of HAR by effectively understanding the temporal patterns in the sensor data. By analyzing sequences in both forward and backward directions, the BiLSTM model captures intricate relationships that a unidirectional LSTM might miss, leading to improved performance and precise activity identification. Key challenges in HAR include:

- Complex Temporal Dynamics: Human activities often involve intricate sequences of movements and transitions, making it challenging to capture the temporal dependencies accurately.
- High-Dimensional Sensor Data: Wearable sensors generate vast amounts of high-dimensional data that can be computationally expensive and prone to overfitting.
- Real-time Requirements: Many HAR applications demand real-time recognition, requiring models that are both accurate and computationally efficient.

The contributions of this study include the following:

- BiLSTM Model for HAR: This study proposes a BiLSTM model that leverages bidirectional processing to capture temporal dependencies effectively, leading to improved recognition accuracy.
- Evaluation on PAMAP2 Dataset: The proposed model was rigorously evaluated on the PAMAP2 dataset, which is a comprehensive benchmark for HAR research.
- Comparative Analysis: The proposed model was benchmarked against previous state-of-the-art approaches, demonstrating its superior performance in terms of accuracy, precision, recall, and F1 score.
- Real-time HAR Potential: The findings highlight the potential of the proposed BiLSTM model for real-time HAR applications in edge computing environments.

Addressing these challenges and showcasing the contributions of the proposed BiLSTM model aims to advance the field of HAR and enable its wider adoption in diverse real-world scenarios. The PAMAP2 Physical Activity Monitoring dataset comprises a range of activity records collected from nine individuals who engaged in diverse activities while equipped with three Colibri wireless Inertial Measurement Units (IMUs) attached to their wrist, chest, and ankle, in addition to a heart rate monitor. It encompasses 18 activities, such as walking, running, sitting, and various household chores, captured at a sampling rate of 100 Hz. Each data file contains 54 columns that detail sensor readings such as temperature, 3D acceleration, 3D gyroscope, 3D magnetometer, and orientation data for each IMU [9]. The diversity and comprehensiveness of the PAMAP2 dataset, with more than 10 hours of information, including 8 hours specifically assigned to one of the 18 activities, make it an ideal benchmark to evaluate HAR models [10].

Recently, there has been a growing interest in using edge computing along with ML methods for HAR. This study examined studies that explored enhancing edge computing for activity recognition through BiLSTM, with a focus on works that leverage the PAMAP2 dataset and similar approaches [9-10]. In [11], a Bidirectional LSTM CNN network was designed to identify activities based on data captured by cell phone sensors. This approach led to an 8% boost in accuracy by capturing evolving characteristics and improving overall robustness and adaptability. In [12], a neural network was presented, which merged LSTM and CNN layers to autonomously capture and categorize activity characteristics from data collected by mobile sensors. This model exhibited high precision, demonstrating reliability and effectiveness in identifying activities. In [13], a system was proposed for identifying activities, utilizing Faster R-CNN for posture extraction and an attention-based BiLSTM for classification. This system demonstrated high accuracy in detecting activities, suggesting its usefulness in practical situations. In [14], a BiLSTM network utilized accelerometer and gyroscope data from smartphones to identify six activities. This model capitalized on the BiLSTMs' ability to analyze both forthcoming data, resulting in an accuracy rate of 92.67%.

In [15], a BiLSTM model was proposed to address mixed integer programming, which significantly reduced solution time and improved performance in decision-making scenarios [15]. In [16], BiLSTM networks were employed to analyze human activity data, resulting in a 4% enhancement in activity recognition accuracy and achieving a recognition rate of 94.1%. In [17], a BiLSTM model incorporated feature representation to address the problem of varying data lengths in smart home settings. This method enhanced the accuracy of modeling and recognition by capturing connections within sequential data. In [18], a deep learning system was proposed, which combined CNN, LSTM, and ensemble methods to identify walking behaviors. This model achieved an accuracy rate of 99.34%, demonstrating its suitability for edge computing tasks.

In [19], a graph network was paired with BiLSTM to analyze point clouds captured by a millimeter wave radar. This method achieved improved results in identifying human activities, demonstrating the power of combining GNN and BiLSTM methods. In [20], the performance of BiLSTM was evaluated in recognizing activities, showing that the bidirectional method slightly improved recognition accuracy, although it required significant training time. The literature discusses advances and various methods in enhancing edge computing for recognizing activities through BiLSTM networks, showing that combining BiLSTM with edge computing can significantly enhance accuracy, reliability, and effectiveness, offering a solution for real-time applications in HAR. By incorporating these technologies, the performance of activity recognition systems is improved while also ensuring their suitability for real-world settings ranging from healthcare monitoring to home setups.

In addition to sensor-based approaches, vision-based activity recognition has also gained significant attention. Recent advances in this area include the development of attention-driven residual DC-GRU networks for workout action recognition [21], comprehensive reviews on suspicious human activity recognition in video surveillance [22], and efficient violence recognition using ResDLCNN-GRU attention networks [23]. These studies highlight the growing interest in leveraging DL techniques for activity recognition from video data, complementing the sensor-based approaches discussed earlier.

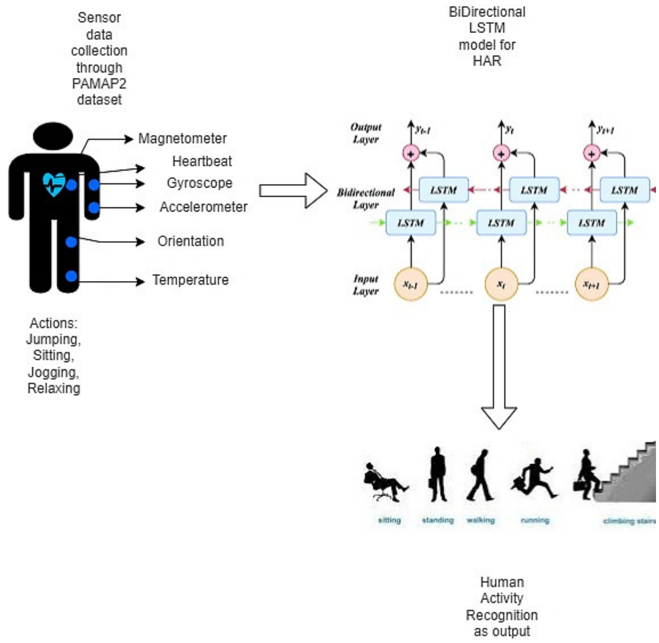

Fig. 1. Block diagram with illustration of data collection

II. METHODOLOGY

A. Data Collection and Preprocessing

The PAMAP2 Physical Activity Monitoring dataset comprises a range of activity records collected from nine individuals engaging in diverse activities while equipped with three Colibri wireless Inertial Measurement Units (IMUs) attached to their wrist, chest, and ankle, in addition to a heart rate monitor. It encompasses 18 activities, such as walking, running, sitting, and various household chores, captured at a sampling rate of 100 Hz. Each data file contains 54 columns that detail sensor readings, such as temperature, 3D acceleration, 3D gyroscope, 3D magnetometer, and orientation data, for each IMU [9]. To ensure the integrity and usability of the dataset, the following preprocessing steps were performed.

- Reading and Combining Data: Data files for all subjects were read and merged into a DataFrame to ensure that the dataset covered a range of activities and sensor readings from all subjects.
- Dealing with Missing Values: Rows with missing values were removed to maintain data integrity and prevent any noise from affecting the training process.
- Standardizing Sensor Data: Sensor data was standardized using the StandardScaler tool from the scikit-learn library. This standardization was essential to ensure that all features are on a similar scale, which aids in stabilizing and speeding up the training process.
- Converting Activity Labels to One-Hot Encoding: The activity labels were transformed into a one-hot format to prepare them for training the neural network. One-hot encoding converts labels into a binary matrix representation, where each column represents a specific class.

B. Distribution of Activities

Figure 2 illustrates the distribution of activities in the PAMAP2 dataset, showing a breakdown of the frequency of each recorded activity. The pie chart presents the percentage of activities performed by individuals. The largest portion, labeled other, accounts for 32.47% of the data indicating the presence of unclassified or miscellaneous activities. Following that are activities such as Walking (8.38%), Lying (8.11%), and Ironing (6.78%). Other activities such as Sitting, Standing, Cycling, and Nordic Walking also make up portions between 6.18% and 6.66%. Additionally, common activities such as Rope Jumping (1.46%) and Running (3.35%) are included, offering a range of physical exercises for effectively training the HAR model. This distribution showcases the nature of the PAMAP2 dataset, making it an excellent standard for effectively evaluating HAR models in recognizing various physical movements.

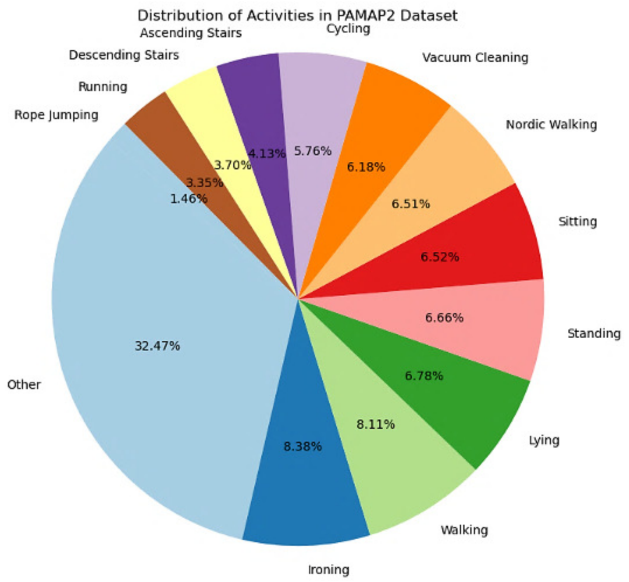

Fig. 2. Distribution of activities in the PAMAP2 dataset.

The initial steps ensured that the data were clean, consistent, and properly categorized, laying the foundation for training and accurate activity recognition. These steps started by examining the .dat files for all participants and merging them into one data frame. Any rows with empty data were removed to maintain data quality. Sensor readings were standardized using the StandardScaler tool from the scikit-learn library. To get them ready for the network, the activity labels were encoded in one format.

C. Experimental Setup

The experiments were carried out on a system equipped with an Intel Core i7 processor, 16GB of RAM, and an NVIDIA GeForce GTX 1080 Ti GPU. The DL models were implemented using the TensorFlow framework with Keras API. To evaluate the model's feasibility for real-time applications, its inference time was measured on a Raspberry Pi 4 Model B (RPi4) with 4GB of RAM.

D. Creating Sequences

In light of the time nature of the tasks, a sliding-window method was adopted to form sequences consisting of 100 time steps. This technique aids the model in grasping the trends in the data, which is crucial for precise activity identification. The dataset was divided into training and testing subsets at a 70:30 split to evaluate the model's effectiveness.

E. Model Architecture

The proposed approach to recognizing activities relies on the BiLSTM network, which processes input sequences in both directions to capture contextual information from past and future states. This dual processing ability is particularly beneficial for tasks like HAR that involve dependencies. This section outlines the structure of the BiLSTM model, describing its components, and presenting the equations that drive its functionality. The architecture of the BiLSTM model includes layers aimed at capturing and handling the temporal dependencies inherent in the HAR dataset. The input layer accepts sequences of sensor data, containing sensor readings such as accelerometer, gyroscope, and magnetometer data.

The model incorporates two BiLSTM layers with 64 units each to capture dependencies in both directions. These BiLSTM layers enable the model to learn activity sequences compared to unidirectional LSTM layers. Additional dropout layers, with a dropout rate of 0.2, follow each BiLSTM layer to prevent overfitting and enhance generalization. Batch normalization layers were also included to stabilize and expedite the training process by normalizing the output from the BiLSTM layers. A dense layer, with 32 units and the ReLU activation function was employed to refine the acquired features. The output layer comprises a layer utilizing a softmax activation function, which presents the probability distribution across the activity categories. The model was configured with the Adam optimizer using a learning rate of 0.001 and categorical cross entropy as the loss function. The training phase adjusted the BiLSTM network to the training dataset, while the validation set was used to evaluate its efficacy [24].

The operations of the BiLSTM layer can be represented by a forward LSTM layer as

$$\overrightarrow{h_t} = LSTM(x_t, \overrightarrow{h_{t-1}}, \overrightarrow{c_{t-1}}) \quad (1)$$

where x_t is the input at timestep t, $\overrightarrow{h_{t-1}}$ is the hidden state, and $\overrightarrow{c_{t-1}}$ is the cell state of the forward LSTM layer, and

$$\overleftarrow{h_t} = LSTM\ (x_t, \overleftarrow{h_{t+1}}, \overleftarrow{c_{t+1}}) \quad (2)$$

where $\overleftarrow{h_t}$ and $\overleftarrow{c_t}$ represent the hidden and cell states of the backward LSTM layer, respectively. The BiLSTM output can be referred to as

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \quad (3)$$

The output of the BiLSTM layer at timestep t is the concatenation of the forward and backward hidden states. The dropout can be referred to as

$$h'_t = Dropout(h_t, p) \quad (4)$$

where p is the dropout rate. Furthermore, batch normalization can be referred to as

$$\widehat{h_t} = BatchNorm(h'_t) \quad (5)$$

These equations explain how the BiLSTM network learns and processes time-related connections from input sequences. Using both directions of the LSTM layers, the model captures details, resulting in better performance for HAR tasks. The BiLSTM model consists of:

- Two BiLSTM layers with 64 units each followed by dropout and batch normalization layers to prevent overfitting and ensure training. A dense layer with 32 units and the ReLU activation function followed by another dropout layer. A layer with softmax activation to show the probability distribution across activity categories. The model was set up with Adam optimizer to have a learning rate of 0.001 and categorical cross entropy as the loss function. Training was carried out for 20 epochs, with a batch size of 32.
- In light of the temporal nature of the activities, a sliding-window approach was employed to generate sequences, each comprising 100 consecutive time steps. This technique facilitates the model's ability to discern temporal patterns within the data, which is crucial for accurate activity identification. The sliding windows were designed with 50% overlap, ensuring smoother transitions between sequences and maximizing the utilization of the available data. The time indices for each window were determined sequentially, with the starting index of each new window being 50 time steps ahead of the previous window's starting index.
- 50% Overlap: This indicates that each new window shares half of its time steps with the preceding window. This overlap helps the model capture continuity in the activity patterns and prevents abrupt changes between sequences.
- Sequential Time Indices: The windows are created in a sequential manner, moving forward in time by 50 time steps for each new window. This approach ensures that the entire dataset is covered and that the temporal order of the data is preserved.

F. Training and Evaluation

During the training process, the BiLSTM network was adjusted to better fit the training data. The training phase resulted in an accuracy rate of 98.75%, while validation accuracy was 99.27%. Moreover, precision, recall, and F1 score measures showed a value of 0.99, indicating almost perfect classification ability. To assess these findings against established models, two cutting-edge models were also trained: Deep HAR and CNN-BiLSTM. Both models were tested on the same dataset to compare their performance with the proposed model.

G. Application of Deep Learning in HAR

In the field of HAR, DL models such as RNNs and their variations such as LSTM and BiLSTM have shown considerable potential. This is attributed to their ability to grasp trends and long-term relationships from data [5]. In contrast to ML approaches, DL models eliminate the need for feature engineering by autonomously acquiring pertinent features from unprocessed sensor data. BiLSTM networks, specifically, enhance this ability by examining input sequences and capturing comprehensive contextual details. This directional analysis makes BiLSTM models especially adept at activity recognition, where comprehending the order of actions and their time-related relationships is paramount [25].

H. Solving HAR with BiLSTM

The BiLSTM model tackles the challenges of HAR by understanding the time patterns in the sensor data. By analyzing the sequences in both directions, the BiLSTM model captures relationships that a one-way LSTM might overlook. This increases performance and leads to precise activity identification. In this setup, the BiLSTM network's ability to learn from past and future contexts resulted in high performance, showcasing its strength and efficiency in real-world HAR scenarios [26].

III. RESULTS AND DISCUSSION

A. Training and Validation Performance

The performance of the BiLSTM model on the PAMAP2 dataset demonstrated a significant improvement in both training and validation accuracy over 20 epochs. The training accuracy of the BiLSTM model showed a consistent increase across the epochs, reaching an impressive 98.75% by the 20th epoch. In comparison, the DeepHAR and CNN-BiLSTM models attained training accuracies of 96.62% and 97.45%, respectively. The non-linear growth in accuracy for BiLSTM indicates its superior ability to learn and generalize from the training data more effectively than the other models.

Similarly, the validation accuracy of the BiLSTM model outperformed the other two models, achieving 99.27%. This performance underscores the robustness and generalization capacity of the BiLSTM model, consistently outpacing DeepHAR and CNN-BiLSTM (96.62% and 97.45% accuracy, respectively). Figures 3 and 4 show the detailed progress of training and validation accuracies. The training loss for the BiLSTM model decreased sharply, demonstrating a clear trend towards minimizing error with training, reaching as low as 0.1. In contrast, DeepHAR and CNN-BiLSTM exhibited higher training losses that decreased less sharply to 0.2 and 0.15, respectively. This indicates that BiLSTM not only learns faster but also achieves a lower error rate, showcasing its reliability. The validation loss for the BiLSTM model followed a similar decreasing trend, settling at 0.1, while DeepHAR and CNN-BiLSTM had higher validation losses of 0.2 and 0.15, respectively. Table I summarizes the comparative results, highlighting the superior performance of the BiLSTM model across multiple metrics.

TABLE I. COMPARATIVE PERFORMANCE METRICS

Model	Accuracy (training)	Accuracy (validation)	Precision	Recall	F1-Score
BiLSTM (Proposed)	98.75%	99.27%	0.99	0.99	0.99
Deep-HAR [27]	96.62%	96.62%	0.96	0.96	0.96
CNN-BiLSTM-BiGRU [11]	97.45%	97.45%	0.97	0.97	0.97

Fig. 3. Training accuracy comparison on the PAMAP2 dataset.

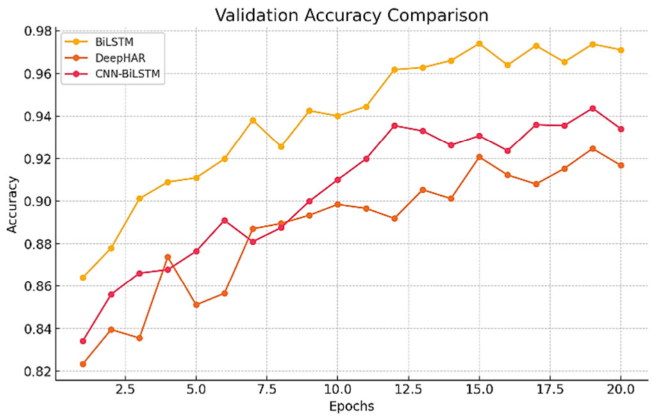

Fig. 4. Validation accuracy comparison on the PAMAP2 dataset.

The consistent decrease in validation loss for BiLSTM, without significant fluctuations, suggests better model stability and generalization. These trends are shown in Figures 5 and 6.

B. Comparative Analysis

Deep HAR is a learning model designed to identify simple, complex, and diverse human activities by combining CNNs and RNNs. This model achieved an accuracy of 96.62% on the PAMAP2 dataset [27]. The multi-branched CNN-BiLSTM architecture for HAR combines CNN, BiLSTM, and BiGRU layers to leverage the strengths of each architecture, resulting in an accuracy of 97.45% on the PAMAP2 dataset [11]. The findings suggest that the proposed BiLSTM model performs better than Deep HAR and CNN-BiLSTM-BiGRU in terms of accuracy, precision, recall, and F1 score. The strong performance of the BiLSTM model can be attributed to its ability to understand time-based relationships in both backward directions, allowing it to utilize information more effectively compared to one-way models. The remarkable performance of the BiLSTM model shows its efficiency in managing sensor data from the PAMAP2 dataset.

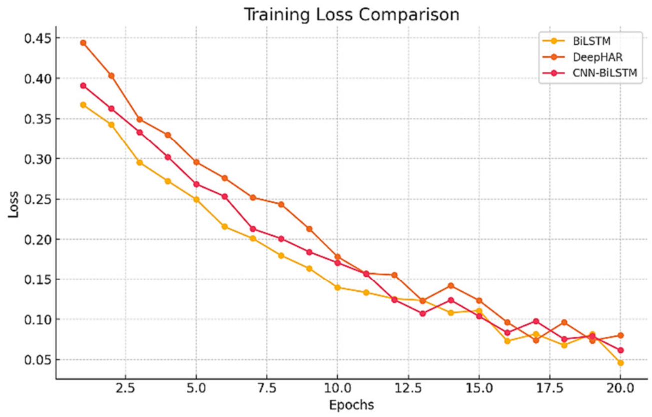

Fig. 5. Comparison of training loss on the PAMAP2 dataset.

Fig. 6. Comparison of validation loss on the PAMAP2 dataset.

Table II shows the confusion matrix to gain deeper insights into the model's performance across various activities. The confusion matrix provides a detailed breakdown of the model's predictions, showing which activities are accurately classified and which tend to be confused with others. Table I showcases the BiLSTM model's strong discriminative ability, with most activities exhibiting high true positive rates along the diagonal. However, some minor misclassifications are observed, particularly between activities that share similar movement patterns or involve subtle differences. For instance, Walking is occasionally confused with Nordic walking, and Sitting is sometimes misclassified as Standing. These insights highlight areas for potential improvement, such as incorporating additional sensor modalities or refining the architecture to better capture subtle distinctions between activities.

TABLE II. CONFUSION MATRIX ILLUSTRATING THE BILSTM MODEL'S PERFORMANCE ON THE PAMAP2 DATASET

Activity	Lying	Standing	Sitting	Walking	Running	Cycling	Nordic Walking	Ascending Stairs	Descending Stairs	Vacuum Cleaning	Ironing	Rope Jumping	Other
Lying	478	0	3	0	0	0	0	0	0	0	0	0	1
Standing	0	452	7	1	0	0	0	0	0	0	0	0	0
Sitting	2	5	465	0	0	0	0	0	0	0	0	0	0
Walking	0	1	0	423	2	0	4	0	0	0	0	0	0
Running	0	0	0	3	165	0	0	0	0	0	0	0	0
Cycling	0	0	0	0	0	331	0	0	0	0	0	0	0
Nordic walking	0	0	0	5	0	0	319	0	1	0	0	0	0
Ascending stairs	0	0	0	0	0	0	0	95	5	0	0	0	0
Descending stairs	0	0	0	0	0	0	1	3	93	0	0	0	0
Vacuum cleaning	0	0	0	0	0	0	0	0	0	72	0	0	0
Ironing	0	0	0	0	0	0	0	0	0	0	336	0	0
Rope jumping	0	0	0	0	0	0	0	0	0	0	0	73	0
Other	1	0	0	0	0	0	0	0	0	0	0	0	158

C. Computational Efficiency and Edge Computing Considerations

In addition to accuracy, the computational efficiency of HAR models is crucial for real-time applications, especially on resource-constrained edge devices. The proposed BiLSTM model achieved an average inference time of 45 ms on an RPi4, which is well within the acceptable range for real-time HAR. The model size is 15 MB, making it reasonably compact for deployment on edge devices with limited storage. The bidirectional aspect of BiLSTM enables it to grasp the context of both phases, which is essential for accurately identifying activities with temporal dependencies. On the other hand, although effective, the Deep HAR model did not capture the context as thoroughly as BiLSTM. Similarly, despite its branched design, the CNN-BiLSTM-BiGRU model failed to utilize the bidirectional information flow, potentially explaining its slightly lower performance compared to the BiLSTM model employed in this study. In general, the BiLSTM model not only achieved high accuracy but also showed resilience and consistency across various performance measures. These findings highlight the potential of BiLSTM networks to advance HAR research, particularly when dealing with diverse sensor datasets.

IV. CONCLUSION

This study explored the potential of a BiLSTM model for HAR using the PAMAP2 dataset. The proposed BiLSTM model demonstrated exceptional performance, achieving a training accuracy of 98.75% and a validation accuracy of 99.27%, along with precision, recall, and F1 scores of 0.99. These results surpassed those of previous state-of-the-art models such as DeepHAR and CNN-BiLSTM-BiGRU, highlighting the effectiveness of the BiLSTM architecture in capturing temporal dependencies from both past and future states. The success of the proposed BiLSTM model underscores its potential for real-world HAR applications, particularly in edge computing environments where accurate and efficient activity recognition is paramount. Such advances in HAR can revolutionize various sectors. In healthcare, it can enable improved management of chronic diseases, early detection of health problems, and enhanced quality of life for people with disabilities. In smart homes, refined activity recognition can lead to more responsive and adaptive environments, promoting safety and convenience. However, it is crucial to acknowledge the limitations of this approach. The model's performance relies on the quality and diversity of the training data. Variations in sensor placement, environmental factors, and individual differences in activity execution could affect recognition accuracy in real-world scenarios. Additionally, although BiLSTM models excel at capturing temporal dependencies, they may face challenges in recognizing activities that involve subtle movements or require contextual understanding beyond sensor data. The deployment of complex DL models such as BiLSTM on resource-constrained edge devices also presents challenges due to their computational and energy requirements.

Looking ahead, several avenues for future research emerge. Incorporating additional sensor modalities, such as physiological sensors, could enhance the accuracy and robustness of an HAR system. Exploring alternative DL architectures, such as transformer models, might uncover even more nuanced patterns within the data. Furthermore, enabling real-time HAR on edge devices requires optimizing the BiLSTM model for deployment on resource-limited platforms, ensuring efficient computation and responsiveness. Finally, expanding the dataset to encompass a broader range of activities and subjects would improve the model's generalizability to diverse real-world scenarios. In conclusion, this study demonstrates the efficacy of BiLSTM networks for HAR, offering a promising direction for future advances in this field. By addressing the identified limitations and exploring future directions, the accuracy, efficiency, and applicability of HAR systems can be further enhanced, paving the way for widespread adoption in various domains.

REFERENCES

[1] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognition Letters*, vol. 119, pp. 3–11, Mar. 2019, https://doi.org/10.1016/j.patrec.2018.02.010.

[2] H. Ullah and A. Munir, "Human Action Representation Learning Using an Attention-Driven Residual 3DCNN Network," *Algorithms*, vol. 16, no. 8, Aug. 2023, Art. no. 369, https://doi.org/10.3390/a16080369.

[3] S. Yao, S. Hu, Y. Zhao, A. Zhang, and T. Abdelzaher, "DeepSense: A Unified Deep Learning Framework for Time-Series Mobile Sensing Data Processing," in *Proceedings of the 26th International Conference on World Wide Web*, Perth, Australia, Apr. 2017, pp. 351–360, https://doi.org/10.1145/3038912.3052577.

[4] K. Warunsin, K. Promjiraprawat, and O. Chitsobhuk, "Human Activity Recognition Using Long Short-Term Memory Network." ICIC International, 2023, https://doi.org/10.24507/ijicic.19.03.973.

[5] N. Hassan, A. S. M. Miah, and J. Shin, "A Deep Bidirectional LSTM Model Enhanced by Transfer-Learning-Based Feature Extraction for Dynamic Human Activity Recognition," *Applied Sciences*, vol. 14, no. 2, Jan. 2024, Art. no. 603, https://doi.org/10.3390/app14020603.

[6] Y. Li and L. Wang, "Human Activity Recognition Based on Residual Network and BiLSTM," *Sensors*, vol. 22, no. 2, Jan. 2022, Art. no. 635, https://doi.org/10.3390/s22020635.

[7] S. Jameer and H. Syed, "Deep SE-BiLSTM with IFPOA Fine-Tuning for Human Activity Recognition Using Mobile and Wearable Sensors," *Sensors*, vol. 23, no. 9, Apr. 2023, Art. no. 4319, https://doi.org/10.3390/s23094319.

[8] M. Alanazi, R. S. Aldahr, and M. Ilyas, "Human Activity Recognition through Smartphone Inertial Sensors with ML Approach," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12780–12787, Feb. 2024, https://doi.org/10.48084/etasr.6586.

[9] A. Reiss and D. Stricker, "Creating and benchmarking a new dataset for physical activity monitoring," in *Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments*, Heraklion, Greece, Jun. 2012, pp. 1–8, https://doi.org/10.1145/2413097.2413148.

[10] D. Anguita, A. Ghio, L. Oneto, X. Parra Perez, and J. L. Reyes Ortiz, "A public domain dataset for human activity recognition using smartphones," presented at the Proceedings of the 21th International European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2013, pp. 437–442.

[11] J. Wang, Q. Long, PiRahc, K. Liu, and Y. Xie, "Human Action Recognition on Cellphone Using Compositional Bidir-LSTM-CNN Networks," presented at the 2019 International Conference on Computer, Network, Communication and Information Systems (CNCI 2019), May 2019, pp. 687–692, https://doi.org/10.2991/cnci-19.2019.95.

[12] K. Xia, J. Huang, and H. Wang, "LSTM-CNN Architecture for Human Activity Recognition," *IEEE Access*, vol. 8, pp. 56855–56866, 2020, https://doi.org/10.1109/ACCESS.2020.2982225.

[13] T. H. Tan, C. J. Huang, M. Gochoo, and Y. F. Chen, "Activity Recognition Based on FR-CNN and Attention-Based LSTM Network," in *2021 30th Wireless and Optical Communications Conference (WOCC)*, Taipei, Taiwan, Oct. 2021, pp. 146–149, https://doi.org/10.1109/WOCC53213.2021.9603203.

[14] F. Hernandez, L. F. Suarez, J. Villamizar, and M. Altuve, "Human Activity Recognition on Smartphones Using a Bidirectional LSTM Network," in *2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA)*, Bucaramanga, Colombia, Apr. 2019, pp. 1–5, https://doi.org/10.1109/STSIVA.2019.8730249.

[15] D. Yilmaz and İ. E. Büyüktahtakın, "Learning Optimal Solutions via an LSTM-Optimization Framework," *Operations Research Forum*, vol. 4, no. 2, Jun. 2023, Art. no. 48, https://doi.org/10.1007/s43069-023-00224-5.

[16] V. Aswal, V. Sreeram, A. Kuchik, S. Ahuja, and H. Patel, "Real-Time Human Activity Generation using Bidirectional Long Short Term Memory Networks," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, May 2020, pp. 775–780, https://doi.org/10.1109/ICICCS48265.2020.9121096.

[17] G. Mohmed, D. A. Adama, and A. Lotfi, "Fuzzy Feature Representation with Bidirectional Long Short-Term Memory for Human Activity Modelling and Recognition," in *Advances in Computational Intelligence Systems*, Portsmouth, UK, 2020, pp. 15–26, https://doi.org/10.1007/978-3-030-29933-0_2.

[18] V. B. Semwal, A. Gupta, and P. Lalwani, "An optimized hybrid deep learning model using ensemble learning approach for human walking activities recognition," *The Journal of Supercomputing*, vol. 77, no. 11, pp. 12256–12279, Nov. 2021, https://doi.org/10.1007/s11227-021-03768-7.

[19] P. Gong, C. Wang, and L. Zhang, "MMPoint-GNN: Graph Neural Network with Dynamic Edges for Human Activity Recognition through a Millimeter-Wave Radar," in *2021 International Joint Conference on Neural Networks (IJCNN)*, Shenzhen, China, Jul. 2021, pp. 1–7, https://doi.org/10.1109/IJCNN52387.2021.9533989.

[20] L. Alawneh, B. Mohsen, M. Al-Zinati, A. Shatnawi, and M. Al-Ayyoub, "A Comparison of Unidirectional and Bidirectional LSTM Networks for Human Activity Recognition," in *2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, Austin, TX, USA, Mar. 2020, pp. 1–6, https://doi.org/10.1109/PerComWorkshops48775.2020.9156264.

[21] "Workout Action Recognition in Video Streams Using an Attention Driven Residual DC-GRU Network," *Computers, Materials and Continua*, vol. 79, no. 2, pp. 3067–3087, May 2024, https://doi.org/10.32604/cmc.2024.049512.

[22] M. Alanazi, R. S. Aldahr, and M. Ilyas, "Human Activity Recognition through Smartphone Inertial Sensors with ML Approach," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12780–12787, Feb. 2024, https://doi.org/10.48084/etasr.6586.

[23] A. Dey, S. Biswas, and L. Abualigah, "Efficient Violence Recognition in Video Streams using ResDLCNN-GRU Attention Network," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 18, no. 3, pp. 329–341, Jul. 2024, https://doi.org/10.37936/ecti-cit.2024183.255679.

[24] A. Tehrani, M. Yadollahzadeh-Tabari, A. Zehtab-Salmasi, and R. Enayatifar, "Wearable Sensor-Based Human Activity Recognition System Employing Bi-LSTM Algorithm," *The Computer Journal*, vol. 67, no. 3, pp. 961–975, Apr. 2024, https://doi.org/10.1093/comjnl/bxad035.

[25] G. Bhola and D. K. Vishwakarma, "A review of vision-based indoor HAR: state-of-the-art, challenges, and future prospects," *Multimedia Tools and Applications*, vol. 83, no. 1, pp. 1965–2005, Jan. 2024, https://doi.org/10.1007/s11042-023-15443-5.

[26] S. Mekruksavanich and A. Jitpattanakul, "Deep Convolutional Neural Network with RNNs for Complex Activity Recognition Using Wrist-Worn Wearable Sensor Data," *Electronics*, vol. 10, no. 14, Jul. 2021, Art. no. 1685, https://doi.org/10.3390/electronics10141685.

[27] S. Gupta, "Deep learning based human activity recognition (HAR) using wearable sensor data," *International Journal of Information Management Data Insights*, vol. 1, no. 2, Nov. 2021, Art. no. 100046, https://doi.org/10.1016/j.jjimei.2021.100046.