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Original Article

An Advanced Deep Learning Structure for Accurate Student Activity Recognition and Health Monitoring Using Smartphone Accelerometer Data

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Abstract

Introduction: The rise of smartphone sensors, especially accelerometers, has expanded the scope of Human Activity Recognition (HAR). HAR plays a key role in monitoring student health by offering real-time insights into physical activity and promoting healthier behaviors. This study aimed to develop an optimized deep-learning model to monitor and classify student activities, using accelerometer data for real-time health monitoring.

Methods: This study developed and optimized a novel deep learning framework using a modified version of Bidirectional Long Short-Term Memory (BiLSTM) networks, enhanced by the Grey Wolf Optimizer (GWO). The BiLSTM framework automates the feature learning process from raw accelerometer data, while GWO optimizes the hyperparameters to improve sequence processing and overall model performance. We employed public datasets, UCI-HAR and WISDM, for validation, using cross-validation to ensure model robustness. The edge computing approach was implemented to enable real-time processing.

Results: The proposed BiLSTM-GWO framework achieved a classification accuracy of 97.68%, outperforming existing methods in recognizing student activities. The model showed enhanced performance in distinguishing between activities such as walking, sitting, and stair climbing, significantly reducing misclassification errors. In addition to accuracy, metrics such as precision, recall, and F1 score were evaluated, all showing improvement. GWO optimization also accelerated convergence, enhancing suitability for real-time applications.

Conclusions: The integration of edge computing into the framework provides real-time analysis and resource efficiency, making it highly suitable for health monitoring applications in educational settings.

Keywords: Deep learning, Student activity recognition, Health monitoring, Smartphone accelerometer, BiLSTM-GWO optimization

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Introduction

Human Activity Recognition (HAR) offers a range of practical applications, including detecting suspicious behavior, monitoring individuals, and especially monitoring patients and students in healthcare and educational environments (1). HAR is the process of automatically identifying and classifying human actions using data from videos and sensors like accelerometers and gyroscopes in smartphones or wearables. HAR is crucial in applications like health monitoring, fitness tracking, and security by providing real-time insights into physical movements. It involves collecting sensor data and using machine learning or deep learning models to classify activities. HAR structures are widely used in different domains, such as urban area studies (2, 3), medical treatment (4), student health monitoring (5), gait analysis (6, 7), human behavior analysis (8), and everyday activity monitoring (9). These systems can be divided into sensor-based or vision-based categories based on the type of information they handle. Notably, HAR models provide numerous research benefits, such as location independence, energy efficiency, ease of use, accessibility, and cost-effective installation. Sensor data collection forms the core of HAR systems, with commonly used sensors including accelerometers, gyroscopes, and magnetometers embedded within digital devices like smartwatches and smartphones (10).

Monitoring student physical activity and health is essential, given its significant role in improving academic performance and fostering healthier lifestyles. Monitoring student health is becoming increasingly crucial in educational institutions due to its direct impact on both academic performance and long-term well-being. The ability to continuously track physical activity and health metrics in real-time allows educators and health professionals to intervene at critical moments, preventing potential health issues before they escalate. By incorporating advanced HAR systems into schools, we can ensure that students maintain a healthy balance between academic responsibilities and physical activity, contributing to better mental and physical health outcomes. This continuous health monitoring, supported by edge computing and real-time data analysis, creates a safer and healthier environment for students, ultimately fostering improved educational experiences. By tracking student activity, valuable insights into their physical health can be obtained, benefiting both educators and students. Advances in wearable technology and HAR enable precise monitoring of student activity levels. This level of monitoring is crucial for preventing long-term health issues and promoting well-being among students. Research suggests that a system combining Internet of Things (IoT) sensors and machine learning (ML) can effectively assess participation in physical education, particularly at the university and high school levels, leading to improvements in students' social, emotional, and physical well-being (11,12). Additionally, methods like Teaching Personal and Social Responsibility (TPSR) have been shown to positively impact personal and social development among secondary school and college students, promoting lifelong physical activity and healthy behaviors (13). These programs also contribute to managing student lifestyles within educational institutions. Integrating IoT sensors and smart technologies into educational settings enhances the ability to monitor student well-being and detect potential health risks early, allowing for timely interventions (14). By monitoring students' daily activities, educators can tailor their teaching approaches to better cater to individual needs. Implementing IoT sensors in student health monitoring and activity recognition systems can enhance health management and reduce the likelihood of medical emergencies by providing real-time data on vital signs (15).

Based on these applications, HAR using smartphone accelerometer data emerges as a crucial research area with potential benefits for health monitoring, fitness tracking, and improving educational environments. Automated systems have proven highly effective in signal analysis and image/video processing, particularly when employing ML and, more recently, deep learning (DL) techniques. A study by Saha et al. (16) focused on using accelerometer data to distinguish six activities performed by smartphone users: sitting, standing, lying down, walking, climbing stairs, and descending stairs, conducted at universities in India. Supervised machine learning algorithms, trained on accelerometer data collected from 16 individuals during their daily routines, successfully predicted these activities with 95.99% accuracy. Embedded sensors, coupled with anomaly detection methods, can identify data samples that deviate from the norm (17).

However, ML methodologies are typically favored when there are adequate labeled databases, sufficient processing power, clear feature extraction methods, and limited training time. Despite their benefits, ML techniques do have certain constraints. First, they cannot handle large unlabeled datasets, requiring domain expertise for processing large amounts of unlabeled data. Moreover, there is no standardized approach for feature extraction in ML. Deep learning (DL) methods (e.g., Region-based CNNs, YOLO architecture, and Recurrent neural networks) are recommended to address these challenges (18). DL algorithms excel at optimizing themselves through simultaneous training and feature extraction.

Studies have shown that utilizing Convolutional Neural Networks (CNNs) significantly improves temporal data extraction in HAR tasks (19-22). Researchers in (23) proposed a more advanced CNN architecture with enhanced convolutional layers and the removal of pooling layers. Another study (24) has introduced an HConvRNN architecture that utilizes multimodal sensors for action recognition. This hierarchical architecture integrates Recurrent Neural Networks (RNNs) with CNNs, achieving superior results compared to benchmark methods in typical indoor settings. To improve HAR performance, a 4-layer hybrid architecture combining Long Short-Term Memory (LSTM) with CNNs was proposed (25). A key finding of this research is that a 4-layer LSTM and CNN hybrid architecture achieved a significant 2.24% improvement in activity recognition accuracy compared to previous state-of-the-art methods.

Luwe et al. (26) further explored DL for HAR using wearable sensors. Their proposed 1D-CNN-Bidirectional LSTM (BiLSTM) structure integrates a 1D-CNN with a BiLSTM network. One-dimensional CNNs excel at extracting important patterns from sensor-generated time series data. The BiLSTM system, with its unique gate mechanisms, effectively encodes long-range dependencies within the feature connections. This powerful combination yielded impressive recognition rates: 94.17% on Motion Sense, 95.48% on the University of California Irvine (UCI)-HAR database, and a perfect 100% on Single Accelerometer data (27).

This research focuses on the critical need for student health monitoring, proposing a novel framework that utilizes smart phone accelerometer data to monitor student physical activity and well-being in real time. Our approach leverages Bidirectional LSTMs and GWO optimization to improve the accuracy, precision, and scalability of HAR tasks, particularly for tracking student health metrics. This methodology automates feature extraction and optimizes the model architecture, addressing limitations inherent to traditional machine-learning methods. The key contributions of this article are as follows:

1. Optimized BiLSTM frameworks for student health monitoring: We propose a modified BiLSTM framework that utilizes smartphone accelerometer data to accurately identify student behaviors in classrooms. This approach has been validated using two datasets, demonstrating its effectiveness as a rapid information processing tool for real-time health monitoring and student activity analysis. Compared to current state-of-the-art strategies, our approach achieves superior performance in terms of F1 score, sensitivity, precision, and accuracy.
2. In-Depth student activity analysis with deep learning: Our mixed DL framework enables a more comprehensive and precise evaluation of student activity information. By utilizing DL algorithms and accelerometer information from smartwatches, the structure can detect patterns in student behavior, promoting healthier habits through monitoring overall fitness levels, sedentary behavior, and exercise routines.
3. Skipping the server for faster analysis: Instead of sending all the data to a central computer, this system analyzes important health information on the device (like a smartwatch) or a nearby device. This keeps things speedy, allowing quicker decisions and responses, which is especially important for real-time applications.

Materials and Methods

We tracked student activity with smartphone accelerometers to understand their health. Figure 1 shows how we built a method to assess their fitness levels during various activities.

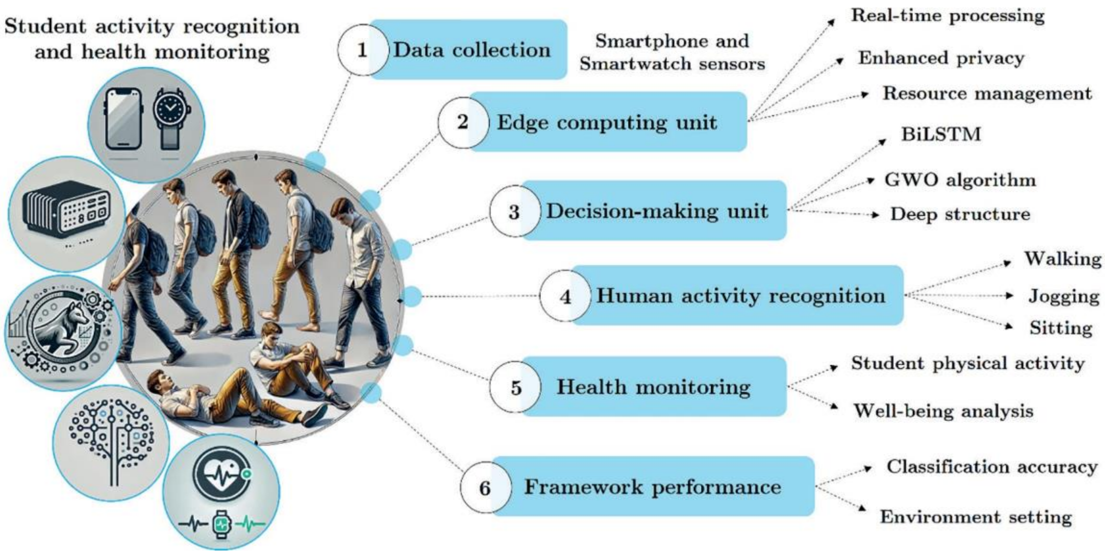

Figure 1: This figure shows a system that uses a combination of deep learning techniques and data from smartphone accelerometers (processed with edge computing) to identify student activities and track their physical health.

We designed a special program usings martwatches to record student data. To ensure transparency, we relied on two public datasets (UCI and Wireless Sensor Data Mining or WISDM) containing data collected from multiple participants (28).

Datasets

The UCI HAR dataset we used includes activity data from 30 people who used Samsung Galaxy S II smartphones (27). These data include signals from a gyroscope (50 Hz) and a three-axis accelerometer. Table 1 shows the number of samples for the acceleration signals in this dataset. Before analysis, we cleaned the sensor data by applying a filter to remove noise. We then used a sliding window approach to collect the data in fixed-sized segments (2.56 seconds) with 50% overlap between windows. Finally, we separated the total acceleration measured by the sensors into body movement and gravity using a Butterworth low-pass filter with a cutoff frequency of 0.3 Hz (effective for removing low-frequency gravity).

To analyze the activity data, we divided it into short segments (windows) and calculated various properties from each segment. These properties considered both how the data changed over time (time domain) and its frequency components (frequency domain). There are 561 properties in total, and details about them can be found in (27). The UCI dataset we used has 7,352 segments for training and 2,947 for testing, for a total of 10,299 segments.

The second dataset we used is called WISDM (28). It contains gyroscope and accelerometer data collected from 51 students utilizing Samsung (Galaxy-S5 model) smartphones. Moreover, all contributors performed 18 different activities (listed in Table 2) for an average of 3 minutes each, resulting in about 70 minutes of data per person. The data were collected at 20 Hz, and each segment was 10 seconds long with 200 readings. We extracted 92 features from each segment's raw data. The dataset had 16,151 segments for training and 6,923 for testing.

Table 1: The sample numbers from the UCI HAR dataset, focusing on acceleration signal data

Activity Category	Testing Sample Count	Training Sample Count
Walking	496	1226
Sitting	491	1286
Walking downstairs	420	986
Lying	537	1407
Standing	532	1374
Walking upstairs	471	1073
Total	2947	7352

Table 2: The number of samples in the WISDM Activity Recognition dataset

No. Samples	Abbreviation	Activity Category
1413	Drib	Dribbling
7352	Br_Tth	Brush Teeth
1242	E_san	Eat sandwich
1374	E_cip	Eat chips
1271	Wlk	Walking
1261	F_Clt	Fold clothes
1180	Str	Stairs
1283	Stn_upstr	Standing upstairs
1314	Jagg	Jogging
1431	Ctc	Catch
1226	Drk	Drinking
1180	Dwn_Str	Typing downstairs
1466	Kik	Kicking
1241	Wrt	Writing
1263	Sit	Sitting
1286	E_sup	Eat soup
1270	Clp	Clapping
1407	E_pas	Eat pasta
23074	-	Sum total

Distributed Computing Platform

Edge Computing processes data near its source, such as on smartphones or IoT devices, minimizing the need to send large datasets to central servers. This reduces latency, increases privacy, and optimizes bandwidth use. In contrast, Distributed Computing spreads tasks across multiple servers or devices, often over vast distances, to handle large-scale computations. While Distributed Computing excels in managing complex, distributed tasks through coordinated systems, Edge Computing emphasizes local, real-time processing, enabling faster decisions without constant communication with a central server. Essentially, Edge Computing focuses on quick, local actions, whereas Distributed Computing manages more extensive, coordinated operations across multiple nodes. Leveraging edge computing eliminates the need to transmit large datasets to a central server unit. Thus, this enables real-time analysis of student activity and health data directly on the wristwatch or a nearby device. Hence, this facilitates faster responses and informed decisions regarding students' health and physical education. Processing data at the edge, as opposed to a distant cloud, minimizes processing latency, which is critical for timely interventions in student health monitoring, especially during emergencies. Edge computing also bolsters student privacy and data security by minimizing the transmission of sensitive health and activity data across networks. Additionally, it allows for customization of analytical algorithms to cater to individual needs or health situations. This empowers personalized health monitoring and activity tracking for each student. Finally, edge computing facilitates distributed analysis, enabling several devices to handle student activity and health data simultaneously.

Optimized BiLSTM

In this section, we describe the optimization of the BiLSTM architecture using the Grey Wolf Optimizer (GWO). The performance of BiLSTM largely depends on the selection of optimal hyperparameters, such as the number of neurons in each layer, the number of layers, and the learning rate. To improve the performance of the BiLSTM, we employed the GWO (Figure 2), a nature-inspired metaheuristic algorithm that mimics the hunting behavior and social hierarchy of grey wolves in nature (29). The GWO algorithm optimizes complex functions by balancing exploration and exploitation phases, making it well-suited for tuning the hyperparameters of classifiers.

Moreover, the GWO simplifies the process of finding optimal hyperparameters for BiLSTM by mimicking the natural hunting behavior of grey wolves. Instead of manually testing countless configurations, GWO enables the model to “hunt” for the best solution by balancing exploration (searching for new possibilities) and exploitation (focusing on the best options). The algorithm organizes the search into a hierarchy where leading wolves (alpha, beta, and delta) guide the optimization, while the remaining wolves adjust their positions accordingly. This dynamic

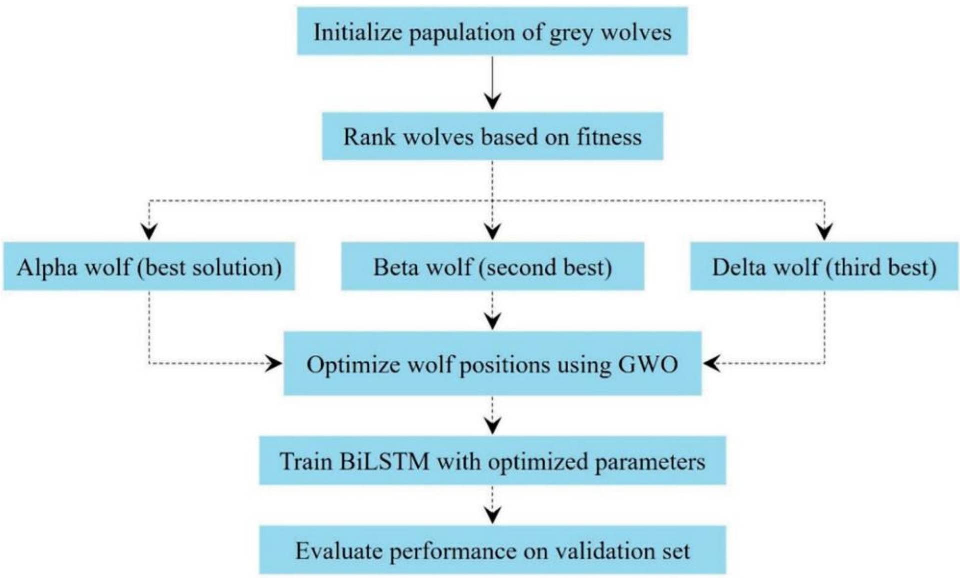

Figure 2: The optimization steps of the GWO algorithm applied to BILSTM networks.

process ensures that the algorithm converges on the optimal hyperparameters, resulting in improved performance for time-series prediction tasks. By utilizing GWO, BiLSTM achieves greater accuracy, faster convergence, and better computational efficiency without the need for exhaustive manual tuning.

The optimization process begins with the initialization of a population of candidate solutions, referred to as grey wolves, each representing a unique set of BiLSTM hyperparameters. These wolves are ranked based on their fitness, which is determined by evaluating the BiLSTM model's performance on a validation dataset. The top-ranked wolves, known as alpha, beta, and delta, guide the search process, while the remaining wolves update their positions based on these leaders. During each iteration, the positions of the wolves are adjusted to converge towards the optimal solution.

This adjustment is governed by the GWO's encircling mechanism and hunting strategies, which involve calculating the distance between wolves and the prey (optimal solution) and dynamically updating their positions. The convergence of the wolves towards the prey ensures that the BiLSTM's hyperparameters are fine-tuned for improved predictive accuracy and generalization.

By integrating GWO with BiLSTM, we achieve a robust and efficient framework for time-series prediction and sequence modeling tasks. The optimized BiLSTM model, tuned using GWO, illustrates superior performance in terms of accuracy, convergence speed, and computational efficiency in comparison to previous methods.

Results

We tested our model's ability to handle various activity states using a recommended classifier. The data were divided into testing and training sets. To ensure robust evaluation, we employed 5-fold cross-validation stratified by student (subject). This technique allows us to assess the model's performance and achieve a reliable validation set.

We compared four different models on data from smartphone accelerometers. The analysis revealed that the BiLSTM-GWO algorithm outperformed the others. It had the fastest processing speed and fewest parameters and delivered the best results. This demonstrates the effectiveness of our methodology for smart grid applications that utilize accelerometers in cell phones to predict load signals in real time. We had four similar methods: Bi-LSTM, LSTM with the GWO algorithm, Bi-LSTM with the GWO algorithm, and an optimized version of Bi-LSTM with the GWO algorithm. We named them Model 1, Model 2, Model 3, and Model 4, respectively

To assess a model's effectiveness, we analyzed its specificity, sensitivity, and accuracy. These metrics present insights into the overall number of accurate predictions. Table 3 compares the results obtained from applying our methods to the WISDM and UCI databases. The table showcases the model's F1-score, Recall, and precision for different activity classes in the UCI dataset.

Interestingly, the accuracy for "Walking upstairs" and "Walking downstairs" is lower than that for other activities. Additionally, these two classes are more likely to be misclassified compared to other combinations. In contrast, the model achieves the highest accuracy for the "Lying" state. These observations suggest that the model performs well for stationary activities but may struggle to differentiate between similar movement patterns like walking downstairs and upstairs. Nonetheless, the overall performance demonstrates the model's robustness across

Table 3: Comparison of the outcomes achieved from the suggested approach with similar models for the average of multiple replicate groups of 5-fold, separately for UCI and WISDM data.

Dataset	Strategy	AVG. of 5-folds				
		Accuracy	Specificity	Sensitivity	Precision	F1-measure
UCI	Model 1	0.9402	0.9505	0.9451	0.9437	0.9417
	Model 2	0.9507	0.9605	0.9554	0.9531	0.9519
	Model 3	0.9650	0.9756	0.9705	0.9685	0.9663
	Model 4	0.9805	0.9912	0.9856	0.9833	0.9810
WISDM	Model 1	0.9253	0.9354	0.9308	0.92875	0.9260
	Model 2	0.9354	0.9456	0.9408	0.93875	0.9361
	Model 3	0.9507	0.9606	0.9554	0.95375	0.9518
	Model 4	0.9656	0.9758	0.9707	0.9685	0.9674

various activity states. Similar performance metrics were calculated for the second dataset (WISDM) but with some excluded human actions. These activities might not be relevant to the educational setting where the model is intended for use. However, the excluded actions did not significantly impact the overall accuracy, as the standard deviation remained low.

Within the WISDM dataset, “Catch,” “Kicking,” and “Sitting” were classified with higher accuracy compared to other classes. On the other hand, “Drinking” and “Clapping” activities displayed lower accuracy. These results present significant insights into the model’s strengths and weaknesses in recognizing different human activities.

A comparison of the performance of three similar models with the proposed method, Model 4, on two datasets, UCI and WISDM, based on all estimated metrics shows that Model 4 has significantly improved most metrics compared to the other models (Figure 3). These results indicate that using Model 4 can enhance accuracy, recall, F1-score, and other evaluation indices, making it an effective method for analyzing UCI and WISDM data.

Moreover, Figure 4 presents the confusion matrix from the classification of activities in the WISDM Activity Recognition dataset. This matrix evaluates the performance of the proposed BiLSTM-GWO model, where each row represents the predicted activity, and each column represents the actual activity. The diagonal cells indicate correctly predicted instances for each class, while off-diagonal cells represent misclassifications.

The model demonstrates high accuracy for activities such as “Brush Teeth” (Br_Tth), “Catch” (Ctc), and “Kicking” (Kik), as reflected by their strong diagonal values. However, there is some confusion between similar activities, particularly those that involve similar movements. For example, the “Sitting” (Sit) class shows misclassifications with activities like “Typing downstairs” (Dwn_Str), indicating a challenge in distinguishing between static postures and subtle movements. Overall, the model performs well across various activities, but further refinement could reduce misclassification in similar categories.

Evaluating the model’s accuracy necessitates verifying metrics like the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve. Widelyadoptedcriteriaandreference points for assessing students’ health and physical activityofferdependablemeasuresforcomparison. Harmonizing the ROC curve’s results with these

Figure 3: Model 4 outperformed three similar models on UCI and WISDM datasets, showing significant improvements in accuracy, recall, and F1-score. This highlights its effectiveness in data analysis.

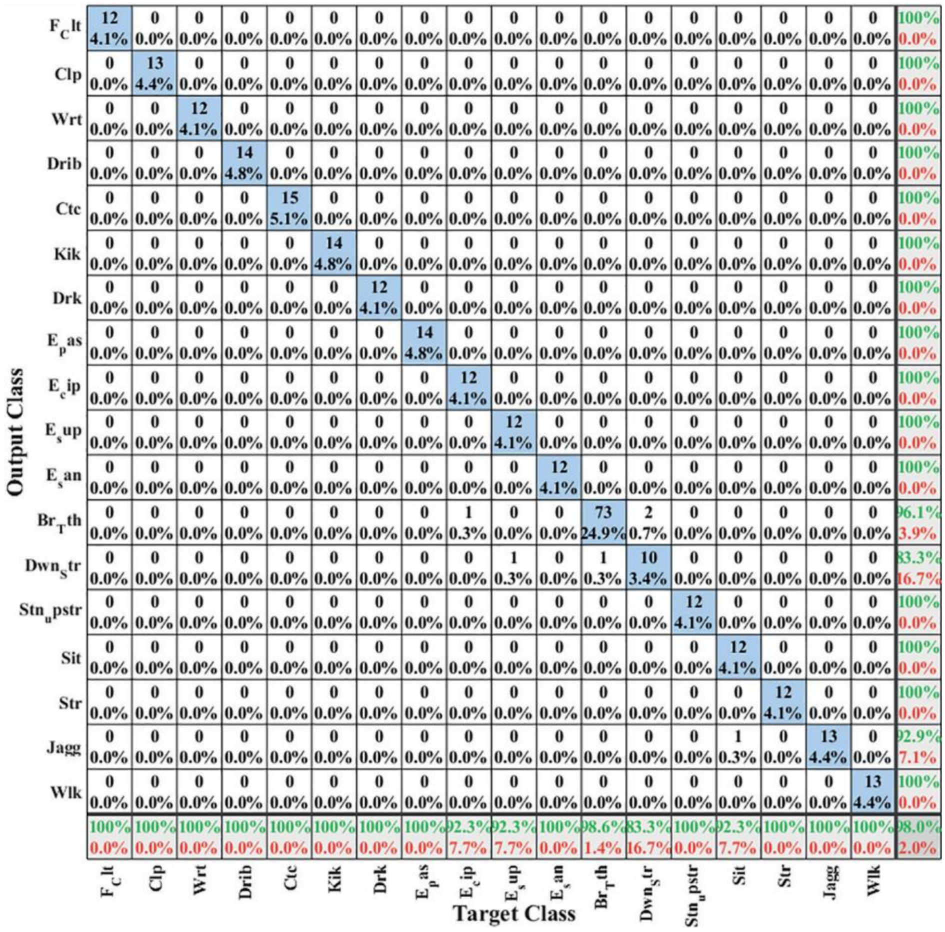

Figure 4: Confusion matrix for the WISDM Activity Recognition dataset classification, showing the distribution of correctly and incorrectly predicted activity categories.

established benchmarks enhances both reliability and consistency. To guarantee the accuracy and dependability of AUC measures for student activity and physical health evaluation, it is vital to conduct separate validation studies that utilize a variety of data sources. These studies should compare the findings to established standards and consider longitudinal data analysis. Figure 5 depicts the generated ROC charts for both datasets, visualizing the model's performance in classifying undetectable acceleration signals from smartphones. The estimated AUC values suggest the model's proficiency in evaluating both student activities and physical health. Moreover, Figure 5 compares the performance of the GWO optimization method for the BiLSTM architecture using the ROC curve against the genetic algorithm (GA) and particle swarm optimization (PSO) methods. The GWO method outperformed the genetic algorithm (GA) and particle swarm optimization (PSO) methods, effectively fine-tuning the BiLSTM parameters better than the other two algorithms.

Discussion

This paper proposes optimizing the BiLSTM architecture's hyperparameters using the GWO algorithm. The proposed GWO-BiLSTM deep learning technique classifies student movement data obtained from smartphone accelerometers to recognize different activities. Hence, our strategy outperforms existing approaches like deep decision fusion (30), LGSRNet (31), CNN variants (32, 33, 35-38), and methods based on handcrafted features (33). Table 4 provides a comparative analysis of the proposed method versus previous research using the WISDM and UCI datasets. The findings demonstrate our model's superior precision, achieving the highest accuracy among the compared methods.

The GWO-BiLSTM model demonstrates significant advantages over other approaches for recognizing student physical activities. Compared to CNNs, GWO-BiLSTM excels when dealing with time-series signals like student movement data, where CNN performance can be limited.

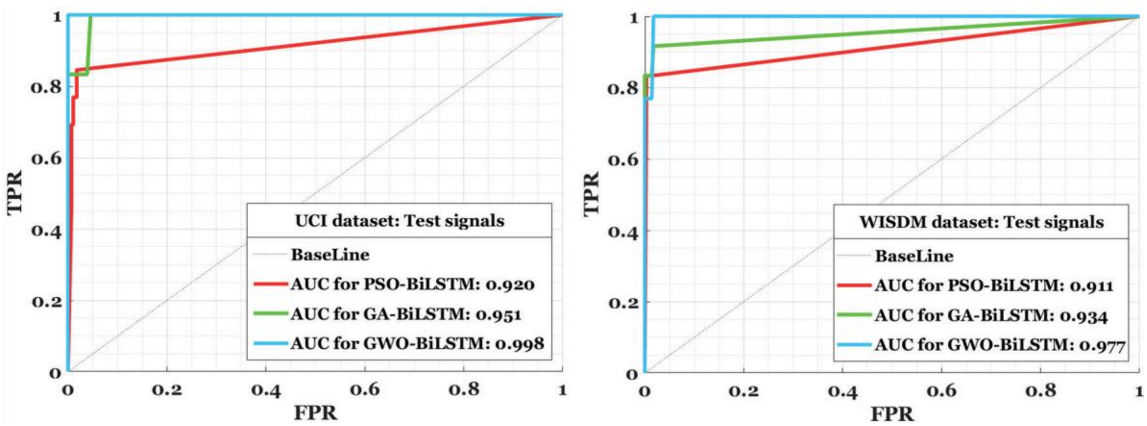

Figure 5: Performance comparison of the GWO optimization method for the BiLSTM architecture using the ROC curve, against the GA and PSO methods, is shown in the left image for UCI dataset analysis, and in the right image for WISDM dataset analysis.

Table 4: A comparative evaluation of the proposed approach against other methods, using the WISDM and UCI datasets

Ref.	Data	Accuracy	Strategy
Xiao et al. (10)	UCI	97.56%	Bayesian-BiLSTM
	WISDM	97.30%	
Zhang et al. (30)	UCI	97.81%	Deep decision fusion
	WISDM	85.00%	
Zheng et al. (31)	UCI	97.32%	LGSR-Net
Li et al. (32)	UCI	97.12%	Improved features and CNN structure
Friday et al. (33)	UCI	96.90%	Hand-crafted attributes and CNN
Kolosnjaji et al. (34)	UCI	96.17%	PCA and Transfer learning model
Jiang et al. (35)	UCI	95.25%	CNN structure
Kim et al. (36)	UCI	95.18%	CNN structure
Zheng et al. (37)	UCI	94.79%	CNN structure
Wan et al. (38)	UCI	93.21%	CNN structure
Proposed model	UCI	98.10%	GWO-BiLSTM
	WISDM	97.59%	

GWO-BiLSTM also surpasses the Handcrafted Features approach. This highlights the strength of deep learning models in automatically and flexibly extracting knowledge from complex data, eliminating the need for time-consuming and error-prone manual feature engineering.

Furthermore, GWO-BiLSTM exhibits superior accuracy compared to LGSRNet and Deep Decision Fusion techniques. This suggests its superior ability to handle intricate and diverse datasets, potentially due to its enhanced capacity to integrate and utilize large amounts of data for informed decision-making. Overall, GWO-BiLSTM offers superior performance in accurately recognizing various student physical activities, especially when dealing with dynamic signals and time-series sequences.

Moreover, edge computing utilizes devices like smartphones, edge servers, or Internet of Things (IoT) nodes for local processing and inference. This approach often requires fewer resources compared to centralized cloud servers. Therefore, GWO-BiLSTM is well-suited for edge computing tasks demanding low processing power, enabling real-time classification on resource-constrained devices. The GWO-BiLSTM strategy consists of two key components: 1) This component excels at automatically extracting features from raw accelerometer information, eliminating the need for human intervention in feature engineering, 2) This optimization procedure combines existing knowledge with newly acquired information to identify the optimal parameters for the BiLSTM network. Notably, a GWO approach can be used for offiine parameter optimization by predicting the probability distribution of successful optimization. This allows the GWO-BiLSTM algorithm to run offiine. Several promising avenues exist for further research.

One of the main limitations we faced in this research was the challenge of working with the available datasets. The small size of the UCI

HAR and WISDM datasets, with only 30 and 51 participants may not adequately represent the broader population, particularly in applications where the model needs to be generalized to larger or more diverse groups. Additionally, while these datasets cover a range of activities, their scope is limited and does not include more complex or varied activities commonly encountered in real-world settings, such as multitasking or activities performed in uncontrolled environments. This restricts the model's ability to recognize a wider spectrum of behaviors effectively. Moreover, the datasets are drawn from a small, specific group that may not fully represent diverse age, gender, or cultural demographics, which could affect the model's generalizability. Lastly, these datasets primarily focus on accelerometer data, with limited use of other sensors, such as gyroscopes and magnetometers. Incorporating multiple sensors could improve accuracy and provide deeper insights into activity recognition.

In addition, in many educational settings, particularly in underfunded schools, access to the necessary infrastructure for implementing smart health monitoring systems may be limited. Schools may require investments in smart devices, stable Internet connections, and cloud-based processing solutions to fully utilize such systems. Partnerships with governmental bodies and private organizations could help bridge these gaps and ensure wider adoption. Another potential challenge is the cost associated with implementing such systems, particularly in providing the necessary smart devices and infrastructure. However, collaborations with educational institutions and securing funding from government or private organizations could offset these costs and make the implementation more feasible.

The broader implications of this study extend beyond the student population, as the framework can be adapted to other domains such as healthcare for monitoring patient recovery, fitness tracking for athletes, or even workplace health management. The edge computing integration allows for real-time analysis and decision-making, which is crucial in these applications for timely interventions and personalized health monitoring. This adaptability makes the model relevant across diverse contexts, including smart city initiatives and elderly care systems.

We fine-tune the hyperparameters of the BiLSTM model by experimenting with different configurations and settings. We aim to incorporate techniques that adapt to changing training parameters. This may involve learning rate schedules or automated adjustment systems based on model performance over time. Incorporating data from additional sensors like magnetometers and gyroscopes may provide a more comprehensive understanding of student's well-being and physical movements. Ultimately, we plan to implement the proposed system in a real-world setting and gather user feedback. This allows us to refine the model, improve its usability, and address any potential issues.

Conclusion

This research presents a robust framework for identifying student activities using smartphone accelerometer data, employing a BiLSTM-GWO (Bidirectional Long Short-Term Memory with Grey Wolf Optimizer) model. The integration of deep learning techniques with edge computing allowed for real-time health monitoring, ensuring timely interventions and personalized analysis of students' physical activity and well-being. The proposed model demonstrated significant improvements in terms of accuracy, sensitivity, precision, and F1 score when compared to traditional machine learning approaches and state-of-the-art deep learning methods. The application of GWO optimization enhanced the model's efficiency, providing superior results in recognizing complex activity patterns from accelerometer data. The broader implications of this study extend beyond student health monitoring. The versatility of the BiLSTM-GWO model enables its adaptation to several domains, including healthcare, fitness tracking, and workplace health management. The integration of edge computing facilitates fast, local analysis, which is essential for real-time applications, making the system suitable for broader use in smart cities, elderly care, and other dynamic environments. By incorporating this system, institutions can promote healthier lifestyles, prevent health issues, and foster better mental and physical well-being.

Future research should explore adapting the proposed framework to other populations, such as the elderly or individuals with special needs, to better capture diverse physical activities and health requirements. Additionally, integrating additional sensors, such as gyroscopes and magnetometers, could provide more detailed data, improving accuracy and expanding the range of recognizable activities. Incorporating online learning algorithms would allow the system to continuously update and improve its performance based on new data, enhancing its adaptability across different environments. Lastly, real-world implementations and user feedback could offer valuable insights into further refining the model and enhancing its practical usability, paving the way for broader adoption of smart health monitoring systems.

Accessibility of Data and Resources

The data used in this research comes from freely accessible online repositories. All the data we analyzed or generated is included in the article and its additional files. The data sources are from WISDM (http://www.cis.fordham.edu/wisdm/) and UCI datasets (http://archive.ics.uci.edu/dataset/240/human+activity+recognition+using+smartphones).

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Approval of Ethics for Studies Involving Animals and Human Participants

Since the authors used well-established and publicly available datasets from external sources, with ethical considerations in mind during dataset development by the original providers, no further ethical approval or consent is required for this study.

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Conflict of Interest

There are no conflicts of interest.

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