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FUTURE HUMAN ACTIVITY PREDICTION USING WAVELET AND LSTM

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ABSTRACT

Future Human Activity Prediction holds significant importance as it enables early detection and monitoring of various aspects, such as elderly care, early fall detection systems, smart-home applications, and E-health monitoring.

A pioneering approach has been developed to achieve this, incorporating the Wavelet transform preprocessing technique for dimensional reduction through signal decomposition. This is followed by the implementation of a deep learning model supported by time series data, enabling real-time monitoring of physical activity.

A novel method has been proposed based on wearable sensor data sources, employing LSTM and time series models, and applied with MHEALTH Dataset. This dataset comprises 12 complex activities and sensor-based devices, ensuring the privacy of patients or participants in real-life scenarios. The results demonstrate that the predicted activity of five steps with an accuracy level for the next day's activity achieved an accuracy of 98%, surpassing the accuracy and complexity compared with state-of-the-art methods.

KEYWORDS: Deep Learning; predict_future_activity; Convolution Neural Network; Long Short-Term Memory; Wearable Sensor; Recurrent Neural Network, Human Activity Recognition.

1. INTRODUCTION

Predicting future human activity based on wearable sensor data by a growing body of knowledge as follows: Authors in [1] propose a system that uses wearable sensor data and deep learning techniques to predict daily physical activities. The system collects data on various parameters such as heart rate, acceleration, and skin temperature, and uses a deep neural network (DNN) model to predict future activities. The authors suggest that this type of system could have potential applications in healthcare, wellness, and sports training; while in [2] proposes a system that uses wearable sensors for activity recognition and prediction in smart healthcare. The system collects data on various parameters such as heart rate, step count, and sleep patterns, and uses a support vector machine (SVM) model to predict future activities. The authors suggest that this type of system could have potential applications in healthcare, wellness, and assisted living. This paper introduces the following contributions:

1. Use powerful feature extraction which had been never used before in human activity prediction using wavelet function of signal processing is applied to reduce the dimensionality of the data and linear encoder to handle multiclass Classification by converting them from strings to integers.

2. Design a robust model that combines The first layer is an LSTM layer with 32 units and a sequence input shape of (n_timesteps, n_features). The return_sequences parameter is set to True to enable the LSTM layer to output a sequence rather than a single value.

3. Propose a novel framework system which is LSTM methods introduce a temporal model then the LSTM layer to especially used for future prediction rather than a traditional spatial temporal model, LSTM model is trained using the Adam optimizer and the sparse categorical cross-entropy loss function.

4. The framework introduced in this work is the first paper method used by using sensor data rather than state-of-the-art using one step only in [3] and video source data in [4] which is not preferred as a source for capturing activities due to privacy for human especially in health care applications.

1.1 Smartphone Sensors:

Components in smartphones detect and measure various physical phenomena, such as motion, orientation, light, sound, temperature, and more. These sensors are integrated into the phone's hardware, allowing various apps and services to interact with the physical environment.

The following are common smartphone sensors and their functions:

Accelerometer: measures the phone's acceleration and orientation, allowing it to detect when the phone is being tilted or moved.

Gyroscope: Measures the phone's rotation around its three axes, enabling it to determine its position and orientation in 3D space.

Magnetometer (Compass): Detects magnetic fields, allowing the phone to determine its orientation relative to magnetic north.

Proximity Sensor: Measures the distance between the phone and an object, allowing it to turn off the screen when the phone is held up to the ear during a call.

Ambient Light Sensor: Measures the amount of light in the environment and adjusts the screen brightness accordingly.

Barometer: Measures atmospheric pressure, allowing the phone to determine changes in altitude and provide altitude-related data to apps.

GPS (Global Positioning System): Uses satellite signals to determine the phone's location, enabling location-based services such as maps and navigation.

These sensors are used in a variety of applications, including gaming, fitness tracking, augmented reality, and virtual reality. They are also used for security purposes, such as unlocking the phone with facial recognition or fingerprint scanning.

1.2 Dataset Analytical Results

The dataset involved ten volunteers with diverse profiles who participated in various physical activities. The participants' body motion and vital signs were recorded using sensors placed on their chest, right wrist, and left ankle. These sensors measured factors such as acceleration, rate of turn, and magnetic field orientation, providing data on the movement experienced by different parts of the body. The data collected for each participant was stored in separate log files named 'mHealth_subject<SUBJECT_ID>.log'. Each log file contained rows of samples corresponding to different sensors and columns representing the recorded data.

The activities performed by the participants were labeled as follows:

L1: Standing still (1 minute)
L2: Sitting and relaxing (1 minute)
L3: Lying down (1 minute)
L4: Walking (1 minute)
L5: Climbing stairs (1 minute)
L6: Waist bends forward (20 repetitions)
L7: Frontal elevation of arms (20 repetitions)
L8: Knees bending (crouching) (20 repetitions)
L9: Cycling (1 minute)
L10: Jogging (1 minute)
L11: Running (1 minute)
L12: Jumping front & back (20 repetitions)

Numbers in brackets indicate the number of repetitions (Nx) or the duration of the exercises (minutes).

2. LITERATURE REVIEW

Forecasting the future poses certain challenges due to the scarcity of available data. Most classification models, therefore, focus on predicting near-term outcomes, such as human movements, without explicitly referring to future events. (DBN), which takes as input manipulated objects and performed actions accuracy is 94%, Objects and actions are separately classified starting from RGB-D raw data [3] The results show that our label prediction approach performed by the proposed sequence-to-sequence learning system tested on different activity analysis datasets and a video description dataset utilizes a network that includes three separate branches: extracts visual features, takes sequential activity features from the observed events, and the third branch captures the features of the last observed activity.

Authors in [5] exhibit superior performance compared to existing methods on two widely recognized benchmarks for predicting future trajectories and generate insightful predictions not only for future paths but also for the corresponding activities. Various methods have been proposed to utilize LSTM sequences in different ways. In one approach, LSTM layers were placed before the Convolution layer (LSTM-CNN) as proposed by the author in [6]. Another approach involved placing sequential Convolution and dropout layers before the LSTM layer (CNN-LSTM) [7]. In [8], parallel LSTM layers (Parallel LSTM-CNN) were combined with the Convolution layer. A novel hybrid deep learning model was proposed in [9] for activity recognition, which coupled a CNN-LSTM with the self-attention algorithm to enhance its predictive capabilities. This model was evaluated by Mhealth datasets. On the other hand, [10] proposed a unique approach to activity recognition using heterogeneous convolution. In this method, all filters within a specific convolutional layer were separated into two groups, and the sensor input was down-sampled into a low-dimensional embedding. One filter group then convolved to recalibrate normal filters within the other group. This approach improved the baseline models significantly. The heterogeneous convolution is simple and can be integrated easily into standard convolutional layers without adding extra parameters or computational overhead. Finally, the actual operation of this method was evaluated on an embedded Raspberry Pi platform. WISDM dataset's previous accuracy, author Catal et al [11] is 94.3%. A new direction of research by authors in [12] in pattern recognition transformation for the area of human activity recognition. Prior studies have not explored the correlation between sample rate and energy consumption. Thus, our research aims to examine the interrelation of various configurations and propose optimal strategies. Low-power sensor nodes in fall detection applications commonly use BLE as their primary wireless communication protocol [13], also reducing data also comes with the disadvantage of losing valuable information, thus making the combined approach proposed by [14] a more advantageous alternative. In their study, data was usually collected at 50 Hz and then transformed to 200 Hz when a potential fall was detected, using an energy-efficient procedure they devised. In detecting and tracking, the k-NN classifier introduced in Ref. [14] exhibited superior performance compared to our LSTM model research and also revealed the optimal sensor combination and data gathering interval for detection and tracking, using KNN-SVM with an accuracy of 97.3. However, during our initial evaluation of the generated model, it was observed that the detector and edge devices caused disruptions in connectivity resulting in erroneous data. To guarantee that the second machine can offer reliable service in the event of connectivity loss of the first station, certain measures need to be put in place, while the method used the LSTM model with a deep-learning accuracy of 95.9 in [16], In previous studies, researchers have utilized general-purpose boards such as the Arduino Fig and Arduino Uno as the basis for fall-detecting sensor nodes [17].

3. METHODOLOGY

The proposed structure of the system is generally described in Figure 2, the following steps should be covered to predict future human activity using an LSTM time series model Pre-processing the data Preprocessing contains the following steps as sequences:

3.1 Pre-processing with Wavelets Transform:

A decomposition level of 4, means that the signal is decomposed into 4 frequency bands. This level of decomposition can provide a good balance between frequency resolution and signal-to-noise ratio and is commonly used in wavelet analysis of time-series data.

The dataset is a time-series dataset containing data collected from tri-axial accelerometers and gyroscope sensors embedded in a smartphone, worn by 30 subjects while performing six different activities.

The wavelet transform can be used to extract features from this dataset, such as the frequency content of the signals. Here's the equation for the wavelet transform:

$$dot(a, b) = \int x(t) * \psi * \left(\frac{t-b}{a}\right) dt \ldots. (1)$$

x(t) is the time-series data from the accelerometer or gyroscope sensor. ψ* is the complex conjugate of the mother wavelet function, which is a mathematical function used to analyze and extract features from the signal, A and b are the scale and translation parameters, respectively, which control the size and position of the wavelet function in the time-frequency plane. wavelet transform uses a variable-sized window, known as the wavelet, to analyze the signal at different scales and resolutions. By analyzing the frequency content of the signals, patterns, and characteristics can be identified which are specific to each activity, which can be used as features for machine learning algorithms to classify the activities performed by the subjects. The wavelet transform equation involves two main parameters: the scale parameter (a) and the translation parameter (b). The scale parameter controls the size of the wavelet in the time-frequency plane, while the translation parameter controls its position. By varying these parameters, signals are analyzed at different scales and resolutions.

3.2. DWT for MHEALTH Dataset:

A mathematical operation is used to decompose a signal into different frequency components at various scales. The general equation for the DWT is as follows:

$$\mathrm{DWT}(x, \psi j, k, \varphi j, k) = \Sigma k\, \psi j, k * (x, \psi j, k) + \Sigma k\, \varphi j, k * (x, \varphi j, k) \ldots\ldots (2)$$

In this equation, the input signal, denoted by x, represents the time-domain data from the m-health dataset. The wavelet function at scale j and translation k is represented by ψj,k. This function captures the detail coefficients, indicating high-frequency components. The scaling function at scale j and translation k is represented by φj,k. This function captures the approximation coefficients, reflecting low-frequency components. (x, ψj,k) and (x, φj,k) represents the inner product of the input signal x with the wavelet and scaling functions, respectively. By applying this equation, the DWT decomposes the input signal into a linear combination of wavelet and scaling functions at different scales and translations. The resulting coefficients provide information about the frequency content of the signal at varying resolutions. It's worth noting that efficient algorithms such as the Mallat algorithm or the lifting scheme are commonly used for implementing the DWT. To adapt this equation to the m-health dataset, substitute x with the specific time-domain signal from the dataset, and select appropriate wavelet (ψj,k) and scaling (φj,k) functions based on your specific analysis objectives.

Implementation of this section is shown in Figure 1 a &b to show analysis of data to amplitude of frequency in a, while in b the results of coefficients analyzed by applying wavelet transform to selected dataset to show detailed coefficients.

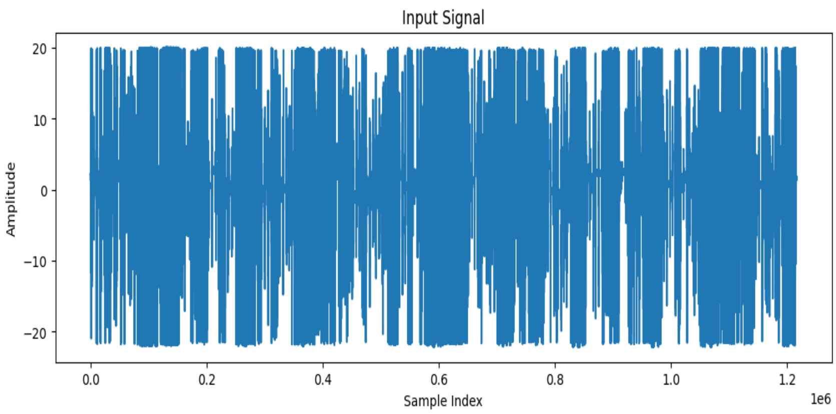

Fig.(1)(a): Input Signal vs Amplitude of Mhealth Datasets

3.3 .LSTM

LSTM is a type of recurrent neural network (RNN) architecture that is designed to better handle long-term dependencies in sequential data. In traditional RNNs, the network maintains a single hidden state that is updated with each new input, and this hidden state serves as a kind of "memory" of past inputs. However, this memory can become overwhelmed by long sequences of inputs, leading to what is known as the vanishing gradient problem, where the gradients used for updating the model parameters become extremely small and the model is unable to learn.

LSTMs address this problem by introducing an additional memory component called a cell state, which is explicitly passed along from one time step to the next, along with the hidden state. At each time step, the network selectively updates and forgets information in the cell state using gates, which are learned parameters that control the flow of information. Specifically, there are three types of gates in an LSTM:

Forget gate: Controls which information to discard from the cell state

Input gate: Controls which new information to store in the cell state

Output gate: Controls which information to output from the cell state to the hidden state.

By allowing the network to selectively update and forget information in the cell state, LSTMs are able to better maintain long-term dependencies and avoid the vanishing gradient problem. In addition, LSTMs can be stacked to create deeper networks, allowing them to learn even more complex relationships in sequential data.

In the proposed system, an LSTM is used to classify human activity recognition data. The LSTM is responsible for processing the sequential input data. The model is trained using the sparse categorical cross-entropy loss function and the Adam optimizer and is evaluated on accuracy during training. Finally, the trained model is used to predict future activity using the predict_future_activity function.

3.4. LSTM for Future Prediction:

A function called predict_future_activity () takes three input parameters: model, input_sequence, and steps_ahead. The code selects the first row of the test set (X_test) and reshapes it into a 2D array with shape (1, window_size, num_features). The function is called with the model, input_sequence, and steps_ahead parameters. The predicted sequence is converted back to the original labels using le. inverse_transform() and printed to the console. Finally, the code predicts the activity level for the next activity by creating a new input sequence X_new with a range of values from 0.5 to 1.6, reshaping it into a 3D array with shape (1, X_new.shape[0], 1), and calling the predict () method on the model. The predicted activity level is then printed to the console.

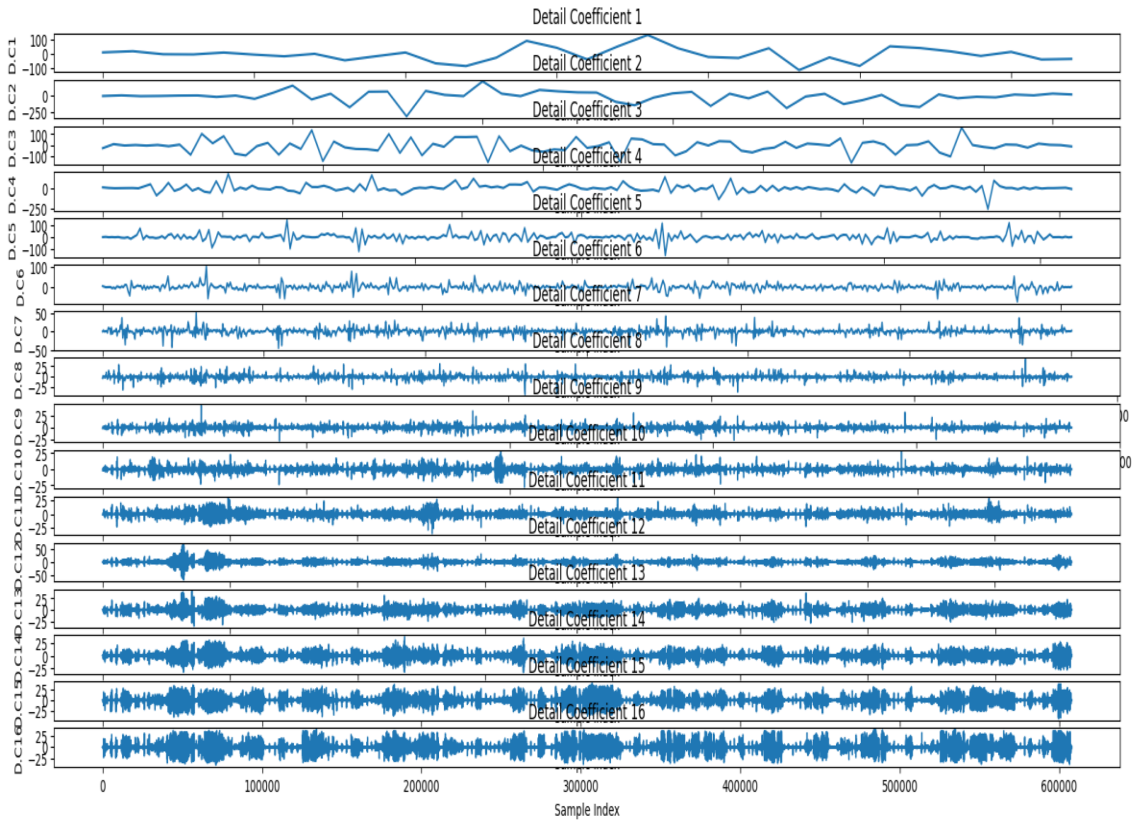

Fig.(2)(b): Detailed Coefficients (D.C.) of Mhealth Datasets

3.5 System Structure

Designing a complete system for future human activity prediction using wearable sensors involves several steps for future human activity prediction using wearable sensors with deep learning approaches. The specific implementation details will depend on the application and the available resources shows in figure 2. Some Proposed system architecture that integrates deep learning approaches: Data Collection, Preprocessing, Feature Selection, Model Training, Model Evaluation, and Deployment. The system can be continuously improved by collecting more data, refining the feature extraction and selection, and fine-tuning the deep learning model based on user feedback and new insights. The structure of the system is described in Figure 2 in general, implementation for the proposed system follows imports of the necessary packages and libraries, including NumPy, Pandas, PyWavelets, Keras, and Scikit-Learn. The dataset is loaded from a CSV file and separated into features (X) and labels (y). The features in X are standardized using the StandardScaler () function to have zero mean and unit variance. The data is split into training and test sets using the train_test_split () function from Scikit-Learn. The labels are encoded using Label Encoder() to convert them from strings to integers. Finally, the features are reshaped to have the appropriate dimensions for the LSTM model. The LSTM model is built using the Keras Sequential API. The first layer is an LSTM layer with 32 units and a sequence input shape of (n_timesteps, n_features). The return_sequences parameter is set to True to enable the LSTM layer to output a sequence rather than a single value. A 1D convolutional layer with 32 filters and a kernel size of 3 is then added, followed by a max pooling layer with a pool size of 2. The output of the convolutional layer is flattened and fed into a fully connected layer with 64 units.

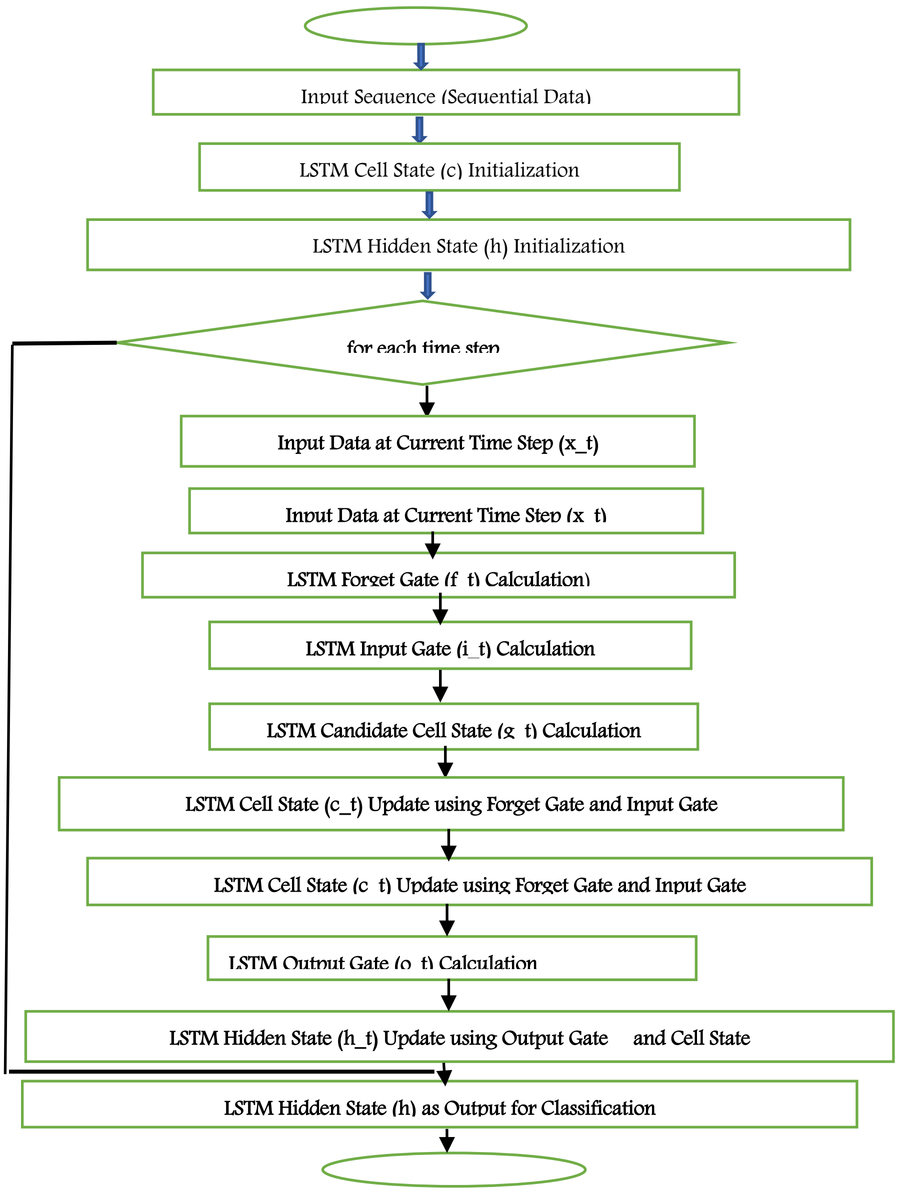

Fig.(3):- General Proposed System Model

4. EXPERIMENTAL RESULTS

The results demonstrate the model's resilience, as explained in the methodology and system structure section. The model is designed to mimic human logic and leverages the MHEALTH dataset to improve its performance. Wavelet transformation was applied for handling time series, while a linear encoder was used for multiclass classification. These techniques were previously described in the earlier section of this paper.

The results indicate that the proposed methods outperform all previous state-of-the-art approaches by establishing a connection between the physical sequence of activities and the arrangement of temporal-spatial steps involved in them.

Table (1): -Results of Next Steps Proposed Methods

Method	Results
Mhealth Predicted next activity:	[0.39675206 0.44743747 0.43720579 0.43400002 0.46099702] Predicted activity: 0.460997
UCI-HAR Predicted activity level for the next activity t1,t2,t3,t4,t5:	0.9892, 305/305 - 2s - loss: 0.0835 - accuracy: 0.9759 - val_loss: 0.0569 - val_accuracy: 0.9840 - 2s/epoch - 6ms/step, epochs=57, test_size=0.3, LSTM(64, Dropout(0.5)

Table 1 shows new powerful results for prediction long time with the highest accuracy rather than a few steps in state of arts due to use for a large range of applications. predictions made using the proposed framework for activity levels within the mobile health (MHealth) Dataset. The forecasted activity levels are as follows:

Predicted activity sequence: [0.39675206, 0.44743747, 0.43720579, 0.43400002, 0.46099702]

Predicted activity: 0.460997, Predicted activity level for the next activity: 0.9892

The first set of results presents a sequence of predicted activity levels for consecutive time steps. Each value within this sequence represents the anticipated activity level at a specific point in time. For example, the predicted activity levels for five consecutive time steps are provided as [0.39675206, 0.44743747, 0.43720579, 0.43400002, 0.46099702]. These predictions are most likely derived from historical data and the patterns learned by the LSTM model. The second result is a single numerical value representing the projected activity level for a specific time step. In this instance, the model forecasts an activity level of approximately 0.4609970152378082. This value corresponds to the expected activity level at a particular moment in time as in Figure 3 with metrics of evaluation per epochs\. The third result is a single numerical value indicating the predicted activity level for the subsequent activity. It suggests that the system anticipates an activity level of approximately 0.98 for the next activity.

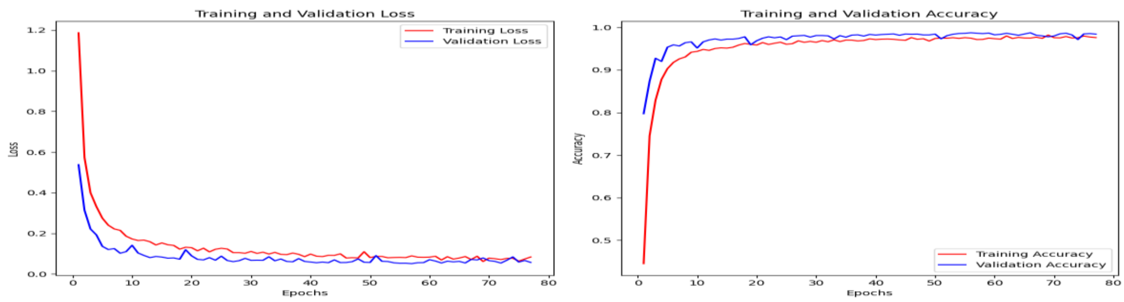

Fig.(3):- UCI-HAR (Loss, Val_Loss) and (accuracy, Val_accuracy)

The proposed framework able to predict activity levels for future time steps, providing valuable insights into potential user behavior and contributing to the advancement of MHealth applications. Nevertheless, it is crucial to assess the accuracy and reliability of these predictions through appropriate validation and testing methodologies before implementing them in real-world scenarios.

Activity prediction, early recognition, and tracking fields have seen numerous proposals utilizing RNNs to forecast future human actions. For instance, [25] has put forward different loss functions to encourage LSTM to recognize actions early in internet videos. Some prior works have incorporated multiple cues in videos for tracking [26] and group activity recognition [27]. Our work, on the other hand, stands out by utilizing rich visual features and focal attention to jointly predict person paths and activities.

Table 2 shows the Anticipation steps compared with our proposed work. The presented model achieves an impressive accuracy of 98% in recognizing human activities through data collected from wearable sensors. A notable advantage of this approach lies in its lower computational complexity, with a time complexity of O(n). This indicates that the LSTM-based model is more computationally efficient compared to the Bi-

The Bi-LSTM models introduced in both [28], [29] by other researchers exhibit accuracies of 95.79% [Model 1] and 97.96% [Model 2], showcasing their effectiveness in human activity recognition tasks. However, it is important to note that these models come with higher computational complexity, specifically a time complexity of O(n^2). Consequently, the training and inference times for these models might be longer when compared to your LSTM-based model.

The Temporal Conv-LSTM model [30] achieves a commendable accuracy of 91.6% in human activity recognition. Its key feature is the adoption of a hybrid architecture that combines CNNs with LSTM units. This innovative approach allows for leveraging the strengths of both CNNs and LSTMs to effectively process the input data. Moreover, the incorporation of parallel feature learning pipelines enhances the efficiency of feature extraction and representation learning. It is mentioned that the Temporal Conv-LSTM model also has the capability to predict future activities, indicating its potential for forecasting upcoming activities based on historical data and learned patterns.

Table (2):-Comparison Varying Anticipation Time Based MHEALTH Dataset

Model	Year	Accuracy	Difference point(s)
Bi-LSTM [28]	2023	95.79	Higher complexity o(n^2)
Bi-LSTM [29]	2023	97.96%	1- Higher complexity o(n^2) 2- Only five daily activities 3- Predict future activity (same our work)
Temporal Conv-LSTM [30]	2022	91.6%	1- A hybrid architecture was employed, consisting of parallel feature learning pipelines 2- High complexity o(n^2)
Our model		98%	Less complexity Using LSTM o(n)

5. CONCLUSION

Paper presents an innovative approach to predict injuries in sports activities by leveraging LSTM and wearable sensor data and wide range of healthcare applications. Through the training of the "predict_future_activity" function, our system gains the ability to make precise forecasts for future time steps. This study significantly contributes to the field of deep learning time series, particularly in its effective handling of activity sequences, signifying a novel and noteworthy undertaking. LSTM-based model outperforms the Bi-LSTM models in terms of accuracy while maintaining a lower computational complexity. The Temporal Conv-LSTM model presents an intriguing hybrid architecture with promising accuracy and the ability to predict future activities.

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