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Real-time Data Collection through Wearable Devices to Quantify Attributes Related to Health and Monitor Human Activity

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Abstract: *Wearable devices are widely used to monitor physiological activity, meeting the rising demand for quality elderly healthcare. This study utilizes wearable technology to gather real-time data on heart rate, oxygen saturation, and hydration levels for insights into the health and daily functioning of the elderly. The discussion covers the information wearable technology can capture, its applications in tracking health issues and promoting healthy aging, and the challenges of gathering, analyzing, and protecting privacy-related data. The abstract suggests future research directions for enhancing wearable technologies in senior healthcare and youth.*

Keywords: elderly people, observe human activity

I. INTRODUCTION

In addition to the significant changes in the medical field today, wearable technology is now widely used to evaluate people's physiological activities. We are trying seize this occasion to witness the senior citizen actives.

Our reason for employing wearable technology is that it has a variety of sensors and is easily accessible from and compatible with smartphones. Family members can monitor their loved ones' health activities with the help of the sensor's information gathered from wearable devices. This watch is designed specifically for children whose parents live alone and are away from home on business trips, giving them a way to keep an eye on their loved ones' health.

Put another way, the goal of this initiative is to employ technology to better comprehend adolescent activities and the elderly. The information gathered might be utilized to create fresh instruments and tactics.

II. LITERATURE SURVEY

A literature review is an important aspect of doing a specific study and providing thorough information in a certain field. While this research is focused on the field of information systems and wearable smart devices.

The need for efficient health monitoring systems for the elderly has increased dramatically as the world's population ages. Wearable technology has become a viable tool for gathering data in real time, allowing for the measurement of certain health-related characteristics and the tracking of elderly people's movements. This review of the literature examines the corpus of research and studies that have been done on the use of wearable technology for real-time data gathering in order to measure health characteristics and track the physical activity levels of the senior population.

In addressing the challenges faced by individuals residing away from their home due to work or business commitments and seeking to monitor the activities of elderly family members or loved ones, existing solutions often involve the use of cameras. However, this approach is associated with considerable costs and limitations.

The use of cameras for remote monitoring presents financial constraints, as it involves the acquisition and maintenance of video surveillance systems. The recorded video sequences, while attempting to infer human actions, encounter drawbacks such as the inability to identify activities if they occur outside the camera's field of view or when individuals are not within the camera's range. This limitation complicates the task of activity identification, reducing the overall effectiveness of the surveillance system.

Moreover, the installation and maintenance of video sensors contribute to the overall expenses, and in the case of real-time video monitoring, the challenges are exacerbated. The real-time aspect of the video surveillance system not only increases the complexity of identification but also hinders the timely delivery of accurate information about the well-being and activities of the monitored individuals to their concerned family members or caretakers.

The limitations associated with the existing camera-based monitoring system underscore the need for more cost-effective and efficient alternatives. As technology continues to advance, exploring innovative solutions that address these drawbacks becomes imperative. This literature review aims to explore and evaluate emerging technologies and methodologies that could provide more effective and affordable means of remotely monitoring the activities and well-being of individuals, especially focusing on the elderly or those residing far from their primary residence due to professional commitments.

III. PRPOSED SYSTEM

As we know Wearable wireless devices have been widely used in recent times to detect individuals' physiological activity in real time and it is very low-cost devices. Which is help us to monitor the activity so we think to modify this device with the help of additional features. For that we are going to use LSTM model and CNN. We are going to add some important features like Heart Rate Monitoring, GPS Tracking, Sleep Tracking. Activity Recognition. Calorie Expenditure, fall, Health-Metrics, Rest, User Engagement and Motivation integrated with mobile applications. Easy to access for very one easy to use all functions we are also try to add more features in future.

IV. RELATED WORKS

Types of Wearable Technology: This section will give a general overview of wearable technology, such as fitness trackers, smartwatches, and other wearables with a focus on health. The sensors that are built into these gadgets—such as accelerometers, gyroscopes, and heart rate monitors—will be highlighted because they are essential for gathering health data.

Important Health Factors for Older People:

Determining and measuring particular health characteristics is necessary for efficient tracking. This section will cover characteristics including temperature, physical activity, sleep habits, heart rate variability, and other pertinent factors that can shed light on an aged person's general health and well-being.

Real-time data collection's viability and accuracy:

Examine research and proof that demonstrates the accuracy and dependability of data gathered via wearable technology. Talk about the difficulties and possible restrictions. such as worries about data privacy, device comfort, and technological limitations.

Early Detection and Prevention:

Examine case studies and research results that show how wearable technology may be used to identify health problems in older people before they become serious. Talk about the ways that proactive treatments resulting from continuous monitoring might enhance health outcomes and lower medical expenses.

Issues and Prospects:

Examine issues related to adopting wearable technology for senior citizens, such as user acceptability, data security, and technological progress. Outline future directions for this field's research and development as well as possible solutions. Finding a right device that give us open-source architecture.

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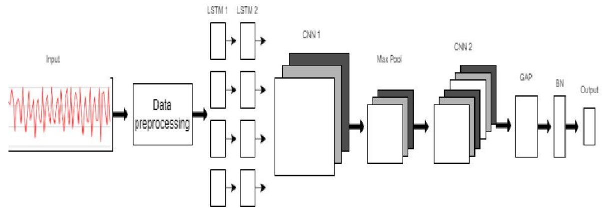
V. ARCHITECTURE



Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that are well-suited for sequential data, making them particularly effective for tasks like human activity recognition. When applying LSTM to wearable devices for human activity recognition, you can follow these general steps:

Data Collection:

For data collection we made over Own IOT device which help us collect the row data for processing. After this we Collect labelled data representing different human activities. This dataset should include time-series data from the sensors in the wearable device, such as accelerometers or gyroscopes. Each data instance should be associated with a specific activity label (e.g., walking, running, sitting, etc).

Data Preprocessing:

Prepare the facts for enter into the LSTM network.:

- Normalization: Scale the sensor data to a standard range to ensure that the model is not biased by different sensor scales.
- Segmentation: Divide the continuous time-series data into fixed-size segments or windows. This helps in creating sequences of data that can be fed into the LSTM.
- Label Encoding: Convert activity labels into numerical representations (e.g., one-hot encoding).

Model Architecture:

Design the LSTM model architecture. A simple architecture for human activity recognition may include:

- Input Layer: Accepts the segmented time-series data.
- Two LSTM Layers: These layers capture temporal dependencies in the data. You may stack multiple LSTM layers for more complex patterns.
- Dense Layer: A fully connected layer for the final output, usually with SoftMax activation for activity classification.

The model that we are utilizing is a sequential model which comprises of 8 layers. The pre-processed data is sent into the model's first layer. ReLU is the activation function that is employed in the first two layers, which are made up of LSTMs with 32 neurons apiece. Convolutional layers, which are utilized to extract spatial characteristics, follow next. However, before we can restructure the CNN layer's 4-dimensional input to (samples, 1, time steps, input dimension), we must first reshape our LSTM output, which has three dimensions (samples, time steps, and input dimension).

There are 64 neurons in the first CNN layer and 128 neurons in the second. There is a Max-Pooling layer in between the first and second CNN layers that carries out the down sampling process. The Global Average Pooling (GAP) layer comes next, which reduces global model parameters by converting multi-dimensional feature maps into 1-dimensional feature vectors. Since there are no parameters to optimize in this layer, we reduce them. The Batch Normalization (BN) layer now appears, aiding in the model's convergence. It normalizes and reconstructs the input data on each batch of training samples to increase training speed and accuracy while maintaining the stability of the output from the preceding layer.

The last layer in our model is the output layer, which is simply a fully connected dense layer made up of six neurons with a SoftMax classifier layer that indicates the likelihood of the classes to which the current sample belongs.

Training:
Train the LSTM model using the pre-processed data. Use a labelled dataset and optimize the model's parameters to minimize the classification error. Be cautious of overfitting, and consider techniques like dropout to prevent it.

Evaluation:
Evaluate the model on a separate test set to assess its performance. Common metrics for activity recognition include accuracy, precision, recall, and F1 score. Adjust the model as needed to improve performance.

Deployment to Wearable Device:
Once the model is trained and evaluated successfully, deploy it to the wearable device. Depending on the device's capabilities, you may need to consider model size and computational efficiency.

Real-Time Inference:
Implement real-time inference on the wearable device. Continuously feed sensor data into the model and obtain predictions for the ongoing activities. This allows the device to recognize human activities in real-time.

Fine-tuning and Updates:
Periodically update the model with new data to adapt to changes in the user's behaviour over time. This can be achieved through a process of fine-tuning or retraining.

Handling Imbalanced Data:
If the dataset is imbalanced (some activities are represented more than others), consider techniques such as oversampling, under sampling, or using class weights during training to address this issue.

Consider Edge Computing:
For resource-constrained wearable devices, consider optimizing the model for edge computing. This may involve quantization, model compression, or other techniques to reduce the computational and memory requirements.
By following these steps, you can effectively implement LSTM for human activity recognition on wearable devices, providing valuable insights into users' activities and behaviours.

VI. CONCLUSION

In conclusion, there is a great deal of potential for real-time health and activity monitoring of senior citizens through the integration of wearable technology with Long Short-Term Memory (LSTM) networks.
The suggested solution provides a thorough approach to elder healthcare by improving on conventional wearables with capabilities like Activity Recognition, GPS Tracking, and Heart Rate Monitoring. Wearable technology's accessibility and cost combined with LSTM networks' methodical application offer a game-changing answer. Problems like resource limitations and data privacy are discussed, highlighting how useful the strategy is.
In addition to addressing the problems with health monitoring now, this convergence creates opportunities for future study and advancement, which will ultimately benefit the aging population's quality of life.

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