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Deep Sense: Deep Learning for Early Staging the Onset of Diabetes Emanating Recognition of Activity Patterns

Mohammed Shamsul Alam[1], Erfanul Hoque Bahadur[2], Md Fokrul Islam Khan[3], Farhad Uddin Mahmud[3], Md Ismail Hossain Siddiqui[4], Abdul Kadar Muhammad Masum[5]

[1]*Department of Computer Science and Engineering, International Islamic University Chittagong Kumira, Chattogram-4318, Bangladesh;*
[2]*Hiperdyne, Tsubosaka Bldg. 3F, 5-9-12 Shiba, Minato-ku, Tokyo 108-0014, Japan.*
[3]*Department of Management Information System, International American University, Los Angeles, USA;*
[4]*Department of Engineering Management, Westcliff University, Irvine, USA;*
[5]*Department of Computer Science and Engineering, Southeast University, Dhaka-1208, Bangladesh*

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*Corresponding Author:
Abdul Kadar Muhammad Masum, Department of Computer Science and Engineering, Southeast University, Dhaka, Bangladesh;
Email: akmmasum@yahoo.com

Abstract: This study presents a comprehensive framework for Human Activity Recognition (HAR) using smartphone sensor data, with a specific focus on identifying activities associated with diabetic risk factors. We investigate the efficacy of two deep learning architectures (Long Short-Term Memory (LSTM) networks and Graph Convolutional Networks (GCNs)) for activity recognition under conditions of limited training data. To address data scarcity, we employ Generative Adversarial Networks (GANs) to augment the training dataset with synthetically generated sensor data, enhancing model robustness beyond what is achievable with real sensor data alone. Continuous accelerometer and gyroscope data spanning daily activities were collected from experimental subjects over a 60-day period. This dataset was used to train and evaluate both LSTM and GCN models, with results demonstrating that the GCN architecture achieves superior performance in recognizing diabetes-related activities such as sedentary behavior, physical inactivity, and irregular meal patterns. Furthermore, we propose a novel risk quantification method that estimates diabetes risk by analyzing the duration and frequency of engagement in diabetes-related activities. We employ cosine similarity to measure the correspondence between activity patterns of diagnosed diabetic patients and experimental subjects, yielding a quantitative risk score. To validate the proposed framework, we conducted clinical HbA1c (A1C) assays on experimental subjects. One subject exhibited an A1C level of 6.1%, corresponding to a prediabetes diagnosis, which corroborated the high-risk classification predicted by our framework. These results demonstrate that the proposed HAR-based approach can accurately assess diabetes risk and classify individuals according to clinically validated diagnostic criteria, offering potential applications in continuous health monitoring and early intervention strategies.

Keywords: Human Activity Recognition; Deep Learning; Diabetes Risk Assessment; Graph Convolutional Networks; Long Short-Term Memory Networks; Smartphone Sensors; Generative Adversarial Networks; Health Monitoring

Introduction

In the contemporary age, the omnipresence of smartphones has seamlessly woven into the fabric of people's everyday existence, serving as a virtual appendage for individuals from diverse backgrounds, including employees, executives, and service workers. Studies unveil that people spend upwards of 15 hours daily engaged with their smartphones, underscoring the pervasive nature of smartphone usage (Chanana &Sangeeta, 2021). Harnessing the multifaceted capabilities of smartphones across various applications has become a wellspring of inspiration. The extensive use of smartphones, coupled with the nuanced ways individuals interact with their devices, offers valuable insights into their lifestyle choices. Capitalizing on this high usage rate, we advocate for the deployment of Human Activity Recognition (HAR) systems to discern patterns in day-to-day activities. The sensor components embedded in smartphones facilitate the collection of a wealth of data linked to physical activity, unlocking concealed patterns within each activity. Thus, the intrinsic sensor capabilities of smartphones significantly ease our pursuit of HAR research.

HAR has found diverse applications, ranging from step counting and health monitoring to recognizing abnormal activities. Yet, untapped domains exist where HAR could prove beneficial, notably in disease diagnosis. Diseases like diabetes, depression, cancer, and insomnia have direct connections to daily human activities (Duong et al., 2005). Research underscores the significant impact of physical activity on the development of these diseases (Weinstein et al., 2004). Existing literature accentuates the positive influence of physical exercise in diabetes prevention. Active individuals, especially those engaged in high-intensity activities like swimming, tennis, and racing, exhibit a significantly lower risk of developing non-insulin-dependent diabetes mellitus (NIDDM) compared to sedentary individuals (Manson et al., 1991). Regular physical exercise can delay or prevent type-2 diabetes, particularly in high-risk individuals (Tuomilehto et al., 2011). Obesity, a central factor in insulin insensitivity, contributes to glucose intolerance and insulin resistance, with approximately 80% of NIDDM patients being obese (Tuomilehto et al., 2011). Higher levels of physical activity correlate with a lower prevalence of type-2 diabetes (Hu et al., 1999). Further research underscores the lower diabetes risk among physically active women participating in activities such as walking, jogging, biking, and tennis compared to those leading sedentary lifestyles (Hu et al., 2001). Increased television viewing time correlates with a higher likelihood of obesity. Motivated volunteers with NIDDM benefit from increased physical activity (Kriska & Bennett, 1992). Long-term exercise regimens are endorsed for individuals experiencing decreased glucose levels and type-2 diabetes, leading to a reduction in hyperglycemia and VLDL (Very Low-Density Lipoprotein) levels containing triglycerides (American Diabetes Association, 2003). Dietary and exercise interventions significantly reduce the incidence of diabetes in individuals with impaired glucose tolerance (Tuomilehto et al., 2011).

Recognizing the early symptoms of diabetes poses a significant challenge, as they can be subtle and easily overlooked. Fatigue, increased thirst, frequent urination, and unexplained weight loss are among the initial signs that may not immediately raise concerns. This lack of awareness and the inconspicuous nature of early symptoms contribute to the alarming statistics surrounding undiagnosed cases. Moreover, these symptoms are often attributed to other factors or dismissed, leading to delayed or missed diagnoses. The insidious onset of diabetes, combined with the absence of apparent discomfort in the early stages, creates a formidable barrier to timely identification. As a result, individuals may unknowingly live with diabetes for an extended period, allowing the disease to progress unchecked. In the context of diabetes, the challenges in symptom recognition contribute to the startling revelation that nearly 46% of individuals with diabetes in various regions, including the United States, remain undiagnosed. Astonishingly, 1 in 4 individuals in the United States are oblivious to their diabetic condition, emphasizing the pressing need for increased awareness and early detection initiatives. This issue extends beyond diagnosed cases, as over 1 in 3 adults in the US, totaling 86 million individuals, are grappling with prediabetes. Shockingly, 9 out of 10 people are unaware of their pre-diabetic status, further underscoring the urgency for comprehensive screening and educational programs (Helmrich et al., 1991). The implications of late-stage diabetes diagnosis are severe, encompassing complications such as retinopathy, amputations, and cardiovascular diseases, which significantly contribute to mortality rates (American Diabetes Association, 2016; Helmrich et al., 1991). Addressing the challenge of early symptom recognition is pivotal in averting these dire consequences and improving the overall health outcomes of individuals at risk for or already living with diabetes.

To address the early detection of diabetes and assess the probability factor, this study concentrates on enhancing the HAR process to track individuals' daily activity patterns and issue early notifications if their activities closely resemble those of diabetic patients. Identifying activities mirroring diabetes symptoms allows for effective monitoring and timely interventions. For example, aerobic exercise is recommended for individuals with NIDDM as it improves glycemic control (Hou et al., 2016).

Activities like walking, running, and cycling are associated with cardiovascular fitness and glycemic control, while routine actions like eating, drinking, and bathroom visits provide insights into urination patterns (Sinclair et al., 2017). Moreover, pinpointing activities such as falling down aids in identifying physical weaknesses, while actions like genital itching, sitting, standing, and sleeping assist in detecting indications of type 2 diabetes or NIDDM (Davies et al., 2019). Physically inactive individuals face a higher likelihood of developing diabetes compared to those incorporating regular physical exercise into their routine.

To gather pertinent data, a tailored Android app was developed to capture sensor readings encompassing tri-axial accelerometers, tri-axial gyroscopes, temperature measurements, and relative humidity values. Subsequently, a pre-trained LSTM model was employed to recognize diabetes symptomatic activities by predicting the mean time spent on each activity. However, the collection of a substantial volume of sensor data at a low frequency proved time-consuming, prompting the exploration of alternative approaches, such as generating synthetic smartphone sensor data. In this context, Generative Adversarial Networks (GANs) were employed to produce synthetic data, subsequently used to train the LSTM model. Additionally, we investigated the application of Graph Convolutional Networks (GCNs) as an alternative to human activity recognition and compared its performance with LSTM. A dataset of anonymous sensor data capturing daylong activities from experimental subjects over a sixty-day period was collected and input into both models. The results showcased the superiority of the GCN model in recognizing human activities, thereby underscoring its potential to enhance the accuracy of our proposed system for diabetes diagnosis.

Data was sourced from specialized diabetes care centres to glean deeper insights into activity patterns associated with diabetes. A questionnaire was administered to collect details about diabetes symptomatic activities and other pertinent factors, including gender, weight, height, family history of diabetes, and blood pressure. Using Cosine similarity, the resemblance between experimental subjects and diabetic patients was gauged, enabling the derivation of risk factors for each experimental subject. The proposed system effectively diagnosed participants in the experiment, with the derived risk factors exhibiting a positive correlation with clinical A1C test results. The A1C test provides a reliable measure of blood sugar levels and strongly correlates with the risk of long-term complications related to diabetes. Furthermore, our proposed system suggested optimal insulin dosages based on real-time activity pattern recognition and carbohydrate intake, potentially enhancing the effectiveness of the insulin regimen.

Literature Review

Since its inception in 1980, HAR has garnered significant interest from researchers due to its diverse applications in fields such as safety, medicine, and human-computer interaction. In order to explore the historical progression of Human Activity Recognition (HAR) systems, researchers have adopted diverse methodologies. These methodologies involve the utilization of sensor data, including tri-axial accelerometers, tri-axial gyroscopes, Relative Humidity, and Temperature sensors. The purpose of employing these sensors is to identify and classify various activities such as sitting, walking, jogging, lying down, walking upstairs and downstairs, cycling, standing, and squatting in the toilet (Anjum et al., 2022; Bahadur et al., 2019; 2021; Barna et al., 2019; Masum et al., 2020; 2018).

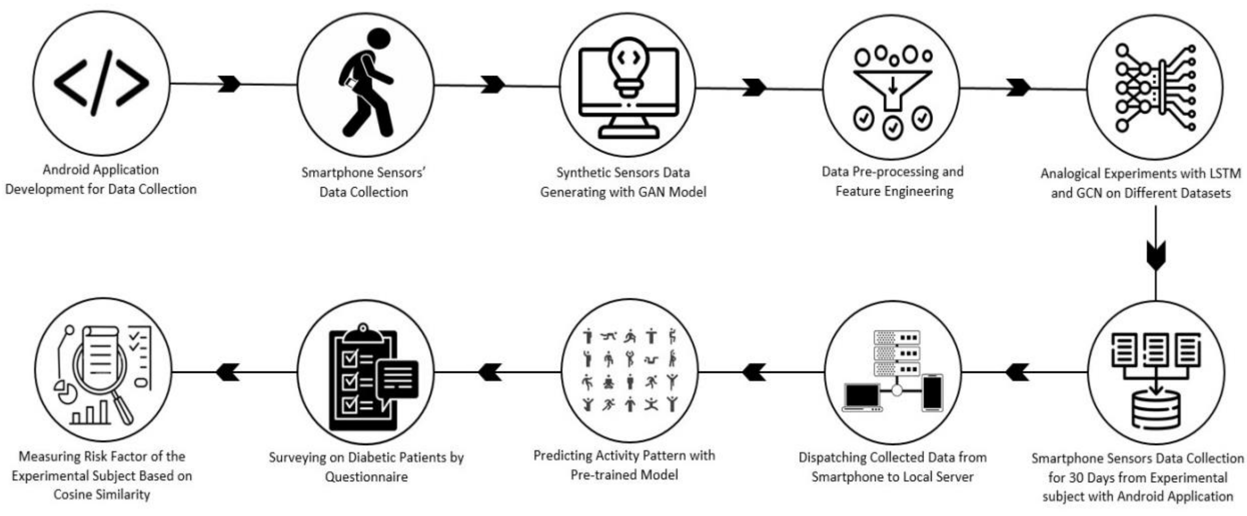

Fig. 1: Outline of the working principle

HAR entails discerning human activities from raw time-series signals captured by embedded sensors in smartphones and wearable devices. This field has garnered considerable interest, particularly in smart home environments, where it is employed for continuous monitoring of human behaviours to support elderly care and rehabilitation efforts. HAR systems typically comprise various operational modules, including data acquisition, preprocessing to eliminate noise and distortions, and classification. While traditional Machine Learning classifiers have been widely used, many of these methods struggle to recognize complex activities effectively. However, with the advent of advanced computational resources, Deep Learning techniques have gained prominence in HAR systems for their ability to efficiently perform classification tasks. The use of deep learning in human activity recognition with smartphone sensors is a rapidly evolving field.

Ramanujam et al. (2021) highlighted the potential of deep learning techniques in this area, particularly in feature extraction and classification. They also emphasize the need for further research to address challenges and improve existing methods. Zhu and Mo (2022) further underscored the benefits of deep learning in this context, particularly in real-time applications and the potential for end-to-end feature learning. However, they also note the limitations and call for further research to address these issues. Using smartphones and wearable devices has witnessed significant advancements, as evident in several key studies. A systematic review provides a comprehensive overview of the field, examining various methodologies employed for HAR with Smartphones (Straczkiewicz& Onnela, 2019). Additionally, Zhang et al. (2022) explored the role of Deep Learning in HAR, specifically focusing on the utilization of wearable sensors, and present an in-depth review of the latest advances in this domain. The significance of transfer learning in HAR using mobile and wearable devices, along with environmental technology, is highlighted in Hernandez et al. (2020), providing valuable insights into the challenges and opportunities associated with this approach. These references collectively contribute to shaping the landscape of HAR research, addressing diverse methodologies and emerging technologies in the pursuit of more accurate and efficient human activity recognition systems. Recent research by Abdel-Salam et al. (2021) provided an overview of deep learning techniques for HAR using wearable sensors.

The study explores the applications of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention-based models in activity recognition. CNNs, traditionally used for image recognition, can be adapted to HAR by treating sensor data as a 1D image, extracting meaningful features for classification (Ji et al., 2013). RNNs, designed for sequential data, are well-suited for HAR as they can model temporal dependencies, exemplified by the successful implementation of Long Short-Term Memory (LSTM) networks (Ordóñez & Roggen, 2016). Graph Convolutional Networks (GCNs) have also shown promise in HAR by capturing spatial and temporal dependencies in data, surpassing traditional deep learning models (Yanet al., 2018). Notably, recent advancements have introduced novel GCN-based approaches for HAR. Ahmad et al. (2021) proposed a multi-layer GCN with residual connections, achieving state-of-the-art performance on HAR datasets.

Feng et al. (2022) incorporated a self-attention mechanism into GCN, reducing parameters and computational costs while maintaining competitive performance. A comparative study confirms the superior performance of GCN-based models over LSTM-based models and other deep learning approaches in HAR. HAR with Smartphone sensors has witnessed significant advancements, particularly with the integration of Deep Learning techniques (Li et al., 2019). This review highlights the transition from traditional ML methods to more sophisticated DL approaches, emphasizing the increasing role of GCNs for superior activity recognition. Further research efforts are expected to refine existing models, address remaining challenges, and explore novel applications of Smartphone-based HAR in various domains.

Materials and Methods

After conducting an extensive literature review to explore the connection between human activities and NonInsulin Dependent diabetes Mellitus (NIDDM), we laid a strong groundwork for the development of a cutting-edge real-time diagnostic system capable of alerting individuals to early signs of diabetes, thus preventing further deterioration. Our primary goal was to improve the performance of Human Activity Recognition (HAR) and establish a strong and reliable system. Additionally, we have discussed the practical implications of this study in the following sections, thereby opening new avenues for significant progress in the field of contemporary science.

Data Collection

In order to promote widespread adoption, user-friendliness, and incorporation of necessary sensors, a suitable device standard was carefully selected. After considering all the factors, it was determined that the

Smartphone would be the optimal solution. Although there was an alternative option in the form of a smartwatch, it was excluded from our choice due to the significant disparity in usage between Smartphones and smartwatches, with Smartphones consistently being assigned greater value.

Therefore, a Samsung Galaxy S4 Smartphone was utilized for the data collection phase as it possessed the required sensors and demonstrated superior performance.

A novel Android application was developed with the objective of collecting sensor data at a reduced frequency, thereby minimizing power consumption. A total of 20 young and physically fit individuals, comprising both males and females, actively participated in the data collection process. The participants were instructed to collect data for various activities, such as walking, jogging, cycling, falling down, sitting, standing, and lying, encompassing different postures and environments, both indoors and outdoors. To ensure the robustness of the data collection process, data was acquired in all conceivable orientations, including flipped, upside down, or downside up.

In order to evaluate the varying degrees of change associated with different activities undertaken by Smartphone users, we utilized accelerometer and gyroscope sensors. The accelerometer measured the acceleration of movement, while the gyroscope captured the angular rotational velocity. Additionally, the Smartphone's relative humidity and temperature sensors were utilized to detect humidity and temperature levels in the surrounding environment. Additionally, environmental factors, such as temperature and humidity discrepancies, play a crucial role in identifying symptomatic activities associated with diabetes. For instance, there can be contrasting conditions between sitting on a chair in a room and sitting on an elevated commode in a washroom.

Apart from human activities, we monitored the usage patterns of the Smartphone itself, which involved placing the device on various surfaces such as chairs, beds, or other surfaces. Furthermore, we observed individuals engaging in activities like browsing, typing, or having conversations while using the Smartphone. These activities were classified separately as irrelevant to avoid any potential influence on the actual data, which could lead to reduced false positive and false negative rates when tracking an individual's activity patterns. Overall, the data collection process resulted in a total of 101,000 instances of fourteen distinct activities.

Synthetic Sensors Data Generation

This study aims to explore the future potential of handling vast volumes of data and harnessing the capabilities of deep learning algorithms such as Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM). Existing literature has demonstrated that deep learning models excel in extracting complex structures and associations from abundant data compared to more limited learning structures. When appropriately described and implemented, deep learning models can effectively comprehend and analyze massive datasets, leading to enhanced efficiency. Deep learning techniques enable the understanding of various data variance elements and enable seamless integration of multiple data types. Additionally, they facilitate adaptive learning processes, enabling users to handle rapidly evolving streaming data by learning from each instance individually. These characteristics make deep learning an effective framework for extensive data analysis, capable of addressing inconsistencies and distortions and providing enhanced interpretability. Conversely, the effectiveness of deep learning heavily relies on a substantial quantity of diverse data examples, allowing the model to search for relevant features and generate corresponding outputs. In the context of our study on identifying diabetic symptomatic activities, it is necessary to obtain a significant amount of sensor data to train both the GCN and LSTM models. However, the process of acquiring such large datasets is time-consuming, especially considering the lower frequency at which deep learning models are trained. To mitigate this issue and expedite the collection of training data, we employed Generative Adversarial Networks (GANs) models to generate synthetic Smartphone sensor data. Generative Adversarial Networks (GANs) are a type of deep learning model used for generating synthetic data that closely resembles real-world data. In machine learning, generative modelling is an unsupervised learning process that automatically detects and learns regularities or patterns in input data so that the model may be used to produce new examples that would have been picked out from feature space.

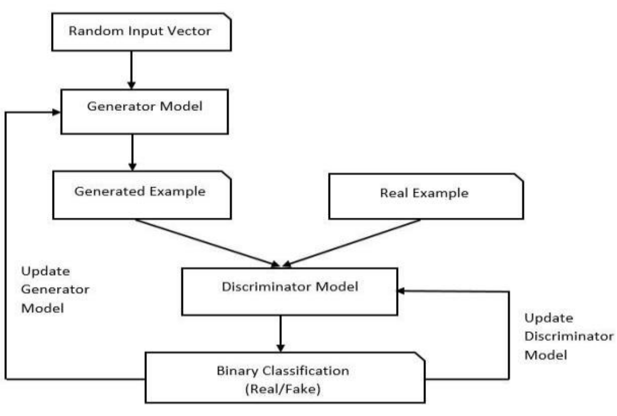

Fig. 2: Architectural model of generative adversarial networks

As framed in Fig. 2, GANs are a model architecture for developing a generative model, but the GAN architecture elegantly organizes the generative model's training as a supervised learning technique. By framing the challenge as a supervised learning issue with two sub-models, GANs are a clever technique for training a generative model. The discriminator model categorizes samples as either actual or fake, and the generator model is trained to generate new instances. Two distributions are compared iteratively, and gradient descent steps are used to update the network weights. The comparison is made with the mean and variance, akin to a truncated matching procedure. In this approach, the generator generates synthetic data, while the discriminator distinguishes between real and synthetic data. The two models are engaged in a zero-sum game and exhibit antagonistic behaviour as per game theory. The discriminator is incentivized when it successfully differentiates between true and fake samples, requiring no changes to the model parameters. Conversely, the generator incurs substantial model parameter updates as a penalty. In cases where the generator successfully deceives the discriminator, it receives a reward, and no changes to the model parameters are necessary, while the discriminator's model parameters are adjusted as a form of punishment. Plagiarism is avoided by accurately conveying this information using original language and proper citation where necessary. On a limitation level, the training process continues until the generator can generate data that is difficult for the discriminator to distinguish from the real data. The generator network takes a random noise vector z as input and generates synthetic data xhat as output. The discriminator network takes real data x or synthetic data xhat as input and outputs a probability D(x) or D(xhat) that the input is real. The generator and discriminator are trained using the following loss functions.

$$\min G \; mazD \; V(D, C) = E\,(x\sim Pdata\,(x)\,)\,[\log D\,(x)] + E\,(z\,(\sim Pz\,(z))\,[\log\,(1 - D\,(G\,(z)))] \quad (1)$$

Where $Pdata(x)$ is the probability distribution of real data x, and $Pz(z)$ is the probability distribution of the random noise vector z. The first term in the loss function encourages the generator to generate data that the discriminator classifies as real, while the second term encourages the generator to generate diverse data:

$$\max D\,V\,(D, G\,) = (x`\sim pdata\,(x\,))] + E(z\sim Pz(z)))\,[\,\log(1 - D\,(G(z)))] \quad (2)$$

Where the first term in the loss function encourages the discriminator to correctly classify real data as real, while the second term encourages the discriminator to correctly classify synthetic data as synthetic.

The overall training objective of GANs is to minimize the generator loss function and maximize the discriminator loss function, which leads to a Nash equilibrium between the generator and the discriminator. At this equilibrium, the generator generates synthetic data that is indistinguishable from the real data, and the discriminator is unable to distinguish between the real and synthetic data.

In the context of generating synthetic sensor data, GANs can be used to generate data that is similar to real sensor data, allowing for the creation of larger datasets for training deep learning models. The generator network can be designed to generate synthetic sensor data that exhibits the same statistical properties as the real sensor data, while the discriminator network can be trained to distinguish between real and synthetic sensor data.

Data Preprocessing

Data collection encounters numerous challenges in the physical domain, including the presence of contradictory, defective, or out-of-range data. Preprocessing involves the conversion of data into a format suitable for analysis by eliminating noisy and conflicting features. In the case of gathering data from Smartphone sensors using an Android application, errors may arise due to device performance overload or other factors, resulting in the presence of invalid values. To overcome these issues, we employed several preprocessing techniques, which are delineated below.

In each dataset or spreadsheet, null values indicate the absence of substantial data in a specific data field. Such null values can emerge due to various factors, such as application errors, faulty sensors, a noisy environment, or movement. Hence, it is crucial to examine and detect any invalid or missing values present in the dataset to mitigate the negative impact of null values on the data. Outliers refer to data values within the dataset that significantly deviate from the rest and can lead to an abnormal distribution of data, thereby reducing the accuracy of the dataset. Whisker's plot serves as a graphical method for identifying outliers by establishing upper and lower limits based on quartiles. Another statistical method, known as the Z-score, measures the distance between a specific value and the mean of the characteristics, utilizing the standard deviation as a scale. Values exhibiting substantial deviation from the mean can be identified as outliers. To identify outliers, upper and lower limits are determined using the box plot chart and subsequently converted into corresponding Z-scores. Any value with a Z-score greater than the upper limit or less than the lower limit is considered an outlier and is excluded from the dataset.

Conversely, if there is a need to scale data to a different range, this can be achieved through min-max standardization. This method allows for the transformation of a dataset comprising features with varying scales or measurement units into a common scale, thereby facilitating more effective understanding of the dataset by the learning algorithm. Min-max standardization scales the dataset within the range of 0 to 1, and subsequently, the standardized dataset is utilized to mitigate issues arising from the presence of disparate scales.

The gravitational field can induce fluctuations in a signal, leading to a loss of smoothness. During our data accumulation process, this issue arose due to the gravitational pull of the Earth. To mitigate this problem, we applied the Butterworth low-pass filter technique to eliminate any anomalies caused by the Earth's gravity. The Butterworth low-pass filter is a signal-processing filter that transforms a generated frequency into a smoother one. During the filtering process, the Butterworth filter eliminates signal values that exceed a certain threshold. Various mathematical formulas, such as the Fourier transform, can be employed to smooth the signal when utilizing the Butterworth low-pass filter. The Fourier transform is an operational method that decomposes any signal and generates a sinusoidal signal. By decomposing a fluctuating signal, it can be transformed into a smooth signal resembling a sinusoidal waveform. Following the implementation of this specific filtering process, significant results were obtained, which are illustrated in Fig. 3 for each axis of every sensor.

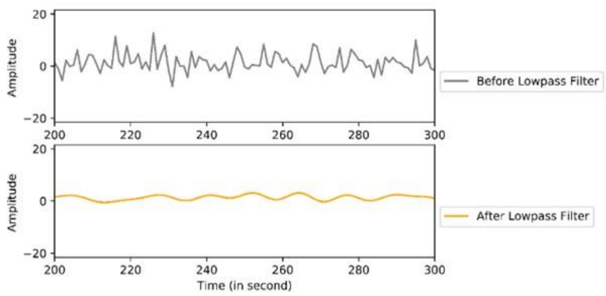

Fig. 3: Generating a seamless signal from accelerometer sensor data (upper) through the implementation of a Butterworth low-pass filter (lower)

The technique of converting categorical data into numerical values is a widely employed approach within the domain of machine learning. One of the prominent methodologies utilized for this purpose is known as one hot encoding, whereby binary values of 1 are assigned to individual categories in separate columns. In the present study, this encoding technique was employed on a dataset comprising fourteen distinct activities, with the objective of recognizing and classifying them accurately.

To effectively reduce the dimensionality of the dataset while retaining the maximum variance present within the data, Principal Component Analysis (PCA) was employed. PCA serves as a valuable tool for dimensionality reduction by projecting the dataset onto a smaller subspace. This projection is achieved by discarding eigenvectors associated with low eigenvalues, as they provide minimal information pertaining to the distribution of the data. The determination of the essential components to be selected is based on an analysis of the explained variance derived from the eigenvalues. Notably, there is no universally accepted approach for determining the optimal number of principal components for a PCA model. In the context of this study, a specific criterion was employed to identify the principal components (PCs) that possessed significant characteristics. This criterion involved utilizing a covariance threshold of 0.1, an eigenvalue threshold of 1.0, and a covariance threshold among the eigenvalues of 0.1. By adhering to this prescribed methodology, a substantial reduction in the dataset's dimensionality was achieved while ensuring the preservation of critical features necessary for subsequent analysis.

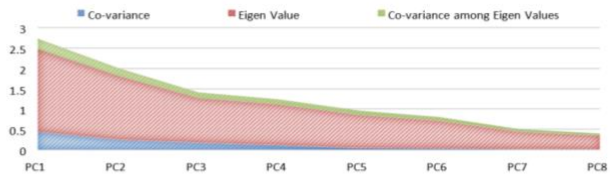

Fig. 4: Selecting Criterion of Principle Components

Human Activity Classifier

Classification, a term in data mining, refers to the prediction of the target category or class of a given instance. It can also be described as determining which class a new event belongs to from a set of possible classifications. These algorithms, referred to as classifiers, group the classifications. Now, we will delve into a detailed discussion of the LSTM model we employed

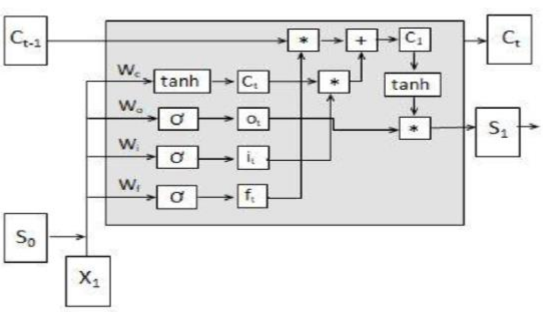

Fig. 5: Architecture of long short-term memory

LSTM, a specialized architecture within the realm of Recurrent Neural Networks (RNNs), is designed to effectively model sequential data. The fundamental concept behind LSTM involves the incorporation of a memory cell capable of retaining information over extended periods while selectively updating or disregarding data based on the input sequence. This memory cell is controlled by three gates: the input gate, forget gate, and output gate. Each gate utilizes a sigmoid function to produce values ranging from 0 to 1. Through the utilization of these gates, LSTM can selectively update or discard data within the memory cell, enabling the modelling of long-term dependencies inherent in sequential data. The output of LSTM is the hidden state, which is a function of the current memory cell state and the output gate. The logistic function determines which data to retain or discard based on the previous hidden state (ht-1) and the input data (tx) during that phase. Following the forgetting state, the cell state is concluded as follows:

$$C_t = ft * C(t-1) \tag{3}$$

Here, the current cell state (C_t -1) and the previous hidden state (ht-1) are disregarded and instead represented as the past cell state (C_t -1) and forgetting state (ft), respectively. The forgetting process is described by the following equation:

$$f_t = -\frac{1}{(1+e^{-(W_{f*}[h_{t-1},\, x_t] + b_f)})} \tag{4}$$

In this equation, the weight matrix and bias vector are denoted as W_f and b_f, respectively. The output vector of the sigmoid function multiplies the cell state, which is then augmented by an input gate. An additional sigmoid function acts as a filter system, determining which entries should be incorporated into the cell state. A vector generated through a hyperbolic tangent function captures potential values. The output of the sigmoid layer and the candidate values from the hyperbolic tangent function are added to the cell state. The procedure guarantees the identification and inclusion of pertinent and vital patterns into the cell state subsequent to the input phase. Consequently, the cell state undergoes a transformation, resulting in the subsequent representation:

$$C_t = f_t * C_{t-1} + i_t * C'_t \tag{5}$$

Here, the sigmoid layer is stored in the input state, while the candidate values are stored in C't. The functions for the input gate and the candidate values are expressed as follows:

$$i_t = -\frac{1}{(1+e^{-(W_{i*}[h_{t-1},\, x_t] + bi)})} \tag{6}$$

$$C'_t = -\frac{(1+e^{-2(W_{c*}[h_{t-1},\, x_t] + b_c)})}{(1+e^{-2(W_{c*}[h_{t-1},\, x_t] + b_c)})} \tag{7}$$

The equations provided incorporate the usage of Bi and Bc as bias vectors and Wi and Wc as weight matrices for the input cell and intermediate cell state. An additional filter is employed to determine the relevant components of the cell state. Once the cell state is established using hyperbolic tangent, a sigmoid function and vector are generated. Both the sigmoid function and vector serve to scale the data within the range of -1 to +1. The resulting vector, obtained from the application of the nonlinear activation function and regulatory filter, is transmitted to the hidden unit as an output. This process effectively captures the most significant sequences. As a result, the cell state generated by the output can be mathematically expressed as follows:

$$C_t = o_t * h_t \tag{8}$$

The vector ht represents the hyperbolic tangent values, while it refers to the regulatory filter. The two functions are presented as follows:

$$o_t = -\frac{1}{(1+e^{-(W_{c*}[h_{t-1},\, x_t] + b_o)})} \tag{9}$$

$$h_t = \frac{o_{t*(1-e^{-2(c_t)})}}{(1+e^{-2(C_t)})} \tag{10}$$

Here, the weight matrix and bias vector for the output gate are denoted as Wo and bo, respectively. In their work, Gers and Schmidhuber (2000) suggested a minor modification to the peephole connection of the basic LSTM model. This modification involves enhancing the peephole connectivity from the inner cells to the multiplicative gates, enabling the model to better capture subtle modulation of spike patterns. As a result of this modification, the forget, input and output gates are updated accordingly:

$$f_t = \frac{1}{(1+e^{-(W_{f*}[h_{t-1},x_t]+b_f)}} \tag{11}$$

$$i_t = \frac{1}{(1+e^{-(W_{i*}[h_{t-1},x_t]+b_i)}} \tag{12}$$

$$o_t = \frac{1}{(1+e^{-(W_{c*}[h_{t-1},x_t]+b_o)}} \tag{13}$$

In a distinct research approach, Lu and Salem (2017) integrated the forget and input gates, separating the process of determining what information to forget from the selection of new data to incorporate. This blended model allows the forget gate to discard input sequences while incorporating current values into the state and omitting older sequences. The resulting cell state is expressed as follows:

$$C_t = f_t * C_{t-1} + i_t * C'_t \tag{14}$$

This model represents a unique method of combining forget and input gates to regulate the flow of information in a recurrent neural network. On the other hand, Graph Convolutional Networks (GCNs) are a type of neural network designed specifically for processing graph-structured data. In contrast to traditional Convolutional Neural Networks (CNNs), which operate on regular grid-like data such as images, GCNs operate on irregular graph-structured data like social networks or molecular graphs. Consider a graph G = (V, E) with N nodes (or vertices) and M edges, where V = {v1, v2, ..., vN} represents the set of nodes and E = {(vi, vj)} represents the set of edges. A graph can be represented as an adjacency matrix A R(N×N), where Aij = 1 if there is an edge between node i and node j, and Aij = 0 otherwise. The graph convolution operation can be defined as follows:

$$h_i^{(l+1)} = \sigma(\sum_j A_{ij} * h_j^{(l)} * W^{(l)}) \quad (15)$$

This equation $h_j^{(l)}$ represents the hidden state of node I at layer l, σ is a nonlinear activation function, and W is a weight matrix at layer l. The output of the graph convolution operation at layer l+1 is the hidden state i of node i at layer l+1. The summation Σ j represents a weighted sum over the neighboring nodes of node i, where the weights are determined by the adjacency matrix A. The hidden state of a node at layer l+1 is a function of the hidden states of its neighbouring nodes at layer l, weighted by the adjacency matrix and transformed by the weight matrix. The activation function σ introduces non-linearity into the model

During training, the weight matrix$^{(l)}$ is learned using backpropagation, similar to traditional neural networks. However, the adjacency matrix A remains fixed as it represents the underlying graph structure and is not learned during training. In practice, multiple graph convolutional layers can be stacked to increase the model's depth:

$$h_i^o = xi \quad (16)$$

$$h_i^{(l+1)} = \sigma(\sum_j A_{ij} * h_j^{(l)} * W^{(l)}),\ for\ l = 0, 1, .., L-1 \quad (17)$$

Here, xi represents the input feature vector of node i. This process is repeated for multiple layers to learn increasingly complex representations of the graph. By considering the local graph structure and learning representations of nodes and edges, GCNs often outperform traditional methods when applied to graph-based tasks.

Multiplying with Aij in the graph convolution operation involves computing the sum of feature vectors for neighbouring nodes, excluding the node itself unless self-loops are present in the graph. This non-normalized multiplication can lead to a change in the scale of feature vectors. This issue can be addressed by introducing self-loops in the graph through the addition of the identity matrix to Aij. Normalization of Aij further mitigates the scaling problem by computing D-1Aij, where D represents the diagonal node degree matrix, resulting in the averaging of neighbouring node features. To achieve more dynamic results beyond simple averaging, a symmetric normalization technique, D-1/2 Aij D-1/2, can be employed. By combining these normalization techniques, the propagation rule proposed by Kipf and Welling (2016) can be expressed as:

$$h_i^{(l+1)} = \sigma(\sum_j D^{-\frac{1}{2}} * A_{ij} * D^{-\frac{1}{2}} * h_j^{(l)} * W^{(l)}) \quad (18)$$

Results

The assessment of the risk factor for diabetes type 2 and NIDDM through the utilization of HAR involves distinct sub-processes that collectively enhance the effectiveness of the system. As depicted in Fig. 1, our methodology involves the identification of early-stage diabetes and the optimization of insulin dosages based on meticulously analyzed activity patterns.

Training the LSTM Model for Activity Recognition

The present study employed a dataset consisting of 101,000 instances of Smartphone sensor data associated with fourteen distinct activities. In order to augment the dataset, a GAN model was utilized to generate an additional 229,873 instances of sensor data. To assess the efficacy of different models, the LSTM and GCN models were applied to three separate datasets: the original sensor dataset, the generated sensor dataset, and the combined dataset, which integrated both the genuine and generated sensor datasets. The LSTM model was applied to each dataset and divided into two segments, with 70% of the dataset allocated for training and the remaining 30% for validation purposes. The dataset was structured using a sliding window approach to create an input vector, where each window represented an input shape comprising a 3D vector. The input shape was composed of a group measure, time steps, and stacked layer size. The batch size was set to 1000, representing the number of distinct instances that were rapidly fed into the network. Time steps denoted units of time indicating the duration of each example within the time vibration series. Stacked LSTM layers were employed to process the input data across all time steps, with the layer size set equal to the hidden layer size of the LSTM model. The output cell of the LSTM model generated a 3D vector. For the purpose of classifying the multiclass attributes, a softmax activation function was utilized in another output layer of the LSTM model. Three datasets were employed to compare the proposed method and determine the optimal classification accuracy. The LSTM model was applied to all three datasets to regulate its parameters, while the GCN model was also implemented on the same datasets to ensure a fair comparison with the LSTM model. Evaluation metrics, including accuracy, precision, recall, and F1 score, demonstrated that the GCN model outperformed the LSTM model. The study evaluated the performance of both the LSTM and GCN models using real and generated

Smartphone sensor data from three distinct datasets. The findings indicate that the GCN model is a more effective approach for sensor data classification than the LSTM model.

Table 1: Performance evaluation of the LSTM model in different datasets

Models	Dataset	Accuracy	Sensitivity	Specificity	F-score
LSTM	Actual Data	97.79%	94.38%	98.81%	94.29%
	Generated Data	98.13%	96.28%	99.39%	95.32%
	Merged Data	98.48%	96.65%	99.54%	95.92%
GCN	Actual Data	98.03%	94.71%	98.94%	95.17%
	Generated Data	98.38%	96.65%	99.73%	95.92%
	Merged Data	98.96%	97.45%	99.80%	96.88%

Table 1 presents the performance results of the model when trained on combined actual and generated datasets, showcasing superior performance compared to individual datasets. The inclusion of the combined dataset, which encompasses a wider range of extensive and diverse data, enhances the model's capacity and introduces a regularizing effect that mitigates the regularization error.

Initially, an LSTM model was trained on the dataset, achieving a notable accuracy of 97.79%, sensitivity of 94.38%, specificity of 98.81%, and an F-score of 94.29% on the actual data. On the generated data, the LSTM model achieved an even higher accuracy of 98.13%, sensitivity of 96.28%, specificity of 99.39%, and an F-score of 95.32%. The model's training matrices exhibit smoothness and consistency due to its reduced parameters and robust regularization techniques. This is evident from the model's low standard deviation of 0.18% across 10folds of the validation data, highlighting its consistency and reliability. However, it is important to note that an experiment was conducted with a GCN model on the same dataset, revealing its superior effectiveness over the LSTM model. The GCN model outperformed the LSTM model, achieving an accuracy of 98.96%, sensitivity of 97.45%, specificity of 99.80%, and an F-score of 96.88% on the merged dataset.

In the existing literature, different approaches have been proposed for activity recognition. Chen et al. (2016) introduced an LSTM-based feature extraction method, while Hernández and Suárez (Hernández et al., 2019) utilized a Bidirectional LSTM model. Ha and Choi (2016) presented the CNN-pf and CNN-pff models, which achieved impressive accuracy rates of 98.26 and 97.92%, respectively, on Skoda and M-health datasets. In our study, we evaluated the performance of the LSTM model for activity recognition in the context of diabetes. However, we also explored the GCN model and found it to outperform the LSTM model in terms of accuracy, sensitivity, specificity, and score. The GCN model showed superior activity detection capabilities and robustness, owing to reduced model parameters, effective preprocessing techniques, and robust regularization, which ensured smooth training matrices independent of fluctuations.

Additionally, Cheng et al. (2021) developed an activity recognition system using commodity WiFi devices with the Gaussian Mixture Hidden Markov Model (GMM-HMM), achieving an average accuracy exceeding 97% on self-collected datasets. Another study evaluated various classifiers, such as k-nearest neighbours (KNN), linear discriminant analysis (LDA), support vector machine (SVM), and random forest (RF) (Nurwulan & Selamaj, 2021). Their findings indicated that combining acceleration and jerk features led to above 87% accuracy for all classifiers, regardless of sensor orientation, effectively capturing changes in body accelerations. To ensure a fair comparison, we incorporated the performance of classical machine learning algorithms, specifically Support Vector Machines (SVMs) and K-Nearest Neighbor (KNN). Using SVMs and KNN, we achieved accuracies of 97.53% and 97.04%, respectively.

Despite the commendable performance of the baseline machine learning algorithms, the LSTM model displayed exceptional activity detection capabilities. Nonetheless, the GCN model surpassed the LSTM model in our study, exhibiting higher accuracy, sensitivity, specificity, and F-score, making it a more suitable choice for this specific task of recognizing symptomatic activities of diabetes. The proposed GCN model achieved a high success rate in recognizing these activities, which is further supported by Fig. 6, resembling a confusion matrix, illustrating significant prediction errors in walking, lying, going upstairs, and cycling activities within the dataset. Both the actual and predicted label quantities are in multiples of thirties in this case. By adopting cutting-edge Human Activity Recognition (HAR) techniques, we can confidently assert the effectiveness of the GCN model in this domain.

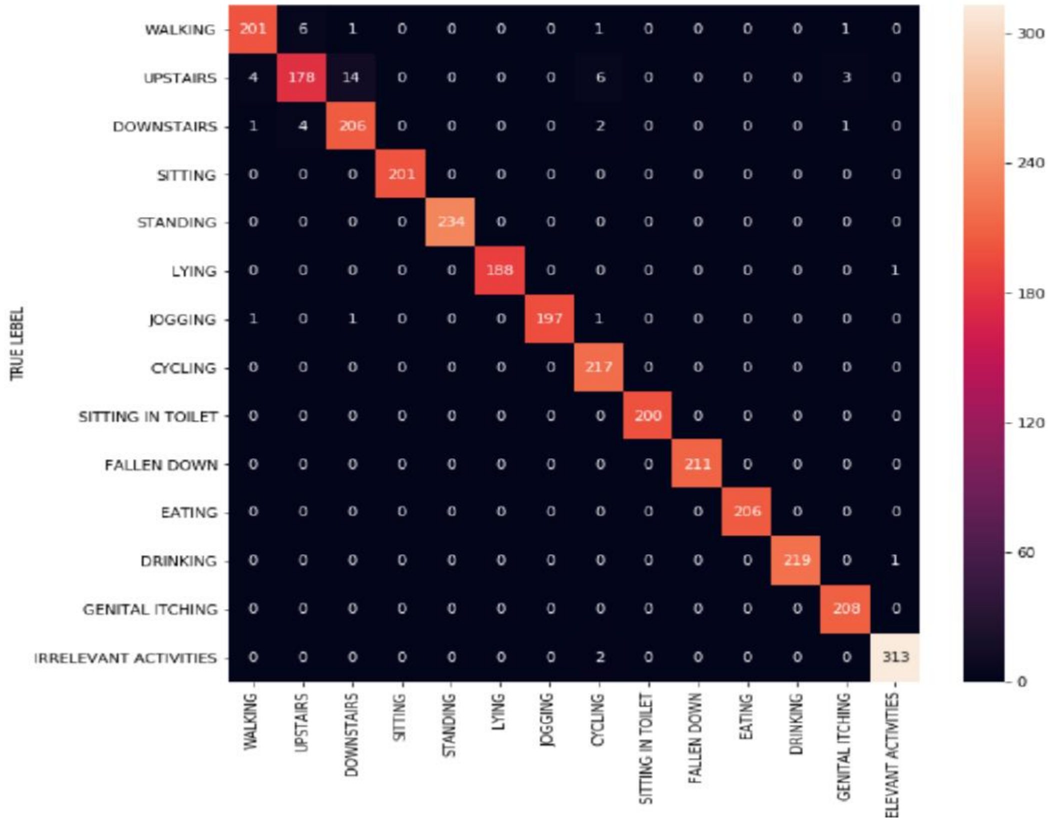

Fig. 6: The confusion matrix of the Graph Convolutional Network (GCN) model was computed using a combined dataset comprising actual samples and generated samples. In this dataset, both the true labels and predicted labels are multiples of ten

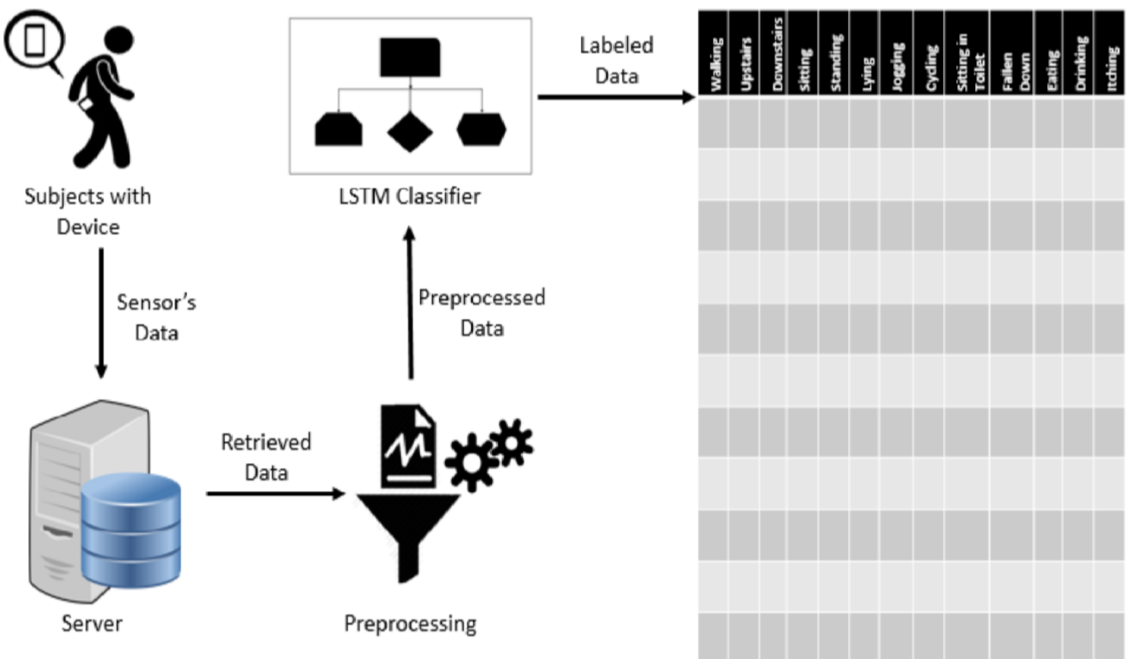

Fig. 7: Working process of tracking activity pattern

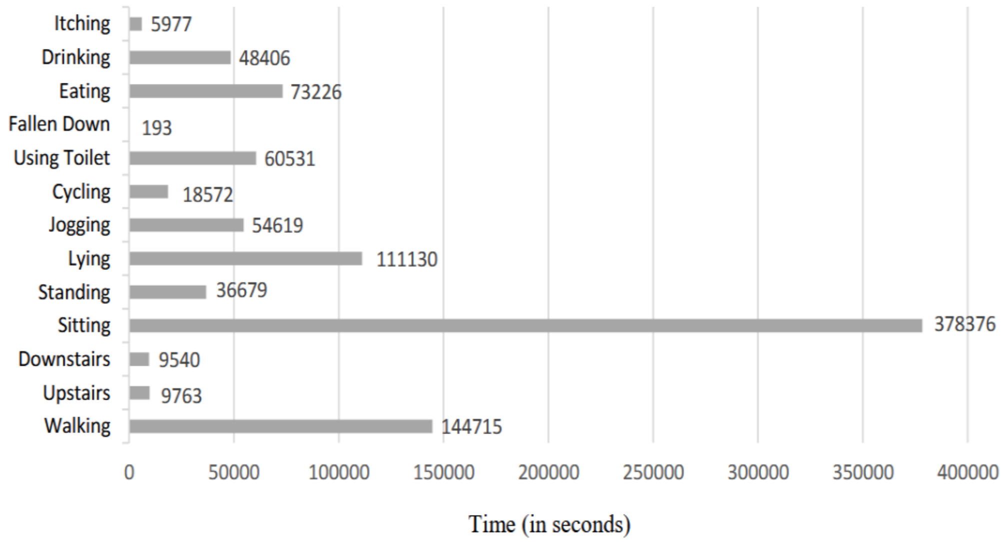

Fig. 8: Activities performed by target subject in 30 days

Based on the discussion, it becomes apparent that our human activity recognition model has undergone comprehensive training, enabling it to make precise predictions regarding the thirteen distinctive activities associated with diabetes symptoms. Consequently, we affirm that the Graph Convolutional Network (GCN) model proves to be a more fitting methodology for this specific objective when compared to the Long Short-Term Memory (LSTM) model. As our human activity recognition model has now achieved a satisfactory level of proficiency, we can advance to the subsequent stage of our undertaking, wherein the assessment of activity similarity with diabetes symptoms is undertaken to identify potential risk factors.

Tracking Activity of Experimental Subject

The GCN model underwent training in order to identify symptomatic activities associated with diabetes. Subsequently, our focus shifted towards monitoring the activity patterns exhibited by the participants in the experimental dataset. To facilitate this, we developed an Android application that enabled continuous data collection from individuals over a period of thirty consecutive days. In this study, we collected six secondary data variables using an Android application. These variables included height, weight, blood pressure, presence of diabetes in first-degree relatives, age, and gender. The height and weight measurements were utilized to determine the Body Mass Index (BMI). Once our Android application and other necessary arrangements were in place, we initiated the process of data accumulation from the experimental subjects. We instructed each subject to always keep the Smartphone in their pocket, ensuring maximum data collection. The application swiftly collected data from the sensors and continuously transmitted it to a server, which was connected to the cloud. After careful consideration of the extensive data produced throughout the uninterrupted data collection phase lasting for a duration of thirty days, we arrived at this conclusion. Moreover, the establishment of a connection between the Android application and the server facilitated the seamless acquisition of daily data.

As a result, the subject's target data continuously streamed into the server for thirty days, with a frequency of 1Hz. Thirty days encompass a total of 2,592,000 seconds, implying that for each subject, we obtained a total of cases equal to or less than 604,800. Ideally, it should have been 951,728 cases; however, various factors such as internet disruptions, accidental device shutdowns, and other similar occurrences resulted in a lower number of cases. This indicates that the experimental subjects provided data for an average of 8.81 hours per day.

The experimental subject provided the primary source of data, which underwent preprocessing using the prescribed preprocessing method. The processed data was then prepared for activity prediction related to the subject's activities within the last thirty days. Subsequently, the data was inputted into our trained Graph Convolutional Network (GCN) classifier model to identify and predict the activities performed by the experimental subject. The procedure was similarly applied to the data collected from each subject. Following the classification of all activity attributes for the experimental subject, we proceeded to measure the duration of time spent on each activity. To accomplish this, our initial step involved determining the frequency of occurrences associated with a specific action.

During the data collection process, we recorded information at a frequency of 1 Hz. This allowed us to determine the total duration of each activity, representing the number of seconds a subject was engaged in that particular activity over a period of thirty days. However, it was necessary to convert the time from seconds to minutes. This conversion was carried out to facilitate the calculation of the average time spent on each specific activity per day. To achieve this, the total number of minutes for each activity was divided by thirty, yielding the standard time allocated to that activity daily. In a specific case where 951,728 occurrences were obtained, these instances were inputted into the classifier model to predict the corresponding activities. Out of the total occurrences, a significant proportion of 378,376 instances were classified as sitting, indicating that the subject spent 378,376 seconds engaged in this activity over the thirty-day period. To obtain the time in minutes, the seconds were divided by 60, resulting in approximately 6,306 min

Considering the need for regular time measurement, the total minutes were further divided by 30 to determine the expected daily time spent sitting. By dividing 6,306 minutes by 30, an average of 210 minutes was established as the daily sitting duration for the subject. By employing this methodology, the total duration of each specific activity performed was computed, providing insights into the time dedicated to each activity over the thirty-day period.

Data Collection from Diabetic Subject

Upon successfully attaining human activity recognition for a comprehensive set of thirteen referenced activities, we embarked on procuring data related to the daily routines of both diabetic and non-diabetic subjects, employing a meticulously designed questionnaire as our data collection instrument. The primary objective behind collecting data on diabetes symptoms was to investigate the performance of the thirteen activities. The primary objective of our investigation was to ascertain the temporal distribution of activities among diabetic patients. These activities encompassed a range of actions, namely walking, sitting, standing, eating, drinking, sleeping, jogging, cycling, ascending, and descending stairs, as well as the occurrences of falls and episodes of genital itching. Our study sought to comprehensively analyze the duration of engagement in each of these activities within the diabetic patient cohort. The duration of these activities was recorded to establish correlations between subjects' everyday activities and their respective durations.

To gather data from patients, we obtained proper certification from the university and sought permission from the relevant authority at Chattogram Diabetic General Hospital. Once permission was granted for data collection from both diabetic and non-diabetic subjects, our research team visited the hospitals and conducted individual interviews to collect the necessary data. We designed a comprehensive questionnaire to capture the data of diabetic and non-diabetic patients. The questionnaire included inquiries regarding the time required for eating, the duration of rest, the frequency of running, and other relevant factors. A total of 97 patients diagnosed with diabetes and 108 non-diabetic individuals participated in this survey, providing their oral consent to voluntary participation in the research. The collected responses were recorded using a Google Form and subsequently compiled into an Excel sheet.

Two physical properties, namely age and weight, were taken into consideration during the analysis. It has been observed that age and weight significantly impact the occurrence of diabetes. Existing research and statistical data indicate that age and weight play direct roles in the development of diabetes, with children having a higher likelihood of type-1 diabetes compared to adults and excess weight being one of the primary causes of type-2 diabetes (Oram et al., 2016). Consequently, we incorporated these two physical properties, age and weight, into our analysis. Once the pertinent information regarding diabetes was gathered, we documented the findings in a spreadsheet.

Computing Similarity

Upon completion of the data collection process, our focus shifted to similarity measures. We determined the average duration of each daily activity based on the experimental subject data. This average duration was utilized as the basis for similarity measurement, and the corresponding risk factor was derived from a 30-day dataset. The concept of similarity measure pertains to a mathematical function utilized for evaluating the proximity between a pair of objects or samples. It serves to quantify the dissimilarities existing between the corresponding features or dimensions of these objects. In the present research, the selection of cosine similarity as the designated similarity measure is attributed to its direct relevance to the activity term, which denotes the frequency of specific exercise events for the subjects under study. By employing cosine similarity, we can effectively compute the cosine of the angle formed between two multivariate inner component space vectors.

In contrast, the Euclidean distance measures the straight-line distance between two multidimensional objects without considering any angular information between them. Unlike the Euclidean distance, cosine similarity incorporates the angle between the two objects, thereby accounting for their characteristics as components of the vector representation. This distinction makes cosine similarity a well-suited metric for our investigation, as it captures the relative orientation and magnitude of the feature vectors, proving beneficial for analyzing the exercise patterns of the subjects. Consequently, the application of cosine similarity facilitates a comprehensive and accurate assessment of the similarities between the objects under examination.

If we represent two points, x and y, in a multidimensional space as separate vectors, A and B, respectively, these vectors form an angle θ. When considering the cosine of θ, we are referring to cosine similarity. However, when seeking the ruler distance, d, between x and y, we are referring to Euclidean distance. The similarity estimation is defined based on the values of θ. When θ = 0, cosθ = 1, indicating that the two vectors are similar. On the contrary, at θ = 90 degrees, the cosine of θ, i.e., cosθ, evaluates to 0, which unequivocally indicates the absence of similarity between the two vectors or objects under consideration. For ease of reference, we shall utilize the notations Ai and Bi to represent segments of vectors A and B, respectively. Moreover, ‖A‖ and ‖B‖ shall symbolize the Euclidean norms of vectors A and B correspondingly. As θ denotes the angle formed by the vectors, the cosine similarity between these objects can be mathematically formulated as follows:

$$\cos\theta = \frac{A.B}{\|A\|\,\|B\|} = \frac{\sum_{i=1}^{p} A_i B_i}{\sqrt{\sum_{i=1}^{p} A_i^2}\sqrt{\sum_{i=1}^{p} B_i^2}} \tag{19}$$

In our work, we employed this cosine similarity to measure the similarity between the data of the target subjects and the patients. For each objective subject and patient, nine measurements were taken, including age, weight, running, sitting, sleeping, walking, eating, jogging, and cycling. To remove the bias introduced by individual dimensions, we preprocessed these measurement values using min-max normalization. After normalizing the data, each row was converted into its corresponding vector representation during the similarity estimation process. Let T be a vector representing a case from the target subjects' dataset, and P be a vector representing a sample from the patient's dataset. Each vector comprises nine vector components representing the nine dimensions. The cosine similarity between these two vectors can be expressed as follows:

$$\cos\theta = \frac{T.P}{\|T\|\,\|P\|} = \frac{\sum_{i=1}^{17} T_i P_i}{\sqrt{\sum_{i=1}^{17} T_i^2}\sqrt{\sum_{i=1}^{17} P_i^2}} \tag{20}$$

To categorize the similarity measures based on the subjects' activity patterns into different levels of risk factors, it was necessary to define the thresholds indicating high, moderate, or low risk. Depending on the closeness value, we established the concept of a risk factor as follows: a higher, moderate, or lower positive correlation value denotes a high, medium, or low-risk factor, respectively. We designate the categories as follows: similarity values greater than 90% are considered high-risk factors, values below 50% are classified as low-risk factors, and values between 50% and 90% are regarded as moderate-risk factors. In the context of cancer classification, gaining a profound understanding of the problem, proposed solutions, and related issues is essential. Notably, diabetes classification differs from other classification applications in terms of the amount of valuable information revealed during the classification process. Accuracy plays a vital role in diabetes classification as it facilitates precise diagnosis of diabetes patients. Hence, it becomes evident that to achieve optimal classification performance and gain meaningful insights into diabetes classification, a thorough exploration of risk factors is crucial. Therefore, the following process quantifies the risk factor as a percentage based on the activity pattern of the experimental subject. Specifically, a similarity measurement process was conducted for an anonymous target subject using data accumulated from 97 diabetes-affected patients. In this research study, we conducted isolated performance measurements for the target subject. A thorough analysis was performed by comparing the data of individuals affected by diabetes with a dataset comprising 97 cases of diabetic patients. Our findings indicate a substantial similarity between the experimental subject and the diabetic patients. For a more detailed visualization, we present a line graph (see Fig. 9) illustrating the correlation values between the experimental subject and the diabetic patients. This graphical representation enhances the demonstration of the observed relationships.

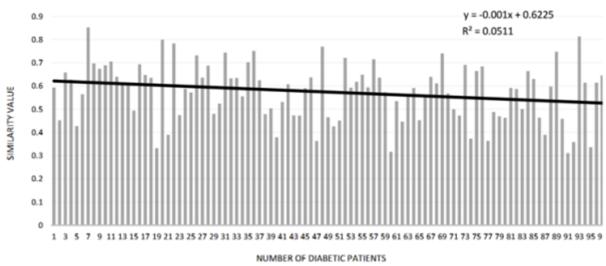

Fig. 9: The correlation coefficients obtained from examining the relationship between the experimental subjects and individuals diagnosed with diabetes

Early Diagnosing of diabetes and Estimating Risk Factors

Current literature on diabetes reveals a limited understanding of the disease, prompting biologists to explore gene interactions and other relevant biological

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information for a comprehensive comprehension of diabetes development. Consequently, diabetes classification encompasses more than just achieving high accuracy; it involves the identification of valuable insights into gene interactions. In this context, the methods described in this section are categorized to explore the impact of activities in the early diagnosis of diabetes and the identification of diabetes risk factors. Broadly speaking, these methods can be divided into two categories. The first category employs a classification approach that treats the data as distributions and makes classification decisions based solely on the distribution of data values, disregarding the contextual meaning of the data. To approach diabetes classification systematically and impartially, we employed a Support Vector Machine (SVM) with a neural network architecture. The SVM model was trained using activity pattern data from both diabetic and non-diabetic patients. Evaluation of the SVM model yielded classification accuracies of 96.94%, 97.27%, and 96.31% for accuracy, sensitivity, and specificity, respectively. These results indicate the potential of the SVM classification model in analyzing the condition of suspected diabetes patients during the diagnosis phase. Subsequently, the activity pattern of an experimental subject was manipulated using the trained SVM model, leading to the prediction that the subject was a diabetic patient.

Nevertheless, relying solely on a single hypoglycemia test to assess the potential for microvascular or macrovascular complications is deemed insufficient. In this context, adopting acute glucose consumption metrics presents a more informative approach to evaluating diabetes. Notably, A1C emerges as a dependable measure of glycemic levels, demonstrating a robust correlation with the risk of long-term diabetes complications. The implementation of the A1C assay also offers several technical advantages over conventional glucose laboratory measurements, encompassing pre-analytic and analytic benefits. Extensive examination, as presented in a study (The International Expert Committee, 2009), highlights the distinctive features of A1C testing concerning diabetes diagnosis, particularly its standardization and alignment with the DCCT/UKPDS guidelines. In support of its accuracy in representing continuous glycemic levels and their associated risk of diabetes complications, the International Expert Committee for the Diagnosis of diabetes has officially recommended the adoption of the A1C assay. Prior research underscores that individuals exhibiting A1C levels greater than 6% but less than 6.5% face a heightened susceptibility to diabetes development. Nonetheless, it is essential to acknowledge that this range should not be regarded as an absolute threshold for initiating preventive measures (Cohen et al., 2010; Organization, 2011; Zhou et al., 2009). Consequently, leveraging the A1C assay alongside other complementary assessments becomes pivotal in comprehensively evaluating the risk of diabetes-related complications.

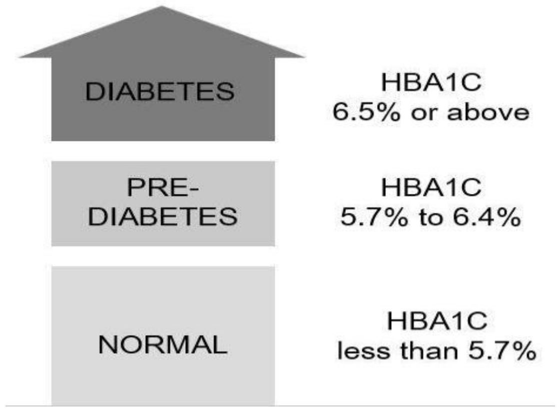

Fig. 10: Scaling of the clinical diagnosing process of HBA1C

The present study involved conducting an assessment of average similarity estimation on the experimental subject, resulting in a calculated value of 57.3916%. This substantiates the alignment between the individual's activities and the characteristic symptom patterns associated with diabetes. Consequently, based on the obtained average similarity measure of 57.3916%, the patient can be classified under the category of moderate risk factor for diabetes. The preceding reference to the sole target subject serves to indicate that the target patient demonstrated a moderate impact attributed to diabetes. Consequently, the primary objective was to determine the risk factor associated with the experimental subject during the clinical process. To achieve this, a comprehensive A1C assay was conducted on the experimental subject, revealing an A1C level of 6.1%. This result confirmed the presence of diabetes in accordance with our established procedure. Therefore, it can be inferred that our approach yielded a significantly high success rate in identifying the risk factor based on activity patterns. A thorough examination of the similarity measures presented in Tab. (2) clearly indicates that our methodology for identifying the risk factor exhibited superior performance. This compelling finding serves as a strong justification for accurately classifying the experimental subject as moderately affected by diabetes, successfully determining the specific risk level of diabetes he is experiencing.

Table 2: Comparison between the clinical test result and early staging of the proposed system

Programmer	Active Sense	Clinical HbA1c Assay
Result	Similarity - 57.3916%	Hemoglobin level - 6.1%
Hypothesis	Moderately affected	Prediabetes

Discussion

The integration of Smartphone-based Human Activity Recognition (HAR) emerges as a transformative avenue for advancing the field of diabetes diagnosis, personalized management of diabetes, and comprehensive data analysis. Our focus is on the development of a sophisticated system tailored for recognizing human activities, particularly those associated with diabetes, utilizing smartphone data. This study proposes a promising approach that capitalizes on the ubiquitous nature of smartphones for early detection of diabetes and proactive management of associated risks, ultimately leading to improved healthcare outcomes for individuals at risk of developing type 2 diabetes and NIDDM. Our findings underscore the significance of employing cutting-edge machine-learning techniques in HAR for precise activity recognition. Both LSTM and GCN models were evaluated, with the GCN model outperforming the LSTM model and classical machine learning algorithms in terms of accuracy, sensitivity, specificity, and F1 score. This emphasizes the importance of leveraging sophisticated models capable of capturing intricate patterns within sensor data, thereby enhancing the efficacy of diabetes risk assessment. To tackle the challenges posed by limited data availability, Generative Adversarial Networks (GAN) were employed to synthesize artificial sensor data. This innovative approach enables the system to transcend dependence on authentic data sources, ensuring robust performance even with constrained datasets. The synthesis of these data methodologies and the introduction of a novel risk assessment paradigm collectively establish a comprehensive framework for the recognition and understanding of human activities.

Our findings emphasize the importance of employing advanced machine learning techniques in HAR for accurate activity recognition. Initially, the LSTM model achieved notable accuracy (97.79%), sensitivity (94.38%), specificity (98.81%), and F-score (94.29%) on actual data, with improved performance on generated data (98.13% accuracy, 96.28% sensitivity, 99.39% specificity, and 95.32% F-score). However, the GCN model demonstrated superior effectiveness, achieving an accuracy of 98.96%, sensitivity of 97.45%, specificity of 99.80%, and an F-score of 96.88% on the merged dataset. The LSTM model displayed exceptional activity detection capabilities, but the GCN model surpassed the LSTM.

The medical diagnosis component of our system also demonstrated promising results. An assessment of average similarity estimation on the experimental subject yielded a value of 57.3916%, indicating alignment between the individual's activities and characteristic symptom patterns associated with diabetes. Based on this measure, the patient was classified under a moderate risk factor for diabetes. A comprehensive A1C assay conducted on the experimental subject revealed an A1C level of 6.1%, confirming the presence of diabetes. This finding substantiates our approach's effectiveness in identifying the risk factor based on activity patterns.

Conclusion

Smartphones have become an integral part of modern life, providing a unique opportunity to leverage technology for public health initiatives. The ubiquitous nature of smartphones makes them an ideal platform for continuous health monitoring and early disease detection. Smartphones are widely accessible across different demographics, making health monitoring tools available to a broad audience. They can continuously collect and analyze health data in real-time, providing timely insights into an individual's health status. The convenience of carrying a smartphone ensures that health monitoring is non-intrusive and can seamlessly integrate into daily life. Interactive applications and personalized feedback can enhance user engagement and adherence to health recommendations. Integrating smartphone-based health monitoring into public health strategies can lead to significant improvements in disease prevention and management. For diabetes, continuous monitoring can help identify early signs of diabetes, enabling timely medical intervention. Smartphones can provide tailored recommendations based on individual health data, supporting personalized diabetes management plans. Analyzing activity patterns and other health metrics can offer insights into behaviours that impact diabetes risk, guiding public health initiatives and individual interventions.

Our research focuses on developing a sophisticated system for recognizing human activities associated with diabetes using smartphone data. This approach leverages the power of GANs to overcome data limitations by synthesizing artificial sensor data. The combination of advanced machine learning models, clinical tests like the A1C assay, and smartphone technology provides a comprehensive framework for early diabetes detection and management. By capturing intricate patterns within sensor data, our system can accurately assess diabetes risk and recommend personalized interventions. This not only aids in early diagnosis but also empowers individuals to take proactive steps in managing their health. The integration of smartphones in this context highlights their potential as a powerful tool for enhancing public health outcomes and addressing the global diabetes epidemic.

In conclusion, our interdisciplinary approach holds great promise in revolutionizing diabetes management by enabling early detection and personalized interventions and, ultimately, fostering a future where individuals can proactively navigate their health journey with confidence and empowerment. While significant strides have been made in this research, avenues for further exploration remain, particularly in enhancing the system's adaptability across diverse scenarios and expanding its utility in health monitoring. The validation of the proposed system's efficacy and generalizability across diverse populations necessitates large-scale clinical trials. The development of adaptive and personalized interventions and feedback mechanisms based on real-time activity analysis has the potential to empower individuals to actively manage their diabetes and prevent complications. As this research moves forward, emphasis on refining adaptability, conducting large-scale trials, and integrating personalized interventions is crucial. Validation, data integration, and personalized interventions have immense potential to revolutionize diabetes care, ultimately leading to improved health outcomes for millions worldwide.

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Author's Contributions

Mohammed Shamsul Alam: Conceived the study, developed the methodology, conducted data analysis.

Erfanul Hoque Bahadur: Contributed to experimental design, validation, and interpretation of results and prepared the initial manuscript draft.

Md Fokrul Islam Khan: Contributed to data collection and validation.

Farhad Uddin Mahmud: Critical review and manuscript editing.

Md Ismail Hossain Siddiqui: Contributed to interpretation of results and revised the manuscript for technical accuracy.

Abdul Kadar Muhammad Masum: Provided supervision, critically reviewed the methodology and results, and contributed to manuscript editing.

Ethics

This article is an original work and includes previously unpublished material.

Conflicts of Interest

The authors have no conflicts of interests to declare.

References

Abdel-Salam, R., Mostafa, R., & Hadhood, M. (2021). Human Activity Recognition Using Wearable Sensors: Review, Challenges, Evaluation Benchmark. *Deep Learning for Human Activity Recognition*, *1370*, 1–15. https://doi.org/10.1007/978-981-16-0575-8_1

Ahmad, T., Jin, L., Zhang, X., Lai, S., Tang, G., & Lin, L. (2021). Graph Convolutional Neural Network for Human Action Recognition: A Comprehensive Survey. *IEEE Transactions on Artificial Intelligence*, *2*(2), 128–145. https://doi.org/10.1109/tai.2021.3076974

American Diabetes Association. (2003). Physical Activity/Exercise and diabetes Mellitus. *diabetes Care*, *26*(suppl_1), s73–s77. https://doi.org/10.2337/diacare.26.2007.s73

American Diabetes Association. (2016). 3. Foundations of care and comprehensive medical evaluation. *diabetes Care*, *39*. https://doi.org/10.2337/dc16-S006

Anjum, F., Alam, S., Bahadur, E. H., Masum, A. K. M., & Rahman, Md. Z. (2022). Deep Learning for Depression Symptomatic Activity Recognition. *2022 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, 510–515. https://doi.org/10.1109/iciset54810.2022.9775922

Bahadur, E. H., Masum, A.K.M., Barua, A., Rabiul Alam, Md. G., Zaman Chowdhury, Md. A. U., & Alam, M. R. (2019). LSTM Based Approach for Diabetic Symptomatic Activity Recognition Using Smartphone Sensors. *2019 22nd International Conference on Computer and Information Technology (ICCIT)*, 1–6. https://doi.org/10.1109/iccit48885.2019.9038185

Bahadur, E. H., Masum, A. K. M., Barua, A., & Uddin, M. Z. (2021). Active Sense: Early Staging of Non-Insulin Dependent diabetes Mellitus (NIDDM) Hinges upon Recognizing Daily Activity Pattern. *Electronics*, *10*(18), 2194. https://doi.org/10.3390/electronics10182194

Barna, A., Masum, A. K. M., Hossain, M. E., Bahadur, E. H., & Alam, M. S. (2019). A Study on Human Activity Recognition Using Gyroscope, Accelerometer, Temperature and Humidity Data. *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 1–6. https://doi.org/10.1109/ecace.2019.8679226

Chanana, N., & Sangeeta. (2021). Employee Engagement Practices During COVID-19 Lockdown. *Journal of Public Affairs*, *21*(4), 2508. https://doi.org/10.1002/pa.2508

Chen, Y., Zhong, K., Zhang, J., Sun, Q., & Zhao, X. (2016). LSTM Networks for Mobile Human Activity Recognition. *Proceedings of the 2016 International Conference on Artificial Intelligence: Technologies and Applications*, 50–53. https://doi.org/10.2991/icaita-16.2016.13

Cheng, X., Huang, B., & Zong, J. (2021). Device-Free Human Activity Recognition Based on GMM-HMM Using Channel State Information. *IEEE Access*, *9*, 76592–76601. https://doi.org/10.1109/access.2021.3082627

Cohen, R. M., Haggerty, S., & Herman, W. H. (2010). HbA1c for the Diagnosis of diabetes and Prediabetes: Is It Time for a Mid-Course Correction? *The Journal of Clinical Endocrinology & Metabolism*, *95*(12), 5203–5206. https://doi.org/10.1210/jc.2010-2352

Davies, T. T., Graue, M., Igland, J., Tell, G. S., Birkeland, K. I., Peyrot, M., & Haltbakk, J. (2019). diabetes prevalence among older people receiving care at home: associations with symptoms, health status and psychological well-being. *Diabetic Medicine*, *36*(1), 96–104. https://doi.org/10.1111/dme.13790

Duong, T. V., Bui, H. H., Phung, D. Q., & Venkatesh, S. (2005). Activity Recognition and Abnormality Detection with the Switching Hidden Semi-Markov Model. *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 838–845. https://doi.org/10.1109/cvpr.2005.61

Feng, L., Zhao, Y., Zhao, W., & Tang, J. (2022). A Comparative Review of Graph Convolutional Networks for Human Skeleton-Based Action Recognition. *Artificial Intelligence Review*, *55*(5), 4275–4305. https://doi.org/10.1007/s10462-021-10107-y

Gers, F. A., & Schmidhuber, J. (2000). Recurrent Nets that Time and Count. *Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium*, 189–194. https://doi.org/10.1109/ijcnn.2000.861302

Ha, S., & Choi, S. (2016). Convolutional Neural Networks for Human Activity Recognition Using Multiple Accelerometer and Gyroscope Sensors. *2016 International Joint Conference on Neural Networks (IJCNN)*, 381–388. https://doi.org/10.1109/ijcnn.2016.7727224

Helmrich, S. P., Ragland, D. R., Leung, R. W., & Paffenbarger, R. S. (1991). Physical Activity and Reduced Occurrence of Non-Insulin-Dependent diabetes Mellitus. *New England Journal of Medicine*, *325*(3), 147–152. https://doi.org/10.1056/nejm199107183250302

Hernandez, F., Suarez, L. F., Villamizar, J., & Altuve, M. (2019). Human Activity Recognition on Smartphones Using a Bidirectional LSTM Network. *2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA)*, 1–5. https://doi.org/10.1109/stsiva.2019.8730249

Hernandez, N., Lundström, J., Favela, J., McChesney, I., & Arnrich, B. (2020). Literature Review on Transfer Learning for Human Activity Recognition Using Mobile and Wearable Devices with Environmental Technology. *SN Computer Science*, *1*(2), 66. https://doi.org/10.1007/s42979-020-0070-4

Hou, J., Sun, H., Xiao, L., Zhou, Y., Yin, W., Xu, T., Cheng, J., Chen, W., & Yuan, J. (2016). Combined Effect of Urinary Monohydroxylated Polycyclic Aromatic Hydrocarbons and Impaired Lung Function on diabetes. *Environmental Research*, *148*, 467–474. https://doi.org/10.1016/j.envres.2016.03.038

Hu, F. B., Leitzmann, M. F., Stampfer, M. J., Colditz, G. A., Willett, W. C., & Rimm, E. B. (2001). Physical Activity and Television Watching in Relation to Risk for Type 2 diabetes Mellitus in Men. *Archives of Internal Medicine*, *161*(12), 1542–1548. https://doi.org/10.1001/archinte.161.12.1542

Hu, F. B., Sigal, R. J., Rich-Edwards, J. W., Colditz, G. A., Solomon, C. G., Willett, W. C., Speizer, F. E., & Manson, J. E. (1999). Walking Compared with Vigorous Physical Activity and Risk of Type 2 diabetes in Women. *JAMA*, *282*(15), 1433–1439. https://doi.org/10.1001/jama.282.15.1433

Ji, S., Xu, W., Yang, M., & Yu, K. (2013). 3D Convolutional Neural Networks for Human Action Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *35*(1), 221–231. https://doi.org/10.1109/tpami.2012.59

Kipf, T. N., & Welling, Max. (2016). Semi-Supervised Classification with Graph Convolutional Networks. *ArXiv:1609.02907*. https://doi.org/10.48550/arXiv.1609.02907

Kriska, A. M., & Bennett, P. H. (1992). An Epidemiological Perspective of the Relationship Between Physical Activity and Niddm: from Activity Assessment to Intervention. *diabetes/Metabolism Reviews*, *8*(4), 355–372. https://doi.org/10.1002/dmr.5610080404

Li, M., Chen, S., Chen, X., Zhang, Y., Wang, Y., & Tian, Q. (2019). Actional-Structural Graph Convolutional Networks for Skeleton-Based Action Recognition. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 3590–3598. https://doi.org/10.1109/cvpr.2019.00371

Lu, Y., & Salem, F. M. (2017). Simplified Gating in Long Short-Term Memory (Lstm) Recurrent Neural Networks. *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*, 1601–1604. https://doi.org/10.1109/mwscas.2017.8053244

Manson, J. E., Stampfer, M. J., Colditz, G. A., Willett, W. C., Rosner, B., Hennekens, C. H., Speizer, F. E., Rimm, E. B., & Krolewski, A. S. (1991). Physical Activity and Incidence of Non-Insulin-Dependent diabetes Mellitus in Women. *The Lancet*, *338*(8770), 774–778. https://doi.org/10.1016/0140-6736(91)90664-b

Masum, A. K. M., Bahadur, E. H., & Ruhi, F. A. (2020). Scrutiny of Mental Depression through Smartphone Sensors Using Machine Learning Approaches. *International Journal of Innovative Computing*, *10*(1), 59–67. https://doi.org/10.11113/ijic.v10n1.259

Muhammad Masum, A. K., Barua, A., Bahadur, E. H., Alam, M. R., Akib Uz Zaman Chowdhury, Md., & Alam, M. S. (2018). Human Activity Recognition Using Multiple Smartphone Sensors. *2018 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, 468–473. https://doi.org/10.1109/iciset.2018.8745628

Nurwulan, N. R., & Selamaj, G. (2021). A Comparative Evaluation of Acceleration and Jerk in Human Activity Recognition Using Machine Learning Techniques. *Proceedings of the 1st International Conference on Electronics, Biomedical Engineering, and Health Informatics*, *746*, 55–61. https://doi.org/10.1007/978-981-33-6926-9_5

Oram, R. A., Patel, K., Hill, A., Shields, B., McDonald, T. J., Jones, A., Hattersley, A. T., & Weedon, M. N. (2016). A Type 1 diabetes Genetic Risk Score Can Aid Discrimination Between Type 1 and Type 2 diabetes in Young Adults. *diabetes Care*, *39*(3), 337–344. https://doi.org/10.2337/dc15-1111

Ordóñez, F., & Roggen, D. (2016). Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. *Sensors*, *16*(1), 115. https://doi.org/10.3390/s16010115

Organization, W. H. (2011). *Use of Glycated Haemoglobin (HbA1c) in Diagnosis of diabetes Mellitus: Abbreviated Report of a WHO Consultation*.

Ramanujam, E., Perumal, T., & Padmavathi, S. (2021). Human Activity Recognition with Smartphone and Wearable Sensors Using Deep Learning Techniques: A Review. *IEEE Sensors Journal*, *21*(12), 13029–13040. https://doi.org/10.1109/jsen.2021.3069927

Sinclair, A. J., Abdelhafiz, A. H., & Rodríguez-Mañas, L. (2017). Frailty and Sarcopenia - Newly Emerging and High Impact Complications of diabetes. *Journal of diabetes and Its Complications*, *31*(9), 1465–1473. https://doi.org/10.1016/j.jdiacomp.2017.05.003

Straczkiewicz, M., James, Peter, & Onnela, J.-P. (2019). A Systematic Review of Human Activity Recognition Using Smartphones. *ArXiv:1910.03970*. https://doi.org/10.48550/arXiv.1910.03970

The International Expert Committee. (2009). International Expert Committee Report on the Role of the A1C Assay in the Diagnosis of diabetes. *diabetes Care*, *32*(7), 1327–1334. https://doi.org/10.2337/dc09-9033

Tuomilehto, J., Schwarz, P., & Lindström, J. (2011). Long-Term Benefits from Lifestyle Interventions for Type 2 diabetes Prevention. *diabetes Care*, *34*(Supplement_2), S210–S214. https://doi.org/10.2337/dc11-s222

Weinstein, A. R., Sesso, H. D., & Lee, 'I. Min. (2004). Relationship of Physical Activity vs Body Mass Index with Type 2 diabetes in Women. *JAMA*, *292*(10), 1188–1194. https://doi.org/10.1001/jama.292.10.1188

Yan, S., Xiong, Y., & Lin, D. (2018). Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition. *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence*, 7444–7452. https://doi.org/10.1609/aaai.v32i1.12328

Zhang, S., Li, Y., Zhang, S., Shahabi, F., Xia, S., Deng, Y., & Alshurafa, N. (2022). Deep Learning in Human Activity Recognition with Wearable Sensors: A Review on Advances. *Sensors*, *22*(4), 1476. https://doi.org/10.3390/s22041476

Zhou, X. H., Ji, L. N., Luo, Y. Y., Zhang, X. Y., Han, X. Y., & Qiao, Q. (2009). Performance of HbA_{1c} for detecting newly diagnosed diabetes and prediabetes in Chinese communities living in Beijing. *Diabetic Medicine*, *26*(12), 1262–1268. https://doi.org/10.1111/j.1464-5491.2009.02831.x

Zhu, Y., & Mo, L. (2022). A Review of Wearable Sensor-based Human Activity Recognition using Deep Learning. *2022 International Conference on Sensing, Measurement & Data Analytics in the Era of Artificial Intelligence (ICSMD)*, 1–6. https://doi.org/10.1109/icsmd57530.2022.10058422