Human Activity Recognition Based on Improved Bayesian Convolution Network to Analyze Health Care Data Using Wearable IoT Device

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This work was supported in part by the Science and Technology Research Plan of Henan Province: Research on Intelligent Physical Signs Monitoring System of Home-Based Elderly Care Based on IoT Technology, under Project 162102310248, and in part by the Pingdingshan University Carry Forward Project: Research on Key Technologies of Intelligent Home Care Equipment for the Elderly Based on IoT Technology, under Project JZ2017026.

ABSTRACT In the current scenario, it is significant to design active learning paradigms for analyzing human activities using Wearable Internet of Things (W-IoT) sensors for health parameter analysis. Further, in the healthcare sector, data collection using decision-making tools uses wearable sensors for monitoring using Cloud assisted Internet of Things (IoT). Although several conventional algorithms and deep learning models show promising results in sensor data analysis for recognizing human behaviors, the evaluation of their ambiguity in decision-making is still difficult and several conventional systems are more complex. Due to the restricted computing capacity, low-power W-IoT devices need an optimized network to manage the healthcare data effectively and efficiently for reliable analysis. Hence, a new Human Activity Recognition based on Improved Bayesian Convolution Network (IBCN) has been proposed which allows each smart system to download data via either traditional Radio Frequency (RF) communication or low power back dispersion communications with cloud assistance. In IBCN, a distribution of the model’s latent variable is designed and the features are extracted using convolution layers, the performance of the W-IoT has been improved by combining a variable autoencoder with a standard deep net classifier. Furthermore, the Bayesian network helps to address the security issues using Enhanced deep learning (EDL) design with an effective offloading strategy. The experimental results show that the data collected from the wearable IoT sensor is sensitive to various sources of uncertainty, i.e. aleatoric and epistemic, as especially named noise and reliability. Furthermore, lab-scale experimental analysis on patient’s health data classification accuracy has been considerably developed using IBCN than conventional design as named Cognitive radio (CR) learning, deep learning-based sensor activity recognition (DL-SAR) and Cloud-assisted Agent-based Smart home Environment (CASE).

INDEX TERMS Bayesian network, wearable IoT, deep learning, aleatoric, epistemic.

I. WEARABLE SENSOR NETWORK FOR HEALTH CARE AND ITS IMPORTANCE
In the present scenario, the wearable sensors have become increasingly more relevant in the fields of health care research and application [1]. Nowadays, reduced size and costs of several wearable sensors are available in the market for monitoring physical and sports activities, tracking, human-computer interaction, rehabilitation, tracking of the elderly patients for the benefit of Ambient living purposes [2]. There would be tremendous progress because it’s from IoT and on the other hand, it does not require personal safety initiatives [3]. Although wearable digital trackers have created a lot of buzz on the press for weight, blood pressure, calories and daily activity, then the difference between tracking medical grade and adequately tracking of information is unknown or understood by many features [4]. In a positive note, IoT recently revealed its iPhone wellness application, which will function like the Health Kit Development Tool to aggregate the health data and other applications [5]. App developers
The paper introduces an HRC system focused on the wireless Wi-Fi sensor and deep learning techniques, which allows smart and wireless devices in an environment to identify the day-to-day activity of individual users. The purpose of this study is not to detect the activity in real-time but to observe the behaviors of the older adults during the day to reduce anomalous behaviors, which are often important for problematic circumstances or emerging circumstances.

The following paper is organized as followed as in section II the detailed study about Wearable Sensor Network for Health Care systems are reported, in section III background study is discussed following with the proposed system in section IV. Section V is discussed with results & discussion and finally, section VI ends with conclusion & future work.

II. BACKGROUND STUDY

In improving road transport safety and efficiency by linking intelligent vehicles over the cables, the Internet of Things (IoT) platform has played an important part. However, there is a need to continue contact and control means that such an IoT model places considerable strain on small spectrum sources. Cognitive radio (CR) [16], through opportunistic manipulation of the underutilized spectrum, may help to reduce the issue of spectrum shortages. However, several problems are introduced in the very complex topology and time-varied spectrum of CR-based vehicle networks. Based on that inspiration, they follow a Deep Q-Learning Approach (DQLA) to develop an optimized data transfer schedule for cognitive vehicle networks to reduce transmission costs, while completely using different modes and tools of communication.

Sensor-based activity recognition seeks broad, high-level information from many low-level sensor readings of human activities. In recent years traditional approaches to pattern recognition have made significant progress. However, the heuristic extraction, which could delay their generalizing success, often relies heavily on these methods. However, for unsupervised and radical learning reasons, current approaches are compromised. Recently, the recent development in deep learning enables automated extraction in high-level features to achieve promising performance in many fields. This paper explores the recent development of deep learning-based sensor activity recognition (DL-SAR) [17]. Traditionally, human activity recognition (HAR) [18] tasks have been solved by using engineered features derived from heuristic processes. Human behavior consists of a complex sequence of motor movements, and effective HAR needs to capture this temporal dynamic. The system is tested on two datasets that are used in the identification of a public incident. Our findings show that our platform performs an average of 4% over competing for non-recurrent challenge.
networks; some of the previous results are over 9%. Our results demonstrate that the frame can be used for uniform sensor modalities where the multimodal sensors can melt to boost performance. To provide insights into its optimization, the main architectural hyperparameters are characterized for efficiency.

A proper action plan may involve computational complex tasks for sensitive data in the home environment. This is the case of behavior recognition, which includes obtaining high-level information about what happens in the home atmosphere and of people’s behavior. This paper proposes a framework for the design, implementation, and recognition of smart home applications in home environments. The system is primarily based on Cloud-assisted Agent-based Smart home Environment (CASE) [19] architecture with Cloud-based agent support and provides simple abstractions that allow smart home applications to be easily built and implemented.

This article discusses the development of the robot-integrated smart home (RiSH) [20], which can be used for research on the support of elderly care, technologies. The RiSH incorporates a robot for home support, a home sensor network, a body sensor network and a mobile computer. The basic service functions are established to recognize the operation of the human body through an inertial measuring unit (IMU) and a home service robot to audio signal the environment. The experiences of the robot reach beyond its onboard sensors in both applications. A high-level application that senses and responds to human falls using the low-level applications is realized. Experiments demonstrate the working of the different components in RiSH and the home service robot’s capabilities to track and assist residents.

Based upon the above research in general-purpose experiments, all these findings are obtained where the form of operation and related data sets are not intended for the ambient learning region. In, an activity recognition approach focused on environmental learning contexts (VSM) and decision trees is provided, as well as dynamic time warping. Eight volunteers with different smartphones pick up data collection and The obtained results achieve an average accuracy of the above methods for the activity recognition function.

III. HUMAN ACTIVITY RECOGNITION BASED ON IMPROVED BAYESIAN CONVOLUTION NETWORK (IBCN)
Within this section, the definition of uncertainty is specified officially for recognition and the Softmax function is restricted within estimating uncertainty. Wearable apps for medical tracking may be known as consumer devices. Such information can be checked at a different rate to save resources and preserve some accuracy. Sensor data can be analyzed locally or remotely with machine-learning algorithms, usually involving calculations, for classification, prediction and decision making.

This wearable device can be considered a lifestyle device, in which the priority of a user may be seen as fitness rather than activity. It is illustrated in Figure (2) to provide an overview of how a current wearable customer fitness method will look concerning the user. This example discusses the various technical factors to provide users with the input they want. Example block diagram of a wearable fitness operation with fitness wearable technology weight burned calories, heart rate, speed, etc is used for calculating the lifestyle applications. The users are tracked via sensors, and other data is entered by themselves which then can be transmitted to a smartphone and a cloud service provider. The data are then analyzed so that the user can understand them. Based on display form, this is returned either to the paired smartphone or to the wearable.

A. WORKLOAD OFFLOADING SCHEME
This section discusses the workload validation, where each time slot workload can be divided between local, active and...
passive computation. Remember that various systems have different processing and energy consumption capabilities.

As inferred from figure.3. Consequently, the design of the discharge scheme aims to break up the workload in three structures following the workload dynamics, the channel conditions, and each boundary interface energy supply. In active offloading, let indicate the power of transmission of the users as $q_{b,j}$ with $T_j$, $h_{b,j}$ is described in the following Equation (1).

$$h_{b,j} = A \log_2(1 + q_{b,j} \frac{|w|^2}{\rho^2})$$ (1)

As inferred From the Equation (1), $A$ is the active transmission bandwidth; $w$ denotes the noise factor of human&$\rho$ determines data rate denoted in the active mode. Any user can transfer data to the HRC server in either passive backscatter or active Radio Frequency (RF) communications have the relationship between the transmissions (figure 3) which is expressed in the following Equation (2)

$$q_{b,j} = \alpha(h_{b,j})(2 \pi + 1)\left(\frac{|w|^2}{\rho^2}\right)$$ (2)

Here $h_{b,j}$ is the constant circuit power, $\alpha$ denotes the offloading sequence time & $\frac{|w|^2}{\rho^2}$ is the active mode transmission. A higher rate of transmission shows that more channel resources are available to receive patient’s information, for instance, bandwidth and energy consumption. Therefore the total workload denoting the cost of humanity is represented in the following Equation (3)

$$h_{b,j} = \frac{q_{b,j}}{S_{c,j} + S_{q,j}} + \sigma_0 q_{b,j}$$ (3)

$s_0 q_{b,j}$ Denotes the activity behavior of the human $S_{c,j}$ is the active node of the human server & $S_{q,j}$ represents the passive node of the human server.

Based on their local experiences, individual users can make decisions about the offload. Here let us optimize for the single server to determine the long term success followed in the Equation (4)

$$h_{b,j} = \sum_{j=0}^{d} A_j (k_j - k_0) + d(k_0) + \epsilon;$$ (4)

$A_j (k_j - k_0)$ represents the behavior of the human during the time of the position; $d (k_0) = \epsilon$ denotes dependent data uncertainty vale and the parameter $\epsilon$ is used for denoting latent variables. The weights of the distribution are assumed as the discrimination function to take account of epistemic uncertainty representing model uncertainty. The uncertainty general expression is expressed in the following Equation (5)

$$y_m = \sum_{i=1}^{d} \psi_j(y_m)(A_j y_n + a_j)$$ (5)

$$\sum_{i=1}^{d} \psi_j(y_m) = \text{determines the function of validity in the ith region and the parameter vector is denoted as } \psi_j = [A_j, a_j]'.$$

The Equation is represented in terms of Human convolution recognition model is expressed in the following Equation (6)

$$h_{b,j} = y_n * B_j(y_n) \text{ and } x_n = A_j y_m + a_i$$ (6)

$y_n$ denotes the transmission weight of the convolution function.

$B_j(y_n)$ = represents the transmission weight of the convolution function.

$A_j y_m$ = posterior weight of the network.

$a_i$ = denotes the latent feature of the function.

In addition to the training set as well as the test set, separation data is evaluated in the training set and test set for the following equation (7) to determine HRC’s output in different cases and define the most suitable architecture for certain networks.

$$y_m = \frac{\sum_{i=1}^{d} A_j (y_n) (A_j y + f_i)}{\sum_{j=1}^{d} A_j (x_m)}$$ (7)

$$\sum_{j=1}^{d} A_j (x_m) = \text{number of repetitions taken for the activity.}$$

Therefore, the network shall be educated in this case on several people not taken into account during the operating process of the network. For a specific situation, the network is trained once before it is actively used for a collection of pre-collected data. When a new person needs to be tracked, the network must not be retrained thus the unbalanced situation is raised and expressed in the following Equation (8)

$$y_m = \frac{A_j (x_n)}{\sum_{j=1}^{d} A_j (x_m)}$$ (8)

$A_j (x_n)$ = denotes the specific data collection.

$\sum_{j=1}^{d} A_j (x_m) = \text{previous data collection repeated number of times.}$

In this case, the network trains all the users monitored throughout the service. This scenario, the preparation of a network for the same users, may produce the most accurate results in an exact approach which needs a large number of
computer resources in a real environment expressed in the following equation (9)

$$A_j = \frac{e^{b_j(x_n)}}{\sum_{j=1}^{M} A_j(x_n)}$$ (9)

$b_j$ = denotes the input element vector.
$M$ = denotes the real numbers.
$A_j$ = represents the corresponding probability function.
$x_n$ = denotes the sum of the normalized exponential function.

Optimization has been completed using the HRC as well as grid analyzes over main hyperparameters that can affect model efficiency by experimenting on different network structures, modifying hidden layer number and layer size. The goal is to learn characteristics from the input of each convolutional network layer described in the following equation (10)

$$h(j, i) = (Q \ast A)(j, i) = \sum_{n} \sum_{m} A(j-n, i-m) Q(n, m)$$ (10)

$Q$ = denotes the subsequent HRC algorithm values.
$h(j, i)$ = represents the resulting matrix function.
$A(j-n, i-m)$ = denotes the training set of values.
$Q(n, m)$ = represents the pooling factor values.

It is useful to use this last procedure to reduce the costs of computation by reducing the number of parameters. Simply put, the completely connected layer $Q_i$ is based on the conventional neural network $A_j$ architectures represented in the following equation (11)

$$A_j = \sum_{i=1}^{m} Q_i(\tilde{b}_i^{j} - a_{ji})/(\tilde{b}_i^{j} - Q)$$ (11)

$\tilde{b}_i^{j} - a_{ji}$ = denotes the optimization values during the time of the training sequence.
$\tilde{b}_i^{j} - Q$ = represents the behavioral action of a human.

The Softmax activation function $A$ is employed in the last layer to estimate neural networks $g$ when the number of neurons is equal to the class number, regardless of the data structure, the input $x$ of normal operation has been shown to often yield more confidence than a lower movement represented in the following Equation (12)

$$A = g(\sigma_0 + \sum_{i=1}^{x} \sigma_i g(\sigma_0 + \sum_{i=1}^{y} \sigma_i y_i))$$ (12)

$\sigma_0$ = denotes the deterministic value of the random variable.
$\sigma_i y_i$ = denotes the weight of the latent variable.

However, a latent variable $y$ is placed over the distribution to capture the random, which is data-dependent uncertainty. The final mark inference can be written as Equation (12) by accepting these distributions overweight and latent variables and treating them as random instead of deterministic values for the following Equation (13)

$$h(j, i) = \int \sigma_0 + \sum_{i=1}^{x} \sigma_i g \ast \frac{\tilde{b}_i^{j} - a_{ji}}{\tilde{b}_i^{j} - Q}$$ (13)

$\sum_{i=1}^{x} \sigma_i g$ = denotes the likelihood function.
$\frac{\tilde{b}_i^{j} - a_{ji}}{\tilde{b}_i^{j} - Q}$ = denotes the weight of the posterior feature.

Thus from the above Equation (13), the values are expressed in the form of independent data to represent the weight of the latent feature in the following Equation (14)

$$h(j, i) = \int \sigma_0 + \sum_{i=1}^{x} \sigma_i g \ast A_j$$ (14)

$A_j$ = represents the value of the independent variable.
The whole training set of the approximation values is estimated in the uncertainty function to reduce the unwanted behavioral action of the human followed in the Equation (15)

$$A_{HRC} = \frac{1}{m} \sum_{i=1}^{x} \sigma_i g / \sigma_i y_i$$ (15)

$\sigma_i g$ = denotes the aleatoric uncertainty function.
$\sigma_i y_i$ = represents the epistemic uncertainty function. Thus to calculate the uncertainty training set of values the approximation of the posterior distribution should be equated and it is represented in the following Equation (16)

$$A_{HRC} = \frac{\sum_{m=1}^{m} A_m X(Y_m)}{\sum_{m=1}^{m} X(Y_m)}$$ (16)

$A_{HRC}$ = representing the behavioral using human recognition convolution.
$\sum_{m=1}^{m} A_m X(Y_m)$ = denotes the training phase samples.
$\sum_{m=1}^{m} X(Y_m)$ = denotes the data signal in an unsupervised manner.

The following parameters are calculated to determine the uncertainty value of the function in the form of return value procedural type thus the samples are denoted in the following Equation (17)

$$A_{HRC} = \exp \frac{\sum_{m=1}^{m} A_m X(Y_m)}{\sum_{m=1}^{m} X(Y_m)} \ast \sum_{i=1}^{x} \sigma_i g$$ (17)

$\sum_{i=1}^{x} \sigma_i g$ = denotes the uncertainty training set of values.
$\sum_{i=1}^{x} \sigma_i g$ = denotes the likelihood parameters.

The network output is estimated for all $m$ samples, the average is the model judgment, and the standard deviation is known as an approximation of uncertainty. Thus the non-confident samples are extracted in the following model which is expressed in the following Equation (18)

$$h(j, i) = HRC = \alpha_1 + (1 - \alpha_1) \ast \sum_{i=1}^{x} \sigma_i g$$ (18)

$\alpha_1$ = denotes the latent feature weight function.
$\sum_{i=1}^{x} \sigma_i g$ = denotes the non-confident samples.

The created values will be more compatible with samples of the classifier is certain, while the classifier would establish distinct labels for non-confidential samples, which contribute to higher standard deviations. Thus the approximation of the sample values in the form of posterior way is expressed in the following Equation (19)

$$HRC = \frac{\sigma_i g}{\sigma_i g_{\text{maximum}}}$$ (19)
\( \sigma_{g_{\text{maximum}}} \) denotes the maximum number of sample values.

Therefore the above Equation measures uncertainty as a mixture of aleatoric and epistemic uncertainties in the combined uncertainty form. The medium of \( z \) is used rather than tests from the approximated posterior to take epistemic uncertainty into account as denoted in the following Equation (20)

\[
h_{b,j} = q_{b,j} + \sum_{i=1}^{X} \sigma_{i} \gamma
\]

It considers a network of wireless sensors with a single hybrid point of access (HAP) and \( N \) devices, which senses and processes data separately. Wearable devices for safety track can be regarded as consumer devices. This information can be collected at a different rate to preserve and recycle energy. Classification, prediction, and decision-making of sensitive data can be analyzed locally or remotely via computationally-intensive machine-learning algorithms (figure 4).

### IV. RESULTS AND DISCUSSIONS

By analyzing its actions in the response to various sources of insecurity, the efficacy is evaluated based on the modeling uncertainty. A good measure of uncertainty should be increased when faced with novel data, such as from new classes or sensors. The same is true in the case of noisy testing of the device.

#### A. AVERAGE ACCURACY ANALYSIS

An HRC-based architecture was used to distinguish data from various activities with a higher precision while offering a relatively limited training collection. The result is interesting as it shows that different HRC systems can be implemented easily with the help of various problem classes. Deep learning needs a high level of computational power to build the network, as with any algorithm for machine learning, while computing resources are less expensive for using a lead network. By using embedded devices as a fascinating option for implementing the pre-trained HRC model with the increasing versatility and flexibility they bring accuracy rates to be higher. Figure (5) shown an improved accuracy in public datasets to the state of the art has obtained at a higher rate.

![Figure 5. Average accuracy.](image)

#### B. TRACKING PERFORMANCE

Health monitoring systems used by the medical industry use the same sensors that can be used in sports and allow for very compatible wearable technology research. Wearable technology is considered as a medical experiment in evaluating spinal motion, but its importance is just as significant in sport. The player and their doctor will communicate further with the same sensors using technology to track the health of living times. Besides, to achieve the best system output with several arbitrary users the ability to update the trained model is essential. Their results showed a greater output on public datasets for the state of the art. The new network parameters can be transferred to the wearable sensor to perform an HRC on-board to detect activities with the greatest efficiency (Figure 6).

#### C. WORK OFFLOADING REWARD AND PROBABILITY ANALYSIS

Figure 7(a) shows the total reward of the proposed algorithm (i.e. energy efficiency minus the price for the MEC discharge service). There is no indication that the IBCN algorithm is highly competitive in contrast to the other methods for discrete control problems for continuous-time and workload allocation. The IBCN method must usually approximate a finite, discrete set of action space which inevitably leads to statistical errors and a reduction in rewards performance. The continuous decision variables are checked more precisely.
compared to the other algorithms. This is checked by both the reward and the probability of the loss, as shown in Figure 7(b). The accurate control in the proposed algorithm will reduce the failure efficiency, i.e., almost every workload can be completed successfully in each slot.

D. POWER CONSUMPTION ANALYSIS

Usually, RF radio’s energy consumption is high due to the emissions of RF carriers. Therefore, low-IoT devices cannot afford data de-based on RF communication, which therefore prohibits them from using the MEC servers. Since both downloading and processing consume electricity, users must manage their energy usage depending on the channel requirements, the energy condition, and the workload. Figure 8 shows the power consumption ratio of the proposed IBCN method. The proposed IBCN achieves less power consumption when compared to other existing methods such as DQLA, DL-SAR, CASE, RiSH.

E. RELIABILITY RATIO ANALYSIS

The reliabilities achieved (Figure 9) have correlated with other results obtained using the same data set for other machine learning models. Within such works, the higher performance model has been selected when more than one machine learning architecture is provided. The outcome is identical with the cutting-edge, although the network for a different purpose has been optimized. The proposal network can be concluded by showing a strong capacity for generalization. Figure 9 shows the reliability ratio of the proposed IBCN method. The proposed IBCN achieves high reliability when compared to other existing methods such as DQLA, DL-SAR, CASE, RiSH.

Based on the results and discussion, the solution proposed has been intended to be applied to devices that would involve the provision of customized information with numerous wearable sensors such as in the case of more homes.
V. CONCLUSION

Within this report, a revolutionary IoT framework is introduced for the long-term, individual monitoring of a person’s activities. Improved Bayesian Convolution Network (IBCN) is proposed by wearable sensors of different kinds of uncertainty for human activity. The device includes a wearable sensor and Deep Learning technology to provide information about a variety of behaviors aimed at deducing suspicious activity. Through experimental analysis, the method is proposed is distinguished between data-dependency and model-dependent in certainty. The solution proposed was intended to be applied to devices that would involve the provision of customized information with numerous wearable sensors such as in the case of more homes. Estimation of different types of uncertainties is necessary to design active learning paradigms and novelty detection and to detect errors and fusion of data that are all relevant to the development of successful and customized recognition systems for activities. The system architecture includes Wi-Fi and Cloud onboard applications so the network can continuously be upgraded with new training sets while adding users. With the architecture of this system, the alternative approach could be utilized to incorporate complex signal processing systems with the use of IBCN technologies to create lightweight, portable and autonomous embedded human recognition systems.

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