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ORIGINAL PAPER

Survival study on deep learning techniques for IoT enabled smart healthcare system

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Abstract

Purpose The paper is to study a review of the employment of deep learning (DL) techniques inside the healthcare sector, together with the highlight of the strength and shortcomings of existing methods together with several research ultimatums. Our study lays the foundation for healthcare professionals and government with present-day inclinations in DL-based data analytics for smart healthcare.

Methods A deep learning-based technique is designed to extract sensor displacement effects and predict abnormalities for activity recognition via Artificial Intelligence (AI). The presented technique minimizes the vanishing gradient issue of Recurrent Neural Networks (RNN), thereby reducing the time for detecting abnormalities with consideration of temporal and spatial factors. Proposed Moran Autocorrelation and Regression-based Elman Recurrent Neural Network (MAR-ERNN) introduced.

Results Experimental results show the feasibility of the proposed method. The results show that the proposed method improves accuracy by 95% and reduces execution time by 18%.

Conclusion MAR-ERNN performs well in the activity recognition of health status. Collectively, this IoT-enabled smart healthcare system is utilized by enhancing accuracy, and minimizing time and overhead reduction.

Keywords Artificial Intelligence · Internet of things · Deep learning · Smart Healthcare · Health Monitoring

1 Introduction

In modern days, there has been extraordinary development in Wireless Sensor Networks (WSNs) and their applications, in terms of data estimation, interoperability, scalability, flexibility, coordination and applications. This improvement in technology along with the novelty in cellular networks, wireless networks, and radio frequency identification (RFID) has put down a well-grounded underpinning for the Internet of Things (IoT). Due to the marvelous improvement in the IoT, smart objects are the general device employed with a diverse range of intelligent, innovative, and novel

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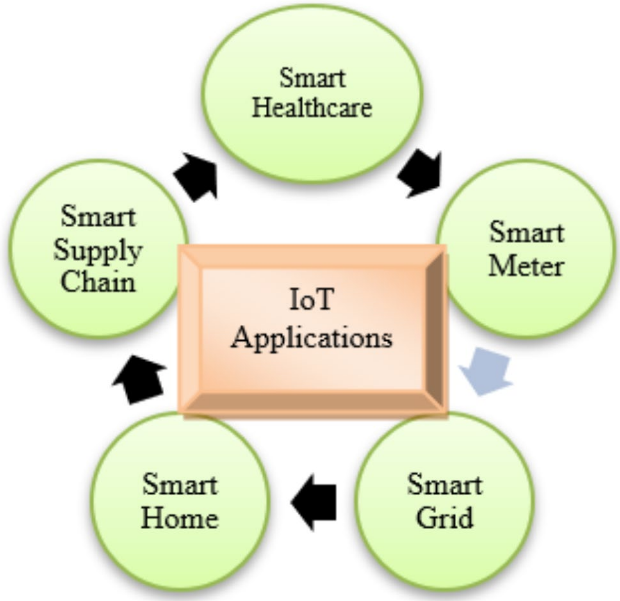


Fig. 1 Applications of IoT

applications. These applications. include smart healthcare, smart meter, smart grid, smart supply chain, smart homes, etc., as shown in Fig. 1.

DL-based feature detection was proposed in [1], which was designed with the prime objective of detecting malware, and the application's behavioral analysis was also done using different classifiers. Moreover, the features that were learned by the detecting system were also found to be reused, so that learning was also transferred towards efficient detection of malware, therefore contributing to accuracy. This was said to be achieved via two different phases.

First, a fully connected network (FCN) takes the extracted features as input, via the softmax activation function. In the second phase, recurrent layers of attention were then used to categorize them either as malicious or benign. Despite an improvement in accuracy, fewer contributions were made regarding precision. To address this issue, a partitioned Deep Convolutional Neural Network (CNN)was proposed in [2], with an intelligent electrocardiogram signal classification via a DL model for IoT–based smart healthcare.

To start with, an IoT-based monitoring model was used to learn the electrocardiogram's features. Following that, the learned features were applied in the form of continuous-time series data, with several atrial fibrillation samples used for further analysis, therefore contributing to improved precision and sensitivity.

A DL-based Internet of Health Framework, called DeTrAs, was proposed in [3], which ensured customized service via three phases. First, sensory movement data were determined by using a recurrent neural network, followed by which an ensemble technique was implemented, to track any abnormality based on both CNN and the timestamp model. Finally, an IoT-based assistance mechanism predicts the abnormality in the case of its presence, which ensures the accuracy of the model.

Although accuracy was said to be attained, the early prediction was the major issue that remained unaddressed. To focus on this issue, a Faster Regional-based Convolutional Neural network (Faster-RCNN) was designed in [4] for pandemic disease prediction. Here, the region proposal network was used to perform disease detection, which ensured a higher detection accuracy was achieved.

1.1 Research gaps

The existing DL concept methods [1] and [3] introduce the vanishing gradient issue of RNN. Metrics such as accuracy, precision, and sensitivity were considered, but the algorithm was not efficient. Due to this, a substantial amount of execution time of the algorithm was needed during healthcare analysis. Moreover, in [2] and [4], the complex hidden features like spatial and temporal factors were not analyzed during an early assessment, therefore compromising the overhead incurred during the healthcare analysis. However, it seemed that the disease identification accuracy was not minimized due to this. Unfortunately, it failed to carry out the prediction at an early stage, but, the detection time was not reduced.

1.2 Motivation for the proposed work

Several DL methods were developed for the IoT healthcare sector. But, the existing DL method failed to minimize the time and overhead-related issues and disease identification accuracy was not detected. Motivated by a DL-based technique called Moran Autocorrelation and Regression-based Elman Recurrent Neural Network (MAR-ERNN) is proposed to extract the outcomes of sensor displacement to predict any potential abnormalities via Artificial Intelligence (AI). In other words, and to be more precise, the technique is designed to minimize the vanishing gradient issue of RNNs, thus minimizing the time involved in detecting any abnormalities, as well as taking into consideration the temporal and spatial factors, and thus reducing the overhead.

Objectives of the proposed work:

- To improve the accuracy, recall, and precision, the proposed Moran Autocorrelation and Regression-based Elman Recurrent Neural Network (MAR-ERNN) is introduced in the IoT healthcare domain.
- To examine the temporal factor, the Conditional Autoregressive Temporal Factor analysis model is applied.

- To exactly discover the correlation between two features, the Moran Autocorrelation Spatial Factor analysis model is employed.
- To predict abnormalities for activity recognition with lesser time and overhead, Gradient Descent ERNN is utilized.

1.3 Contribution

The most important contributions of this paper are the following:

- Implementation of MAR-ERNN, for removing the effects of sensor displacement in activity recognition, as compared to existing works. MAR-ERNN is designed with the help of the Moran Autocorrelation Spatial Factor analysis model, Conditional Autoregressive Temporal Factor analysis model, and Gradient Descent ERNN.
- Determination of the correlation between two features using the Moran Autocorrelation Spatial Factor analysis model, comparing it with existing autocorrelation techniques.
- Enhancement of the prediction accuracy using the Conditional Autoregressive Temporal Factor analysis model, comparing it with conventional regression techniques.
- Use of Gradient Descent ERNN, to increase computational efficiency in the activity recognition prediction, with time and overhead reduction, comparing it with a conventional deep neural network.

The paper is organized as follows; in Sect. 2, some details will be given on the smart healthcare domain, by underlining contributions in the state-of-the-art of healthcare sectors; Sect. 3 discusses the idea of DL challenges, specifically in the IoT, from a smart healthcare point of view. Next, a comprehensive discussion on the role of DL techniques for the analysis of IoT in the healthcare domain is included, along with a novel proposal in Sect. 4. Finally, Sect. 5 describes all the conclusions from this study.

2 Related works

In recent years, have been an increase in the development of new medical IoT devices coupled with the Internet, within the framework of associated healthcare. To perform healthcare processes, DL applications are used to access the hospitals' electronic health records, and also medical records created by medical IoT devices.

To regulate the information transfer between devices in an accurate manner, it can be used the Internet of Medical Things (IoMT), with a Product Life Cycle Management (PLM), as referred to in [5]. A smart healthcare monitoring system in IoT in real-time was proposed in [6]. A smart healthcare monitoring system was presented in [7], to facilitate the system that works as a smart healthcare model, and decides priority depending on gathered health metrics from sensor nodes. The designed method gathers authenticated physiological data from patients via GSM, with the assistance of the logic-based algorithm to obtain the status of the patient. Nonetheless, the disease identification accuracy was lower. Emerging IoT methods in smart healthcare are discussed in [8], nevertheless, a higher classification rate was not attained. A secure remote health monitoring method was introduced in [9] for early disease diagnosis, which uses a lightweight block encryption scheme to attain security for health and medical data. With data mining techniques, patients' health statuses are estimated via smart medical IoT devices, where lightweight secure block encryption methods guarantee the protection of patients' sensitive data. However, the data security level was not higher.

Security and privacy issues are described in [10] in five technical aspects. But, associated standards and technical specifications need to be enhanced in healthcare. A detailed study on security in smart healthcare is studied in the studies of [11], [12], [13], [14], [15]. AI applications were studied in [16]. It consisted of disease diagnostics and detection, living assistance, biomedical information processing, and biomedical research. Deep Convolutional Neural Networks (DCNNs) were introduced in [17] to correctly identify physical activities, although their accuracy was not improved. The predictive data analysis method was introduced in [18], with the purpose of increasing accuracy. However, the error rate was not reduced. A novel and intelligent healthcare system was developed in [19] with the help of a fuzzy neural network. But it failed to get more patient data. IoT-Based Healthcare Support System was introduced in [20] to observe the patient's health conditions and to solve both security and privacy concerns. To address this issue, the advantage of IoT-enabled technologies was utilized in [21] for energy savings, by smoothening the association between human and smart healthcare systems to the most feasible significant magnitude.

Devices enabled with sensors face specific issues during the association and conjunction with other domains, for example, the information sharing and cooperation between medical experts or healthcare centers with patients, during diagnosis, so treatments can be provided accordingly. To address the quality of services like time and overhead, Grey Filter Bayesian Convolution Neural Network (GFB-CNN) was proposed in [22], with a real-time analysis with aid of Grey Filter Bayesian Convolution Neural Network.

A cognitive healthcare framework was designed in [23], using a range of healthcare smart devices, whose data is sent to a cognitive model for further processing. Finally, DL was applied for the decision-making task, to improve accuracy. To observe the retinal images, hybrid architecture was designed in [24] for IoT healthcare. A super-resolution (SR) model for retinal images employs a multi-kernel support vector regression (SVR) to enhance the quality of the images. However, it is not focused on a complete IoT-based eye care model, which needs less human involvement. DL-based methods were introduced in [25] for Brain tumor classification (BTC), but the computational overhead was not reduced.

The combination of IoT and DL was developed in [26] for different smart city applications. DL-based IoT-oriented infrastructure was introduced in [27] for providing security and privacy in smart city applications. DL concepts were presented in [28] for biomedical applications and a CNN model was introduced in [29] to improve classification accuracy, however, the execution time was higher.

An IoT-based non-invasive automated patient discomfort monitoring was developed in [30], with the inclusion of a DL-based algorithm, however, in this study, there was precision evaluation. Another method, called Generalize Approximate Reasoning-based Intelligence Control (GARIC), was designed in [31], which used regression rules with patient data from different IoT devices. In addition, a DL mechanism was also used to treat patients with the identified disease.

Another automatic heart disease analysis was proposed in [32], by employing ensemble DL in edge computing devices. A Machine Learning (ML) algorithm named DL Modified Neural Network (DLMNN) was developed in [33], with the purpose of identifying Heart Diseases (HD). However, the error rate was not minimized. Enhanced DL-assisted CNN was introduced in [34], which was used to enhance patient prognostics of HD, but precision was not enhanced by using these methods of advanced AI. A smart healthcare monitoring framework was introduced in [35] to enhance HD detection accuracy, which was based on the ensemble DL model and feature fusion methods. However, the processing time was not reduced. In [36], several COVID-19 diagnostic techniques that depend on DL algorithms were tested with pertinent adverse samples.

Home energy savings with the aid of eco-feedback is frequently contemplated as a time-consuming or even disturbing task, due to the requirement of repeated human interference. This may exhibit the system's incompetence in acquiring the users' alternates when pro-environmental aspects have occurred. An IoT-based framework was introduced in [37], which acquired real-time symptom data of the different patients, to identify the coronavirus suspects in an early stage. This was done with the purpose of monitoring the therapeutic reaction of those who have previously recuperated from the virus. As the virus-based diseases are in a heightening stage and with the absence of real-time samples, the extensive confront is to identify the DL best predictive model that could provide better results with the constrained training samples. To reduce the overall impact of infection, a Multi-Task Gaussian Process (MTGP) model was designed [38] for efficient prediction of the COVID-19 epidemic globally. The latest innovative technologies developed in the field of IoT-based smart health monitoring systems can be looked at in [39] and [40]. The various types of scalable telehealth services used to support patients infected by COVID-19 and other diseases during this pandemic can be analyzed in [41]. There are several existing wearable monitoring devices and respiratory support systems designed to assist coronavirus-affected people [42], and others that were developed to support infected patients with respiratory diseases [43].

A DL technique based on the combination of a CNN and long short-term memory (LSTM) was designed [44] to diagnose COVID-19 automatically from X-ray images. A convolutional neural network was developed in [45] to extract deep and high-level features from X-ray images of patients infected with COVID-19. The systems developed in [46] for COVID-19 diagnosis use DL techniques, being able to provide insights into well-known datasets used to train these networks. A combined architecture of CNNs and RNNs was introduced in [47], to diagnose COVID-19 from chest X-rays. The contributions of DL at several scales were designed [48] to control the ongoing outbreak. Data mining models were developed in [49] for the prediction of COVID-19 infected patients' recovery, using an epidemiological dataset of COVID-19 patients.

Several computational intelligence techniques were introduced in [50] for the prediction of coronary artery heart disease. Three ML models such as Decision Tree, Random Forest (RF), and XGBoost are proposed in [51] and are used to predict cervical cancer from behavior and its variables. Five different supervised ML techniques named support vector machine (SVM), K-nearest neighbors, random forests, artificial neural networks (ANNs), and logistic regression are compared in [52]. ML algorithms are applied in [53] to anticipate the 1-year endurance of patients and also to discover the features' importance. An expert scheme was designed in [54] for the classification of liver disorders using RFs and ANNs. A novel modality was introduced in [55] for the prediction of breast cancer, using SVM and K-Nearest Neighbors. A 10-fold cross-validated mathematical model was developed in [56] to detect breast cancer using symbolic regression of multigene genetic programming (MGGP).

In [57], a systematic review of the existing sensor-based fall detection and rescue systems facilitators was presented. A comprehensive review of state-of-the-art fall detection technologies in [58] shows the most powerful DL methodologies in this application. Fall detection systems based on data from smartphone sensors that employ one of TBA were designed in [59]. A centralized unobtrusive IoT-based device-type invariant fall detection and rescue system was developed in [60] for monitoring a large population in real-time. A wearable electronic device was designed [61] to assist visually impaired people and to help them to travel independently, without external aid while monitoring the real-time location information of these individuals. A new hybrid encryption scheme was introduced in [62] to increase healthcare data security in IoT-enabled healthcare. But, the computational overhead was not reduced. A secure framework for SDN-based Edge computing was developed in [63] for IoT-enabled healthcare systems. However, it failed to use the machine-learning algorithm for enhancing the accuracy. Crow Search Optimization algorithm-based Cascaded Long Short Term Memory (CSO-CLSTM) algorithm was introduced in [64] to detect the disease diagnosis. But, the computational complexity was not minimized. Improved Fuzzy Inspired Energy Effective Protocol (IFIEEP) was introduced in [65] for providing higher energy. A new smart healthcare model was designed [66] by using Edge-Fog-Cloud computing. However, it failed to minimize the computation overhead.

2.1 IoT and DL for smart healthcare based on computer vision

Wearable DL was introduced in [67] by using DL, IoT, and wearable technologies (WT) concepts. The ML-based patient load prediction model was developed in [68] to predict future patient loads, but it failed to consider the current health status. DL-based ambient assisted living environments were presented in [69] for medical applications. An architectural design of a smart blind assistant was designed in [70], with the aid of a DL system. A new lung segmentation method was introduced in [71], with a Mask R-CNN Model for CT images.

Novel IOT architecture for medical monitoring was discussed in [72] for decreasing the time. An IoT system for health monitoring was developed in [73] to help patients in avoiding hospital visits, through viral epidemics. Blockchain-orchestrated DL approach for Secure Data Transmission was introduced in [74] named “BDSDT”. DL and blockchain-empowered security frameworks were examined in [75] to reduce latency and improve throughput. But, the accuracy was not enhanced.

2.2 IoT and DL for smart healthcare based on natural language processing

Natural Language Processing (NLP)-based sentiment analysis was introduced in [76] to identify Alzheimer’s disease (AD). A survey of ML techniques was developed in [77] for big data analysis in IoT smart health. Federated learning was employed in [78] and [79] healthcare, without any precision enhancement.

2.3 IoT and DL for smart healthcare based on signal processing

Biomedical Signal Processing was introduced in [80] for Smarter Mobile Healthcare with the aid of Big Data Analytics. DL techniques were utilized in [81] for sensing the data in smart health services. Dependable Gesture Recognition (DGR) was introduced in [82] to enhance the remote monitoring of healthcare system performance. The IoT-based distributed healthcare system (IoT-DHS) was introduced in [83]. A DL algorithm was introduced in [84] to improve the accuracy of health monitoring.

Existing works have introduced the issue that the presence of malware, the execution time was higher, and the overhead incurred during the healthcare analysis was compromised, the early prediction was not performed, the error rate was higher, detection time was higher, prediction accuracy was minimal, classification time was higher, and prediction time was higher. To address the above-said issues, MAR-ERNN is designed for IoT-enabled smart healthcare systems for activity recognition to predict abnormalities. Table 1 provides the comparative analysis of the literature survey done in this study.

3 Healthcare time-series data analysis using dL

In the last few years, analysis based on time-series factors has been used to monitor the pattern in which health variables for activity recognition change over time. Healthcare perspective analysis based on a spatiotemporal analysis has supplementary advantages over specific spatial or time factors. They allow the researcher to concurrently analyze the endurance of patterns over time and throw light on any unexpected patterns concerning activity recognition.

IoT plays a vital role in the healthcare domain. IoT-based healthcare systems are used to observe real-time human activities, that keep track of the records of patients. The latest improvement in the field of DL permits us to work with difficult data on the IoT-enabled data gathered from health service applications.

Table 1 Analysis of Literature Survey

Reference Number	Method Name	Contribution	Merits	Demerits
1.	DL-based feature detection	DL-based feature detection was proposed to detect the malware and the application's behavioral analysis was done using different classifiers.	Malware Detection Accuracy was higher	Execution time was higher
2.	Partitioned deep CNN	A partitioned deep CNN was proposed to learn the electrocardiogram features by using the classification of the electrocardiogram signal.	Better precision and sensitivity were attained	Compromising the incurring overhead during the healthcare analysis
3.	DL-based Internet of Health Framework named, DeTrAs	DeTrAs were proposed to ensure the customized service via three phases. Sensory moment data were obtained using a recurrent neural network, followed by an ensemble technique used for tracking abnormality based on CNN, and the timestamp model`	Accuracy was said to be ensured	Early prediction remained unaddressed
4.	Faster R-CNN	Faster-RCNN was designed for pandemic disease prediction.	Early detection was ensured with higher detection accuracy	Compromising the overhead incurred during the healthcare analysis
5.	COVID-19 diagnostic techniques	COVID-19 diagnostic techniques were tested with pertinent adverse samples based on DL algorithms.	An efficient performance was attained.	Computational overhead was higher.
6.	IoT-enabled technologies	The advantage of IoT-enabled technologies was used for energy saving, to smoothen the association between human and smart healthcare systems to a significant feasible magnitude.	Better precision was attained	The error rate was higher.
7.	IoMT with Product Lifecycle Management (PLM)	IoMT with PLM introduces for regulating information transfer between devices in an accurate manner.	Better sensitivity was attained	Computational overhead was higher.
8.	An IoT-based framework	The framework was introduced to identify the coronavirus suspects in the early stage.	Accuracy was said to be ensured.	Detection time was higher
9.	Multi-Task Gaussian Process (MTGP) model	MTGP is used for efficient prediction of the COVID-19 epidemic.	Minimizing the overall impact of infection	Prediction accuracy was minimal.
10.	Generalize Approximate Reasoning-based Intelligence Control (GARLIC)	GARLIC acquires information about the patient from IoT devices by using regression rules.	Early disease identification was attained.	The error rate was higher.
11.	GFB-CNN	GFB-CNN uses Grey Filter Bayesian Convolution Neural Network in real-time analysis to address the qualities of services.	Time and overhead were addressed	The error rate was higher
12.	Cognitive healthcare framework	A cognitive healthcare framework was designed with healthcare smart devices and sent to a cognitive model for further processing. DL was applied for decision-making.	Higher Accuracy was attained.	Computational overhead was higher.
13.	Automatic heart disease analysis	The ensemble DL models are used to perform the automatic heart disease analysis.	The prediction accuracy was improved	Prediction time was higher.
14.	Smart healthcare monitoring system	A smart healthcare system was introduced to observe a patient's critical health signs and room information.	The error rate was minimal.	However, computational overhead was higher.
15.	Smart healthcare monitoring model	A smart healthcare monitoring model was presented to identify the priority patient treatments with the aid of a smart healthcare model.	Computation overhead was reduced	Disease identification accuracy was lower
16.	Emerging IoT methods	Emerging IoT methods in smart healthcare were discussed to analyze 9561 articles in IoT smart health	Emerging IoT methods supported panoramic knowledge.	The classification rate was not attained
17.	Secure remote health monitoring model	A secure remote health monitoring model was introduced to discover the disease's diagnosis at an early stage.	Secure data communication was achieved by using the designed framework	Data security level was not higher

Table 1 (continued)

Reference Number	Method Name	Contribution	Merits	Demerits
18.	Security and privacy problems	Security and privacy problems were discussed with five technical aspects.	Transmission efficiency was improved	Associated standards and technical specifications need to enhance in healthcare.
19.	Hybrid architecture	The architecture was designed for IoT healthcare for analyzing the fundus images process	Image quality was improved	A hybrid architecture was not focused.
20.	DL IoHT-driven technique	IoT framework was discussed to identify cervical cancer.	Accuracy was improved	Diagnosis of critical diseases was not performed
21.	DL-based techniques	DL-based techniques were introduced for BTC	Performance was enhanced	Computational overhead was not reduced
22.	ML technique named DLMNN	DLMNN was developed to identify the HD	The security level was higher and time was lower	The error rate was not minimized
23.	Enhanced DL-assisted CNN	CNN method was introduced to enhance the patient's prognostics of heart disease	Patient accuracy and reliability were increased	Precision was not enhanced by using advanced artificial intelligence.
24.	Smart healthcare monitoring framework	A smart healthcare monitoring framework was introduced by using ensemble DL and feature fusion techniques to improve heart disease prediction accuracy.	Classification performance was attained	Processing time was higher

In this section, a method named MAR-ERRN is described, with a healthcare perspective concerning IoT applications. MAR-ERNN is designed with three different processes Moran Autocorrelation Spatial Factor analysis model, Conditional Autoregressive Temporal Factor analysis model, and Gradient Descent ERNN. The above three different processes are important for detecting abnormalities with consideration of temporal and spatial factors. The architectural design of the MAR-ERNN method is illustrated in Fig. 2.

As shown in Fig. 2, spatial factors concerning activity recognition are considered utilizing the Moran Autocorrelation factor whereas the time series factor is determined based on the Conditional Autoregressive factor. With these two factors, a DL technique called ERNN is designed for use in a smart healthcare environment.

3.1 Moran Autocorrelation spatial factor analysis model

Moran Autocorrelation Spatial Factor analysis model is utilized to precisely identify the correlation between two features. Autocorrelation refers to the procedure via which persons living in the vicinity together may be more homogeneous than those living further away. For example, an activity recognition in India is states closer to each other may be more similar than states which are further away from each other. In comparison to the conventional correlation mechanism, Moran Autocorrelation is used to identify the correlation between two features for neighboring states. This is evaluated as the following:

$$\alpha = \mathrm{MA} = \frac{\mathrm{N}}{\mathrm{W}} = \frac{\sum_{\mathrm{ij}} \mathrm{w_{ij}} \left(\mathrm{att_i} - \mathrm{att}'\right)\left(\mathrm{att_j} - \mathrm{att}'\right)}{\sum_{\mathrm{i}} \left(\mathrm{att_i} - \mathrm{att}'\right)^2} \quad (1)$$

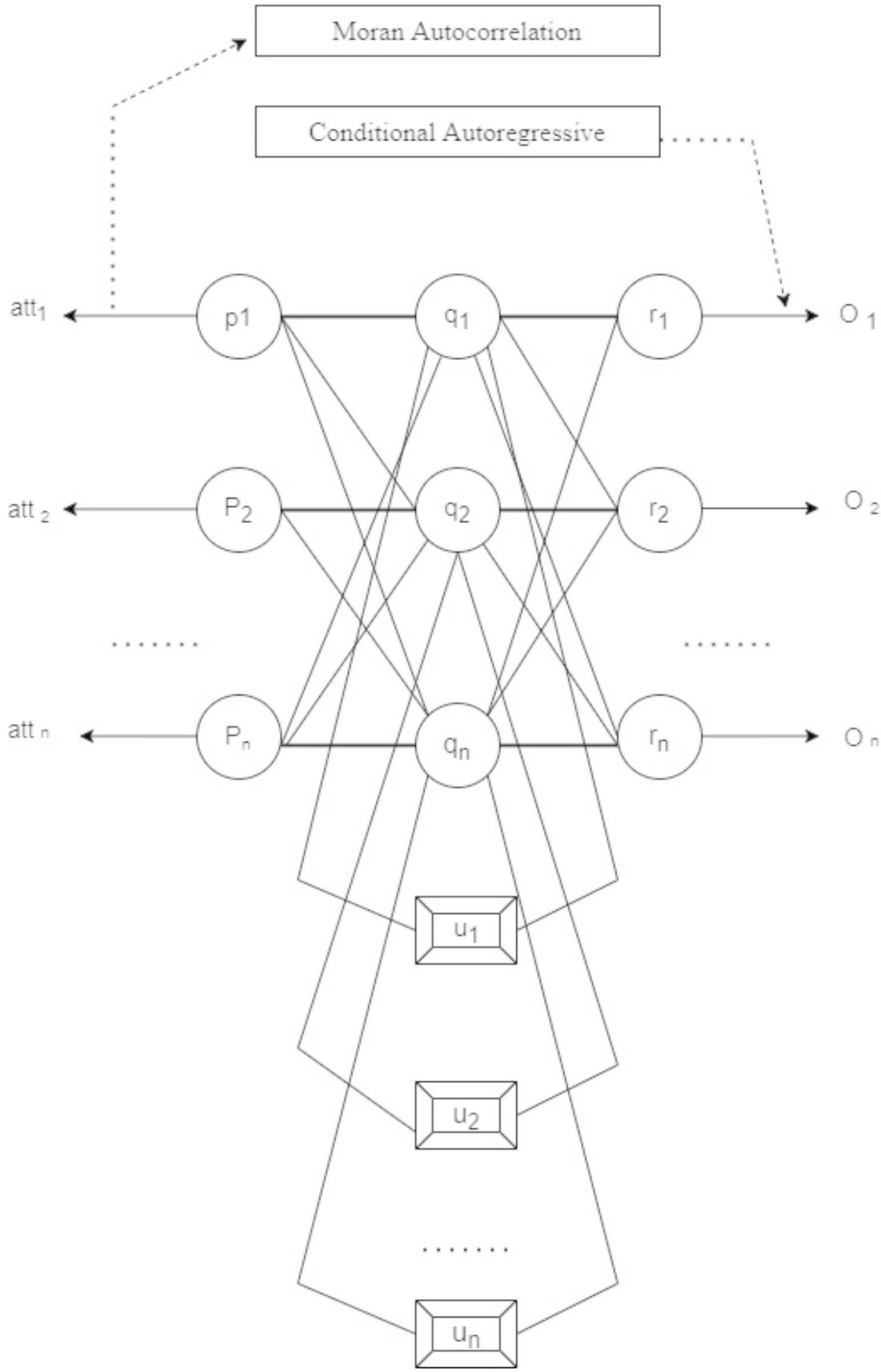
where 'MA' denotes the Moran Autocorrelation, 'N' represents the number of spatial units (i.e., number of instances), and 'W' is the sum of all '$\mathrm{w_{ij}}$' with '$\mathrm{w_{ij}}$' representing the spatial weight matrix, for the attribute of interest '$\mathrm{att_i}$' and mean of attributes 'att'', respectively.

3.2 Conditional autoregressive temporal factor analysis model

The conditional Autoregressive Temporal Factor analysis model is usedto attain a higher prediction accuracy. In our work, another factor of consideration is the temporal aspect modeled on the time series data, where the outcome variable for a wide range of physical activities depends linearly on its previous values. To analyze this temporal factor, Conditional Autoregressive (CAR) is utilized. The indispensable objective is that the likelihood of the values (i.e., warm-up) evaluated at any moment is dependent on the level of the corresponding homogeneous activity values (i.e., cool-down). Then, the CA for the expectation of a specific observation '$\mathrm{att_i}$' (i.e., warm-up) is as follows.

$$\mathrm{EXP}\left(\mathrm{att_i} | \mathrm{att_{I \neq j}}\right) = \mu_{\mathrm{i}} + \alpha \sum_{\mathrm{j \neq i}} \mathrm{w_{ij}} \left(\mathrm{att_j} - \mu_{\mathrm{i}}\right) \quad (2)$$

Fig. 2 Architectural design of MAR-ERNN



where the expectation 'EXP()' for a specific physical activity observation 'att_i' (i.e., warm-up, cool-down, etc.) The expectation is calculated based on the mean value of all the observations 'μ_i' and the consideration of spatial factor output 'α', in addition to the weight 'w_{ij}' assigned for each activity set.

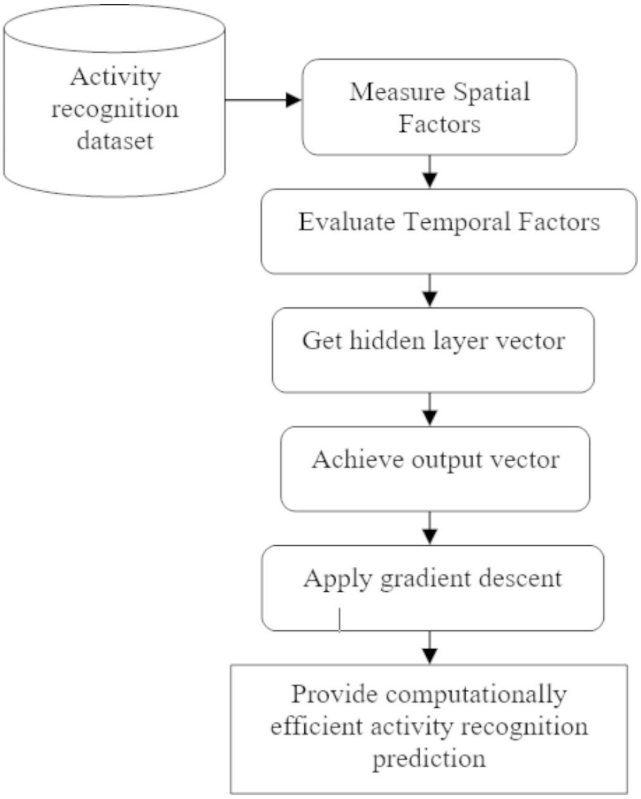


Fig. 3 Gradient Descent ERNN

Table 2 Description of REALDISP Dataset

Dataset	REALDISP Activity Recognition Dataset
Number of Attributes	120
Number of Instances	1419
Dataset Characteristics	Multivariate, Time-Series

Table 3 Comparative result of precision, recall, and accuracy using proposed MAR-ERNN and Existing DL-based feature detector [1], Partitioned Deep CNN [2], DeTrAs [3], and Faster-RCNN [4]

Methods	Parameters		
	Precision	Recall	Accuracy
MAR-ERNN	97.85	95.55	98.35
DL- based feature detector [1]	97.00	90.15	98.00
Partitioned Deep CNN [2]	97.50	93.5	96.30
DeTrAs [3]	95.15	88.25	88.63
Faster-RCNN [4]	93.00	85.00	98.00

3.3 Gradient Descent Elman recurrent neural networks

Gradient Descent ERNN is used to predict the activity and deviations that are owing to abnormalities with minimum time and overhead. In this section, an ERNN model is proposed. In this work, we have trained and fine-tuned a Deep Neural Network using the ERNN to extract the wide range of physical activities and possible deviation abnormalities. The logic of this method is to increase the performance as well as reduce the gradient issue, therefore reducing the time involved in detecting any abnormalities. Also considering both temporal and spatial factors leads to the minimization of the incurred overhead. The block diagram of the Gradient Descent ERNN is shown in Fig. 3.

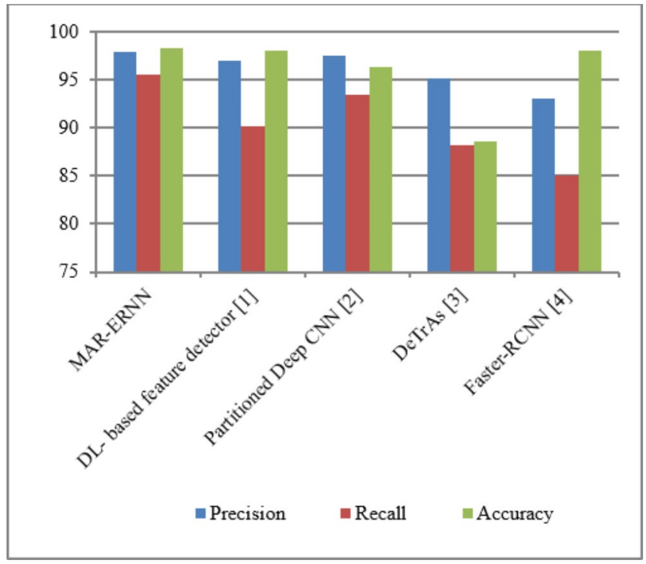


Fig. 4 Performance measures of accuracy, recall and precision using proposed MAR-ERNN and Existing DL based feature detector [1], Partitioned Deep CNN [2], DeTrAs [3] and Faster-RCNN [4]

Figure 3 explains the flow processes of the Gradient Descent ERNN for providing computationally efficient activity recognition prediction. The ERNN consists of a three-layer network represented horizontally as '$_{\mathrm{p}}$', '$_{\mathrm{q}}$', '$_{\mathrm{r}}$', in addition to a set of context units'$\mathrm{U} = \mathrm{u}_1, \mathrm{u}_2, \ldots, \mathrm{u}_\mathrm{n}$'. The central layer is associated with these context units togetherwith weight. At each time step, the input or the attribute representing a different activity set is fed forward and is mathematically expressed as given below.

$$\mathrm{H}_\mathrm{t} = \sigma_\mathrm{H}\left(\mathrm{W}_\mathrm{H}\mathrm{att}_\mathrm{t} + \mathrm{U}_\mathrm{H}\mathrm{H}_{\mathrm{t}-1} + \mathrm{b}_\mathrm{H}\right) \tag{3}$$

where the hidden unit at a specific time 'H_t' is derived based on the activity function '$_{\sigma_\mathrm{H}}$', attributes or features forming different activity sets 'att_t', context unit 'U_H', W, H, b is parameter matrices and vector and bias factor 'b_H' respectively. Similarly, the output forming the measure for abnormality observation is mathematically expressed as given below.

$$\mathrm{O}_\mathrm{t} = \sigma_\mathrm{O}\left(\mathrm{W}_\mathrm{O}\mathrm{H}_\mathrm{t} + \mathrm{b}_\mathrm{O}\right) \tag{4}$$

where the output at each time interval for benchmark activity recognition in ideal conditions is 'O_t', based on the activity function '$_{\sigma_\mathrm{O}}$', weight factor 'W_O', hidden unit output 'H_t

' and bias factor '$\mathrm{b_O}$'. Finally, the gradient descent 'γ_t' is evaluated as given below.

$$\gamma_t = \frac{(\mathrm{att_n} - \mathrm{att_{n-1}})\left[\mathrm{O_t}(\mathrm{att_n}) - \mathrm{O_t}(\mathrm{att_{n-1}})\right]}{\left[\mathrm{O_t}(\mathrm{att_n}) - \mathrm{O_t}(\mathrm{att_{n-1}})\right]^2} \quad (5)$$

The pseudo-code representation of Gradient Descent Elman Recurrent Neural Network is given below.

Input: Dataset 'DS',
Attributes $\mathbf{A} = \mathbf{att}_1, \mathbf{att}_2, \ldots, \mathbf{att_n}$

Output: Computationally efficient activity recognition prediction

1: Begin
2: For each Dataset 'DS' with Attributes 'A'
3: Estimate spatial factors using (1)
4: Estimate temporal factors using (2)
5: Obtain the hidden layer vector using (3)
6: Obtain output vector using (4)
7: Estimate gradient descent using (5)
8: Return estimated output
9: End for
10: End

As given in the above Gradient Descent ERNN algorithm, with an activity recognition dataset provided as input, the objective of the algorithm remains to as predicting the activity and any deviations, due to abnormalities with minimum execution time and overhead. First, spatial factors or spatial variations in health outcomes are obtained, using the Moran Autocorrelation model. Followed by, the acquisition of the next activity monitoring at different time intervals, Conditional Autoregressive is used. Finally, the actual activity recognition and any deviation are designed by using gradient descent to minimize time and overhead.

4 Results and discussion

A detailed discussion of MAR-ERNN with REALDISP Activity Recognition Datasets is presented in this section. In addition, it is presented the strengths and weaknesses of some works with the same purpose, that use DL-based feature detectors [1], Partitioned Deep CNN [2], DeTrAs [3], and Faster-RCNN [4]. This is done, so they can be compared to the proposed MAR-ERNN, so conclusions can be made regarding the contributions and novelty of this survey using REALDISP Activity Recognition Dataset obtained from[85].

The REALDISP (Realistic sensor displacement) dataset has been originally collected to investigate the effects of sensor displacement in the activity recognition process in real-world settings. It builds on the concept of ideal placement, self-placement, and induced-displacement. The ideal and mutual-displacement conditions represent extreme displacement variants and thus could represent boundary conditions for recognition algorithms.

From Table 2, REALDISP Activity Recognition Dataset is used in real-world applications, to scrutinize the consequences of the displacement of the sensor with the aid of the activity recognition process. The dataset is constructed with three different types of placement. As far as the ideal and mutual-displacement conditions are concerned, they denote the alternatives and hence could constitute boundary specifications for recognition patterns. On the other hand, self-placement contemplates a user's viewpoint of how sensors could be attached. The dataset comprises a large number of extracted physical activities, sensor modalities acceleration, and participants. It includes 33 different behaviors, like, walking, running, jogging, jumping up, jumping rope, etc. with 9 different sensors positioned at 17 different subjects.

The experimental process is attained with several metrics such as accuracy, precision, recall, execution time, and computational overhead. The implementation is conducted with the hardware specification of Windows 10 Operating system, core i3-4130 3.40GHZ Processor, 4GB RAM, 1 TB (1000 GB) Hard disk, ASUSTek P5G41C-M Motherboard, Internet Protocol.

In Table 3; Fig. 4 it is possible to see the accuracy, precision, and recall of the proposed methodology (MAR-ERNN), as well as comparative results using a DL-based feature detector [1], Partitioned Deep CNN [2], DeTrAs [3], and Faster-RCNN [4]. The accuracy, precision, and recall of the proposed method are 98.35%, 97.85%, and 95.55%, respectively. It is possible to see that the MAR-ERNN method leads to better outcomes.

In the case of [1], though the DL technique was used for healthcare purposes, more emphasis was placed on malware detection accuracy rather than abnormality detection accuracy. Similarly, in [2], though classification accuracy was ensured using deep CNN, time series patterns were not concerned. In the case of [3], even with the assistance of a DL mechanism for predicting Alzheimer's patients, the performance was considerably compromised due to the lack of strategic interaction. Finally, with the regional proportional network applied in [4], COVID-19 detection accuracy was assured, but at the cost of a considerable amount of time. In addition, recall, accuracy, and precision using MAR-ERNN were found to be 95.55%, 98.35%, and 97.85%, respectively. However, both recall and precision were found to be lower in all four conventional techniques. The improvement was due to the application of the Gradient Descent ERNN algorithm. By applying this algorithm, a gradient descent was applied to the deep-learned features that in turn arrived at the local minimum function. The stable convergence during activity recognition was produced and contributed to

Table 4 Comparative results of execution time and computational overhead using proposed MAR-ERNN and Existing DL-based Feature Detector [1], Partitioned Deep CNN [2], DeTrAs [3], and Faster-RCNN [4]

Methods	MAR-ERNN	DL-based feature detector [1]	Partitioned Deep CNN [2]	DeTrAs [3]	Faster-RCNN [4]
Execution time	0.125ms	0.215ms	0.285ms	0.325ms	0.385ms
Computational overhead	2KB	4KB	3KB	3KB	5KB

a high value of both recall, accuracy, and precision when compared to four conventional techniques.

On the other hand, to enhance the learning and classification process, by using the softmax activation function in [1], whereas with 7-layer CNN applied in [2], for significant ECG classification, a small amount of recall and precision was said to be compromised. Also, with the lack of prediction optimality in [3] and fine-tuned architecture in [4], recall and precision were less focused than detection accuracy.

Looking at the accuracy results, it is possible to conclude that MAR-ERNN shows improvements when compared to [1], [2], [3], and [4]. Therefore contributing to an accuracy of 98.35% using MAR-ERNN, whereas the accuracy of 98.00% for [1], 96.30% for [2], 88.63% for [3], and 98.00% for [4]. In Table 4, the outcome analysis of different parameters is tabulated using the same number of participants with similar activity recognition.

First, from looking at Table 4 and the comparative results of both Execution Time and Computational Overhead using the proposed MAR-ERNN and the four conventional methods: DL-based feature detectors [1], Partitioned Deep CNN [2], DeTrAs [3], and Faster-RCNN [4], it is inferred that the computational overhead using the MAR-ERNN method is comparatively less as compared to the others. On the other hand, in the case of [1], recurrent layers of attention LSTMs were employed, though the minimum loss was ensured, but at the cost of time. Similarly, with the CNN structure for ECG learning [2], despite the improvement observed in training and testing errors, a significant amount of time was said to be incurred. With the ensemble learning for tracking abnormalities in [3] and using sensory movement data, tracking accuracy was mainly trained though the computational time involved in tracking the abnormality was not focused. The reason for reducing the time to apply the Moran Autocorrelation model in the proposed method is to correlate with different attributes during activity recognition.

Despite the higher amount of detection accuracy being attained using regional-based CNN in [4], the time factor was found to be high. With these results, on average, the computational overhead using the MAR-ERNN method for 10 different experiments conducted at different time intervals was found to be better by 9% compared to [1], 11% compared to [2], 15% compared to [3] and 20% compared to [4].

The second factor for analysis from Table 4 is the execution time involved in the detection. It was found to be 0.125ms with the application of the MAR-ERNN method. On the other hand, the four existing techniques are observed at 0.215ms, 0.285ms, 0.325ms, and 0.385ms, respectively. However, in the case of the DL-based feature detector [1], though it surpassed the previous baseline model, a significant amount of time was said to be consumed. Also, by employing a deep auto-encoder network in [2], the error rate was considerably reduced, but at the cost of execution time. Finally, with abnormality tracking being the main concern in [3] and [4], the time factor was not involved, though it contributed to detection accuracy. The improvement in execution time for activity detection from a healthcare perspective using MAR-ERNN was due to the application of the Moran Autocorrelation model, Conditional Autoregressive Temporal Factor analysis model, and Gradient Descent ERNN. First, correction is measured. Next, the likelihood of values evaluated at any time is dependent on the level of the corresponding homogeneous activity. Followed by, the activity and deviations are identified by applying Gradient Descent ERNN This, in turn, assisted in the reduction of the execution time and overhead for detecting abnormalities and inactivity detection. With these results, on average, the execution time using the MAR-ERNN method for 10 different experiments was found to be better by 12% compared to [1], 14% compared to [2], 19% compared to [3], and 25% compared to [4], respectively.

5 Conclusion

In this paper, a survival study of various DL techniques in the IoT healthcare domain is performed. We have completely analyzed the literature while choosing the most pertinent and up-to-date surveys to identify the research gap. Moreover, we have also stowed complete and state-of-the-art literature on DL-based techniques in IoT smart health. A complete discussion of their strengths and weaknesses along with a novel proposal was also provided. Several research concerns and questions were discussed, which stimulated the researchers to make the most of them in the future. Moreover, several issues that were elevated due to the appearance and architectures of IoT, i.e., Internet of Medical Things (IoMT), and DL techniques were exhaustively discussed to make it easier to reach a comprehensive IoT perception to the public. Memory consumption was not used as a variable for this study. In this way, a vision that meticulously combines this innovative technology in almost all areas of applications and that will specifically take advantage of our daily lives soon will be realized. DL provides us with a new angle to address the conventional issues and assists us in getting an in-depth insight into the smart healthcare domain of IoT with minimal time and overhead.

The proposed MAR-ERNN carried out experimental evaluation using factors such as accuracy, execution time, accuracy, precision, recall, execution time, and computational overhead from REALDISP dataset and compared to five conventional works. The proposed method also tries to enhance the effectiveness of the system for monitoring in terms of execution time, and computational overhead. The proposed approach addresses healthcare monitoring and demonstrates rational accuracy and cost savings with respect to the systems in use. The study was tested and found to be effective, accurate, and efficient for the purpose. In future work, the proposed method is applied in the medical field to properly identify the disease with minimum time.

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Code Availability The code is available from the first author upon reasonable request.

Declarations

Compliance with ethical standards None.

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