IoT Based Smart Health Monitoring with CNN Using Edge Computing

S. Vimal[1], Y. Harold Robinson[2], Seifedine Kadry[3], Hoang Viet Long[4], Yunyoung Nam[5]

[1] Department of IT, National Engineering College, India
[2] School of Information Technology and Engineering, Vellore Institute of Technology, India
[3] Faculty of Applied Computing and Technology, Noroff University College, Norway
[4] Division of Computational Mathematics and Engineering, Ton Duc Thang University, Vietnam
[5] Department of Computer Science and Engineering, Soonchunhyang University, South Korea
svimalphd@gmail.com, yhrobinphd@gmail.com, s.kadry@bau.edu.lb, Hvlong@utc.edu.vn, ynam@sch.ac.kr

Abstract

In the last years, healthcare monitoring has followed a great upwards grown compared to the past decade with the intrusion of the Internet of Things (IoT). The IoT based health paradigm has a vibrant role in health care services to enhance data processing and data prediction. Fall accidents are common in the elderly persons. IoT with Artificial Intelligence (AI) provides a major paradigm to predict the human control, to analyze the cause of human tendency. Fall detection is a major prevailing need with the elderly person, and in order to mitigate this problem an AI based deep Convolutional neural network is proposed to analyze the cause of falling. The deep convolution neural network has been proposed together with the fog and edge computing to analyze the health monitoring tasks. This work analyses the architecture and motions of the persons for fall detection with the sensor nodes. An experimental study is carried out with a benchmark dataset and the higher accuracy in the classification is obtained with this proposal in the simulation results.

Keywords: IoT, Health care, AI, Convolution neural network, Fall detection

1 Introduction

Health monitoring is a priority in health treatment and diagnosis in this modern world. The abnormal conditions prevailing in a human system are analysed with the electrocardiogram (ECG), electromyography (EMG) and Electro dermal activity (EDA). These mechanisms make a traditional analysis with the human and hence the data may be essential. Fall detection is one of the major priorities for the elderly person. Nowadays many wearable devices are prevailing in the market to detect the body mass index or heart rate monitoring, for example, with low cost and light weight. The collected information data is stored and transmitted wherever needed with the help of a gateway. However, there may be drawbacks and failures prevailing with the wearable in terms of data collection and energy monitoring due to lack of battery backup, data transferring, improper network connectivity etc.

The expected growth of things is around 20 billion in 2020 and 25 billion in 2025. Due to low energy constraints, low memory processing, and faster transmission and reliability, most people and organizations are using these things [1]. For normal people, they are using these things for smart homes, smart farms, pet monitoring, child monitoring, printers, voice assistants, etc. These things are working by sensing the surrounding environment and sending information to the base station through some communication channels like WiFi, Wi-Max, Zigbee, and LoRa (Long Range). Nowadays, many wireless devices are been used, one among them is the low power wide area network (LowPAN) technology. The LoRa has a modulation for enabling the long range communication with low power enablement. LoRa is an IoT application device essentially used in smart cities development, across sea communication, low power communication with low access points. LoRa is an effective -WiFi communication that has the access with more connectivity than Bluetooth, Zigbee, LTE-A and RFID [2].

Low accuracy in fall detection is a major problem; most smart home management systems now use home appliances that detect the human activity with a high edged camera and data transmission through the network. To address these issues in real time monitoring a three edged paradigm is proposed with wearable fall detection, microphone fall detection and the vision fall detection. With these techniques, human perception is captured with the accelerometer and a smart phone with the help of GPS that provides

*Corresponding Author: Yunyoung Nam; E-mail: ynam@sch.ac.kr
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connectivity with the family persons to initiate a request [3]. A wearable device has been used to monitor the causes and to predict the fall using genetic algorithms, even though the paradigm is assumed to be focused in the fall analysis, hence vision based fall is taken into consideration with proposed AI based deep convolution networks [4].

In vision based approaches human emotions are also considered, as happiness, sadness, relaxation, for fall analysis with the pose recognition [41]. Most of the studies use the SVM algorithm to focus the algorithmic prediction of the fall detection. The facial expression and the image processing domain have been analyzed with the path analysis in the human system for fixing the emotions. The affective state is also one of the paradigms to analyze the fall for elderly person. Another method is proposed that the detection of the crowd behavior has been analyzed using the posture recognition, that may be one of the metrics to detect the human actions behaviors [42]. Various analyses of the continuous and real time monitoring data are carried out. A comparison has been done with the various devices for prediction and it is observed that the LORA is best efficient analysis given.

The fall down happens across the world for old aged peoples and the fall down is assumed to be of 9% till 2016 and it may increase to around 30% in the near future. The fall down may cause bad injuries leading to death and majority happens with peoples above 60 years. This is assumed to be a major problem for the old peoples. It has very bad consequences to their families, health care systems and to the public. Even though there are lot of WBAN to detect the fall detection using the sensors with the support of cameras, the system performance is facing lot of issues in false fall analysis. The False likelihood approach is happening in larger due to the technological advancements, the application proposed here will overcome those false approach. The falling happens due to age, physical condition and other health parameters [45-46].

The challenges and limitations imposed on fall detection mainly focus on the performance of deployment, flexibility and usability. The elderly person might get adopted to the system proposed and proper flexible usage has to be done. The privacy issue and due to senor issues the fall detection with the elderly person is monitored and the main issue here is the adaptability of the proposed system. Besides, the elderly person cannot be expected to use the smart phone all the time to deal the smart environment. It's been a major issue in the dataset to identify the issue concerned for proposing the system. The traditional system uses the wired camera and lack of battery supply is one of the concerns, hence the proposed will able to mitigate the backup supply through edge connectivity devices. The proposed segment can deal the issues in indoor as well as outdoor environments. The proposed system has been analysed with the elderly persons history of health, usage of assistive devices, Gait deficit and every elderly issues are been monitored. However the technology growth has an impact on the flexibility how far the elderly peoples use the proposed model.

This work proposes a combined architecture for fall detection with AI, edge computing, Fog computing, IoT technologies [5]. The proposed model builds a complete framework for the IoT based health care solutions that overcome the existing limitations prevailing in the data storage, data acceleration and data monitoring. Edge gateways are being used with the AI to detect the human fall more accurately and with a more precise calculation [43].

The following are the main contributions of this research paper:

1. A deep convolution neural network based real time fall detection system considering human emotions. The IoT based framework is framed using the Hadoop Distributed File System (HDFS) module. Map reduce has been used to demonstrate the feature extraction and the extracted images are compared using the data processing unit. The on body sensor devices are used to fuse the higher layer prediction with the massive data streams.
2. A study of the performance with the dataset with fall and non fall events to analyze the fall without touching the privacy of the users. CNN based data signals are analyzed for the fall detection using the accuracy level.
3. This paper proposes an Edge/Fog based data transmission once the fall is detected using the accuracy prediction in the deep neural network.

The remaining paper is organized as follows: section II focuses on the Related works. Section III focuses on the system model with the deep convolution neural network and IoT framework to predict the fall with the accuracy level. Section IV proposes an Edge/Fog based data model to predict with the real time data transmission and dataset analysis. Section V concludes the paper with the proposed elaboration and future direction is discussed.

2 Related Works

The fall is a major unhealthy cause for the elderly people throughout the world. The fall may cause a functional risk in the elders with a decrease in mobility and an inability in the life quality matters. IoT based fall detection is applied for estimating the indoor environments, the low power sensor nodes actively participate in the network with the smart devices and the cloud computing. A 3D axis accelerometer is proposed to establish the usage of 6LowPan device to support the data collection related to elderly movements in the real time environment [6]. The high efficiency in fall detection is analyzed with the decision tree structure in the data modeling in establishing the fall detection and hence the data can be monitored with the smart IoT Gateway. If a fail is detected in the human structure an alarm will be posted to monitor the group activity in the family members who analyze the notification and move for recovery the elderly people [7]. The storage device is used to monitor the network with the health care access to the detection of the fall with the system, to follow a medical modeling, and determines the accuracy and prediction [8].

The fall detection is the biggest concern prevailing in the health care sectors due to elderly age sector of people in the group. It is observed that the 50% of injured people are having an age group of 65 [9]. The fall detection devices are assumed to be expensive and cannot be afforded by all the age groups. Therefore, an adaptable system has been proposed for the old age homes and the smart city is planned with the clinical explanations supported by the AI and IoT powered intelligence in the detection [10]. The fall has been assumed to be detected with a framework based on smart IoT and AI in terms of sending the data to the cloud and the nearby edge devices are assumed to be for tracking data, providing the needed for the real time analysis [11]. The architecture has been proposed with the Mbient Lab, an open source streaming software has been used with the long term memory network for fall detection. The fall detection is trained and assumed to control the detection towards the mobiact dataset, being the final accuracy of 95.8% [12].

The framework based on a nonlinear model-prescient controller (NMPC) has been proposed and that achieves fall detection due to the individualized glucose level digestion system, comprising of two symmetrical models and a repetitive neural network. This approach takes the input as patients information with respect to dinner ingest, glucose estimations, insulin implantation rates, and insulin level, and advances for glucose forecasts [44]. The foremost common models are based on a proportion based necessarily derivate controller and a model-predictive controller (linear and non-linear) [14]. A model-predictive step by step learning control had been given based on a data-oriented linear autoregressive exogenous model [13].

The new technique has proposed that, in wireless body area network (WBAN), data framed from different types of wearable, invasive, or non-invasive sensors, provide the ability for real-time decisions and intellectual healthcare services for better diabetes monitoring. The authors presented a structured representation to ensure high data quality and accuracy in WBANs for effective and real time diabetes monitoring [16]. The structured representation is a set of DQ dimensions to verify that the data extracted from sensors, processed, and delivered are of high quality so that diabetes patients and experts are able to make accurate, high-precision diagnoses, and real-time treatment predictions [15].

The enhanced technique has presented that the health care is reduced to be of the mobility with the following demand in the developing countries to follow an assistive control in the public for the elderly person to properly encourage a home treatment and after being discharged from the clinic. Interactive applications have been integrated with the intelligent and the resources of the mobile development. A fog micro data centre network is connected and is analyzed using the data set in the micro fog to generate a reduced level in the energy to achieve the health monitoring in the clinical observation [18]. It is observed to enhance the data processing in a low latency with the resource limitation [17]. The system has been evaluated using the image recognition and fall detection by the sensor with smart devices. The fall detection accuracy is established to be of the ratio of 54% performance enhancement [19].

A smartwatch (Internet of Things) gadget has been proposed that identifies the fall using the streaming accelerometer information. The smartwatch is associated with the smartphone to perform the computation; it is basic for the location of fall on a real-time premise without getting the delay in communicating with the cloud server. In this approach the information is too moderate for the protection of information. The mass sum of fall detection strategies requires more equipment and programming these make them more costly and unattainable to the community. Using the smartwatch to assemble the information is an advantage to distinguish the fall discovery. Fall detection is done with the support of both the support vector machine and naïve Bayes machine algorithms. By adjusting the recurrence of the spilling information, the drop detection model is illustrated. This demonstration gets the precise positive rate of the fall detection in real-universal with 93.33% exactness. These results are competitive with the custom made of expensive sensors.

A Fall Detection system based on the Internet of Things (FallDS-IoT) has been designed into a wearable framework to identify the falls of older individuals, utilizing accelerometer and spinner sensors to induce exact results of fall discovery. They classified the everyday exercises of elderly individuals into resting, sitting, walking and falling. They utilized two well-known machine learning algorithms, specifically K-Nearest Neighbors (K-NN) algorithm and decision tree. Avoiding falls represents a major wellbeing chance for the elderly people. In case the circumstance is not alarmed in time, this leads to misfortune of life or disability within the elderly people, which diminishes the quality of life. The resultant correctness for the produced dataset was 98.75% and 90.59%, individually. Subsequently, it was concluded that K-NN gives more exactness in recognizing falls and this strategy is utilized for classification. At whatever point a fall happens, a message illuminating almost the fall will be sent to an enlisted phone number through a Python module.

Another method has been proposed to create an honest instance acknowledgment to reduce the mischievous effects after the effect of falling. The fall detection is the main important area of the research because of it's nearly association with the old people healthcare. All the developed researches and tested methods consolidate the Artificial Intelligence for the fall detection. These kinds of methods are factored by the related merits and demerits. The focus of the proposed method is to identify the approaches and focus on the automated fall detection approaches that are consolidated, being the vibration measurement as a key tool. Also, the applicability over the approaches is described, as well as challenges that are correlated with the fall detection using the vibration measurement tools. The summary of the primary approaches involved in the fall detection method serves to determine a different approach based on consolidated sensors used to improve the performance of the whole system.

The remote healthcare monitoring has been developed over the past decade along with the expanded penetration of the internet of things platforms. These types of IoT based frameworks are used for the improvement of the standard of healthcare administrations through real-time data securing and handling. However there are some limitations in conventional IoT architecture. It cannot appropriately perform in regions with a poor internet connection. Hence, to overcome the lack of network infrastructure, low power wide area network (LPWAN) technologies including long-range communication protocols such as LoRa are used as potential candidates. LPWAN technology has restricted transmission bandwidth, which is not appropriate for high data rate applications such as fall detection frameworks or electrocardiography monitoring. In this manner, the requirements for the edge of the network are data processing and compression. The combination of edge and fog computing, LPWAN technology, IoT and deep learning algorithms form the proposed system architecture with integrated artificial intelligence, which is used to perform health monitoring tasks. Through the use case of fall detection, the possibility and viability of this architecture using repetitive neural networks is illustrated. From the sensor node and edge gateway the fall detection system is implemented to cloud services and end-user applications. The average precision of 90% and an average recall of 95% is achieved through the use of inertial data in fall detection.

The Internet of Things demonstrates the process of healthcare system to monitor the patient's health in real-time [47]. Several sensors are used to capture the information from the hospital environment and analyze the exact situations of the patients [48].

Besides the gap in the existing model is that old peoples suffering fall detection cannot utilize the smart phone technologies due to their access and usage. The proposed model will outline an image extraction and if any changes in the normal human positioning will be reported to the system model. The traditional systems discussed in the survey utlises the maximum IoT modeling with smart phone applications, however the proposed model monitors the physical positioning of the user and claims the result using the AI techniques.

3 System Model

The model has been proposed with five layers having a sensor, edge gateway, fog layer with LoRa connectivity, cloud layer and the application layer with user connectivity. The collected data can be used to predict the blood diagnosis, glucose level and the related information for handling the treatment in the dedicated environment. The collected data is communicated to the edge devices via a wifi connectivity to preprocess the data in the network.

The system is modeled with three levels of data modeling as follows:

- The data model 1 contains the edge devices connected with the IoT sensor nodes. The elderly people is detected with the image feature and the binary storage is pertained in the container. The images are stored in a temporary server and the process continues with the feature extraction from the data and the result is sent to the data model 2.
- The data model 2 applies the deep convolutional neural network to detect the fall with the support of features from data model 1, the data model 2 collects stored image and performs the task with the deep neural processing.
- If an emergency alarm is detected, the data server reflects the data to the clinical observation.

In the data model 2, a signal processing unit is activated with the HDFS support to manipulate the distributed processing, and HBASE for storage access with the binary images. The HDFS performs a parallel processing with the data from light weight Internet of Medical Things (IoMT) devices. A time sequential analysis of the collected sampled data is performed in the parallel processing and hence the data is assumed to be of the downrange of sampling with 125HZ. Band Pass filtering is applied with the HDFS to monitor the data model 1 future images. Figure 1 represents the proposed model using the IoT-Edge based fall detection.

The fog layer using the wireless Accessible LoRA provides a dynamic allocation in terms of real time interaction and in the environment using the network components for fall detection. The speed of computing, storage and all the networking provides the smart

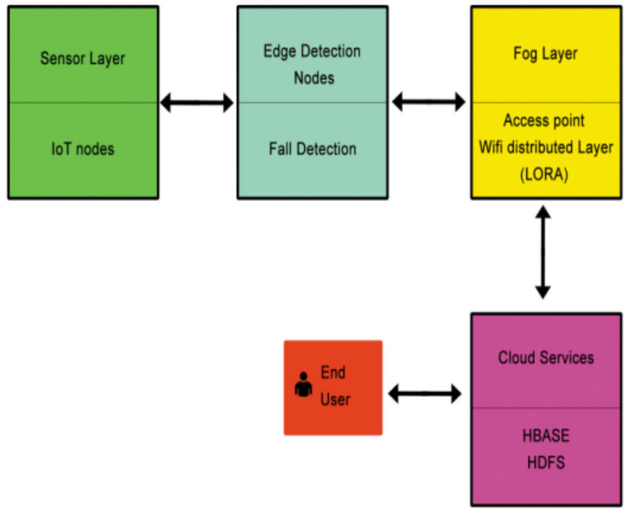

Figure 1. Proposed Model

applications control unit with the IoT devices. The edge layer will out perform the working control of fog layers using the dynamic physical and logical resource allocation in the server with low latency and the high quality computing. While dealing with the Cloud layer HBASE and HDFS supports the dynamic characteristics with the management plane using the VM migration and in VM monitoring phase. The data collected form the sensor network is been controlled by the controllers in data model 2 and then transferred to the gateway and the central server. This creates a redundancy in data while using the model 2. The central server will prevent the data preprocessing, filtering and the data acquisition.

3.1 Binary Image Classification

The process deals with the three phases in training, feature detection and fall detection. in the phase of training, the negative images and positive images are extracted using the deep neural network with the training model, feature detection is done in sensor to establish the edge based connectivity to explore the network in the model [20]. When the fall state is identified during more than 75 seconds, it is sent to the clinical observation. The time and frequency domain features are extracted from the various sensor nodes. The extracted features are used to estimate the mean, the standard deviation, to measure the heart rate variability [21].

The images are extracted from the detected person and are processed with the light condition in the deployment of sensor and hence the output image is not conditional on the sensory inputs [22]. The traditional SVM algorithms are needed to clarify the noise separation in the images, and hence the data can be exploited with the noise classification as shown in eq. (1).

$$p(i, j) = \frac{250}{1 + eP(x, y)^{250\Sigma_{(i-1, j-1)}^{(i+1, j+1)}}} \quad \textbf{(1)}$$

The image features are classified based on the features in the deep convolution network using the classification as formation of the gradient vector in the direction in the subsequent formation in the setup [23]. The pixel value in the binary image is calculated with the parametric values in the $px(X, Y)$.

$$px(i, j) = w(i+1, j) - w(i-1, j) \quad \textbf{(2)}$$

$$px(i, j) = w(i, j+1) - w(i, j-1) \quad \textbf{(3)}$$

$$px(X, Y) = \sqrt{px(i, j)} + px(i, j) \quad \textbf{(4)}$$

The power spectral density (w) is estimated for the signal measured within the computing environment as shown in Eq (2) & Eq (3). The Eq (4) shows the final calculation of the parametric value representation using the binary image and the spectral density is depicted as in Figure 7.

3.2 Deep Convolution Neural Network (CNN) Based Fall Detection

Convolutional neural networks have shown to be a successful method for recognizing different targets, such as human activities gestures or even scleras. The Convolutional neural network has been stated as the feed forward neural network that has been developed for handling the deep network structures. The design has been formulated with three layers of convolution layer, pooling layer and fully converged layer.

Design of the hybrid classifier involves the following processes,

1. Feature Extraction
2. Training a pure feed forward CNN classifier with Back Propagation
3. Replacement of output layer of CNN

The raw data had several issues while dealing with the attribute selection. First, the number of attributes was relatively larger than the number of samples, so a feature selection or a feature reduction method would be useful [24]. Therefore, the feed forward ANN classifier and variance threshold methods were adopted to select features based on their importance scores. The variance threshold method filters out features with variances lower than the threshold. Hence, the filtered data set contains high variance attributes only. Both data selection methods were used in later experiments to see which method provided a better result [25].

The convolution layer compares the kernel for providing the better solutions in the search space for the same features, the important features are classified based on the observation, the pooling layer performs a down sampling of data for the generalization in the network, the features with less parameters are reduced by the down assumptions in the deep convolution in the layered control. The network is trained for the given input iteratively [26]. Each iteration the error between the target and the achieved output is calculated. The error for the j[th] iteration is defined as follows as shown in eq (5),

$$F(x) = (t_i - a_j)^2 \quad \textbf{(5)}$$

t_j and a_j are the targeted and the achieved output respectively . The network is trained by adjusting the weights and the bias so that the MSE gets minimized [27]. The MSE estimates the posterior probability function for the classification problem. Here with the gradient descent method, the Back Propagation (BP) method uses the calculated MSE at each layer to adjust the value of the interconnected weights [28].

Back propagation is an algorithm that supports the Multi Layer Perceptron (MLP) that determines the error driven learning for the CNN [29].MLP signals the feed forward network to learn the dataset to analyze if the data is malignant or benign based on True Positive (TP) and False Positive (FP) detection rates. The backpropagation process depicts the error based derivative on each neuron weight. The error has been segmented in to positive and negative errors, adding a small negative error in the positive feedback lessens the network error [30]. Levenberg-Marquardt back propagation as shown in equation (6) has been used to analyze the weight change in the neurons with the average of squared errors where the weight of neuron y in x^{th} layer is $w_{x,y}$, the momentum rate, learning rate and the derivatives are shown as a, D and n-1.

$$\Delta w_{x,y}(n) = \frac{\delta D}{\delta w_{x,y}} + a w_{x,y}(n-1) \quad \textbf{(6)}$$

The feed forward and the forward propagation is assumed to be of the control in the composite function analysis in the setup and hence the sigmoid and pooling operations have been estimated with $O = \{o_{01}, o_{02}, o_{03}, \cdots, o_{0M}, o_{11}, o_{12}, o_{13}, \cdots, o_{1M}, o_{21}, o_{22}, \cdots, o_{2M}\}$

$$N_F = F^{(\text{pooled})} \text{ o } F^{(\text{Convol})} \text{ o } F^{(\text{con layer})} \quad \textbf{(7)}$$

The feed forward network is established in the input as O and the N is predicted as the output in the output convolution layer, where in the convolution layer M is assumed to be of the output layer where $M = \{M_{01}, M_{02}, M_{03}, \cdots, M_{0M}, M_{11}, M_{12}, M_{13}, \cdots, M_{1M}, M_{21}, M_{22}, \cdots, M_{2M}\}$

$$N = O * M = M^T O_{mn+|M|} - 1 \quad \textbf{(8)}$$

The backward propagation and the derivative is assumed to be in the range parameters of $1 \le i \le M$. The partial derivative has been assumed to be

$$\frac{\partial N}{\partial m} = O_{n+i-1} \quad \textbf{(9)}$$

The partial derivative of the output N with respect to the input deviations and the backward propagations are assumed to be of the control in the parametric representation [31]. The activation function is represented as the linear unit in the parametric representation as

$$\frac{\partial N_{n-i+1}}{\partial Om} = M \quad \textbf{(10)}$$

The pooling layer is assumed to be of the layered approach with the 2x2 function estimation in the observation metrics followed as

$$\text{Convol (p)} = \max (0, \text{p}) \quad \textbf{(11)}$$

The function aggregate is assumed to be of the control in the pooling layer, which is structured as the formations of the convolution setup in the

$$N = t\, (\text{Convol (p)})_{(\text{n-1})\,\text{m+1: nm}}) \quad \textbf{(12)}$$

$$t(\text{Convol (p)}) = \max (\text{Convol (p)})) \quad \textbf{(13)}$$

The cost based function is assumed to be of the ratio in the control difference or error in the ground pass estimations.

$$E(M, b, O, L) = \frac{1}{2\,\|L - NF\|} \quad \textbf{(14)}$$

The gradient of the error is established with the sequential arrangement in the performance with the $\frac{\partial N}{\partial M} donewith$

$$\frac{\partial E}{\partial E} = \frac{\partial E}{\partial P}\frac{\partial P}{\partial m} = \sum_{n=1}^{|oy|-y|+1} \gamma\rho On + i - 1 \quad \textbf{(15)}$$

where the gradient is performed with the operation in the error $\gamma\rho On$ for the backward propagation

$$\gamma\rho On = \frac{\partial E}{\partial \rho On} = \frac{\partial E}{\partial P}\frac{\partial P}{\partial \rho On} = \sum_{n=1}^{|w-y|+1} \gamma\rho On + W \quad \textbf{(16)}$$

from equation (16) it is observed that the relative gradient descent follows the upgraded version in the deep convolution model that extracts the high level features in the different kernels with the convolution product to pooled method, with the linearization in the convolution parameters that has been estimated [32]. Figure 2 depicts the feature extraction based CNN model.

3.3 Edge-IoT- Cloud Gateway for Data Processing

The proposed methods and models illustrate a processing via edge gateway with AI based algorithms in the Fall prediction. The AI service can be able to detect a human fall with the prediction mechanism in the higher level of accuracy with the wifi enabled LoRA device to monitor the progress in the scheduling

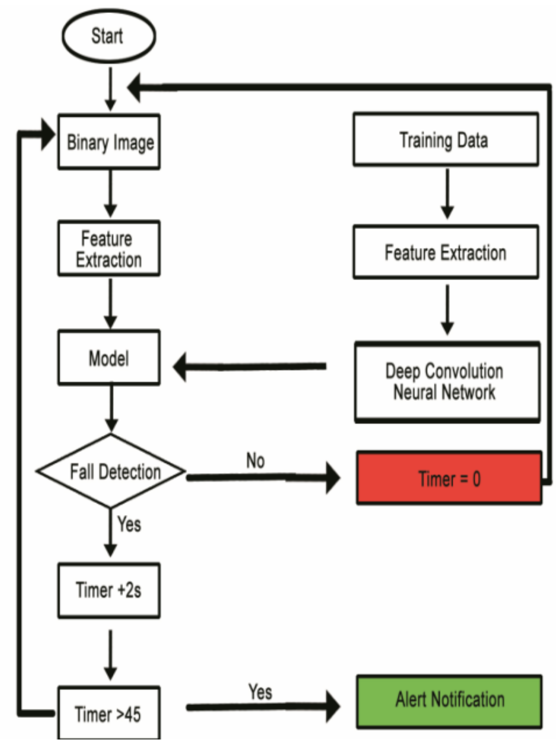

Figure 2. Binary Image Analysis and Feature Extraction using Deep CNN

up of tasks in the human centric systems. The data has been collected and sent to the data enablement in the data control in the prospectus manner [33]. The processed data and the results are enriched in the motivational work towards the parallel processing with deep learning algorithms. The storage has been processed with the big data mechanism in the cloud storage with HDFS and the data are stored in the hbase mechanism. The LoRA is a low latency utilized process enabled with the duty cycle regulations in the process of storage, security services and the localizations. Edge gateway is highly essential to provide advanced gateway with security, storage and virtual gateway in the predetermined environment [34]. The fog assisted health care environment ensures the connectivity and data sharing using the LoRA gateway and the essential facts have been highlighted with the perception of following in the predetermined area. The fog-IoT-Cloud and deep learning algorithms have been constructed altogether work in the way to measure the connectivity with the parametric value. The data gathering has been done with the measurement of the accessing devices using the AI based data assumptions in the categorization of the algorithmic approach [35].

The CNN has been trained with the alignment and a public dataset has been established with the wearable node establishing the data format in the equivalent way of organizing the data set with different assumptions such as W, X, Y and Z parameters are studied in the analysis with the approach of SVM and ANN taken in to consideration and compared with the essential platforms [36]. The Hbase has been used in the platforms to enable the parametric analysis using Cent OS with kali Linux platform. The end user implementation has been established with the trained dataset and the trained data set is utilized with the data normalization and preprocessed is analyzed with the key platforms. The data is normalized and encoded enabling the flexibility in the design of the sensor node [37].

The proposed work is segmented in two possible ways to speed the indexing of large scale database image using the HDFS. The distributed file processing has been done in the image database with the HDFS setup. The performance of the image searching and indexing with the retrieval is good enough in HDFS and it is faster with the unstructured databases such as Hive or any big databases [38]. The image searching in the big databases is done with the CNN algorithm which emphasizes a big approach in the feature vector of the image queried from the image databases [39]. The demerits in the CNN is the processing time with high memory usage and the computation processing, which is larger comparable with the SVM and Naïve Baiyes theorem .CNN is considered to do the optimal analysis in the image database [40]. The computation is done with the cache model and non cache model in the spark architecture. The work is comprised of a comparative survey with the hbase based mechanism to predict the computation time and the model framework. The cluster formation based on CNN with the parameters of every node with specification that produces the MapReduce and HDFS node is illustrated in Table 1. The cluster formation has been done to work on the data set with the edge devices computing the name node and data node, Figure 3 represents the IoT based convolution model.

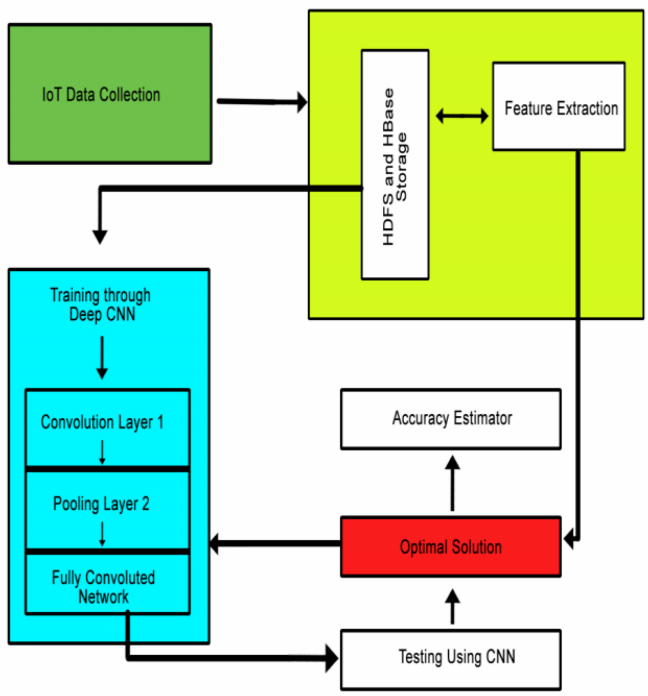

Figure 3. IOT based Convolution model

Table 1. Cluster formation used for CNN

Cluster para meters in nodes	Specification	Map Reduce	HDFS Node
0, 1	4 CPUs, 7 Crores/CPU	Key	Name
0, 2	4 CPUs, 7 Crores/CPU	Slave	Name
0, 3	4 CPUs, 7 Crores/CPU	Key	Name
1, 0	4 CPUs, 7 Crores/CPU	Slave	Name
1, 1	4 CPUs, 7 Crores/CPU	Key	Name
1, 2	4 CPUs, 7 Crores/CPU	Slave	Name
1, 3	4 CPUs, 7 Crores/CPU	Key	Name
2, 0	4 CPUs, 7 Crores/CPU	Slave	Name
2, 1	4 CPUs, 7 Crores/CPU	Key	Data
2, 2	4 CPUs, 11 Crores/CPU	Slave	Data
2, 3	4 CPUs, 11 Crores/CPU	Key	Data
3, 0	4 CPUs, 11 Crores/CPU	Slave	Data
3, 1	4 CPUs, 11 Crores/CPU	Slave	Data
3, 2	4 CPUs, 11 Crores/CPU	Slave	Data

4 Experimental Observations

The dataset includes 150 images corresponding to the fall and the non fall assumption. The positive and negative images have been classified accordingly to the parallel, horizontal and vertical classification in the fall detection. The state of the person is assumed to be fall and non fall based on the conditional section with the fall stated as ‘F’ and the non fall stated as ‘NF’. When the condition fails with the fall and a wrong detection is made, it is assumed to be state ‘EF’, when the condition fails with the non fall and a wrong detection is made it is assumed to be state ‘ENF’.

The condition is stated as:

- Always Positive (AP) as count is predicted as state ‘F’
- Always Negative (AN) as count is predicted as state ‘NF’
- Partial Positive (PP) as count is predicted as state ‘EF’
- Partial Negative (PN) as count is predicted as state ‘ENF’.

The performance in the prediction is estimated with the following metrics in Eq. (17) to Eq. (20)

$$\text{Accuracy}=(AP+AN)/(AP+AN+PP+PN) \quad \textbf{(17)}$$

$$\text{Error}=(PP+PN)/(AP+AN+PP+PN) \quad \textbf{(18)}$$

$$\text{Precision}=(AP/(AP+PP)) \quad \textbf{(19)}$$

$$\text{Recall}=(AP/(AP+PN)) \quad \textbf{(20)}$$

The dataset provides the images with 870 pixels per image and the dataset has been splitted to perform the implementation for the training and the evaluation is done for overfitting. The training set uses the image samples of 55,000 samples and the test has been done with the 12,000 samples. The Deep CNN has been used with the hidden layers for accuracy and increases the accuracy of the model using the batch size of the images. The validation is done by applying a threshold with the loss function in the dataset. If error increases in this validation, the overfitting causes. In this system the threshold value has been set higher to predict the overfitting and prevent it an earlier stage. In compared to FCNN and CNN, the Deep CNN will reduce the model complexity and reduce the overfitting by model. The samples has been used with more than 500 epoch and overfitting is checked with the training and the validation accuracy for each epoch values at training.

The accuracy and the error of the system predict the general ratio to establish the system ability in the fall detection parameters values propagation. The person falls perpendicular and towards inclination in the camera angle, however detection depends on the way of parameterizing the data W, X, Y, Z with the inclination which has been analyzed. The Table 2, Table 3, Table 4 and Table 5 shows the accuracy and error estimation for the proposed method and other approaches as shown in Figure 4 as the angle within the centerline and the ground. Table 6 illustrates the fall detection of the proposed technique with other methods to illustrate the accuracy and the error detection percentage using WXYZ data.

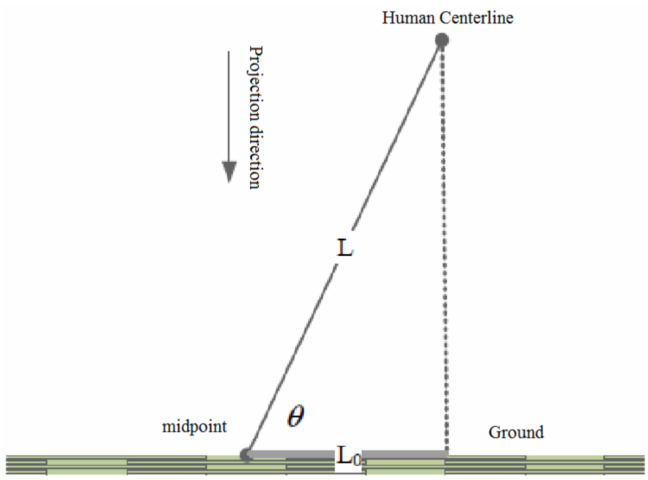

Figure 4. Fall detection prediction with inclination angle based on the proposed model

Table 2. Comparison of fall detection of the proposed model with SVM and ANN using X data

METHOD	AP	AN	PP	PN	ACC (%)	ERR
SVM	195	194	5	7	97.3	-3
ANN	198	196	3	0	99	-2.1
Proposed CNN	200	200	0	0	100	-1

Table 3. Comparison of the fall detection of the Proposed model with SVM and ANN using Y data

METHOD	AP	AN	PP	PN	ACC (%)	ERR (%)
SVM	196	195	5	3	97.6	-3.2
ANN	197	196	3	7	99	-2.2
Proposed CNN	200	200	0	0	100	-1.3

Table 4. Comparison of the fall detection of the Proposed model with SVM and ANN using Z data

METHOD	AP	AN	PP	PN	ACC (%)	ERR (%)
SVM	3	194	5	196	97.3	-3
ANN	1	196	3	197	99	-2.1
Proposed CNN	128	200	0	78	100	-1

Table 5. Comparison of the fall detection of the proposed model with SVM and ANN using W data

METHOD	AP	AN	PP	PN	ACC (%)	ERR (%)
SVM	2	194	5	196	97.3	-3
ANN	0	196	3	197	99	-2.1
Proposed CNN	156	200	200	0	100	-1

Table 6. Comparison of the fall detection of the proposed model with SVM and ANN using WXYZ data

METHOD	AP	AN	PP	PN	ACC (%)	ERR (%)
SVM	245	194	5	404	48.1	-2
ANN	267	196	3	407	46	-2.1
Proposed CNN	567	200	0	15	94	-0.8

The table 7 shows a comparison in terms of the precision and accuracy estimation for the development in the predetermined task allocation. The recall value is appeared to be 0 for SVM and ANN but for the Proposed CNN it is observed to be 1.

Table 7. Comparison of the precision and recall in the proposed model with SVM and ANN using WXYZ (hybrid) data

METHOD	AP	AN	PP	PN	Prec accuracy	Recall
SVM	195	194	5	7	97.3	1
ANN	198	196	3	0	99	1
Proposed Deep CNN	200	200	0	0	99.7	2

The accuracy prediction has been done using the hybrid model data set and it shows that the CNN gives the varied increase of 98% compared to other algorithms as shown in Figure 5. The hybrid data is a fusion of the data samples from WXYZ data sets and the accuracy is monitored throughout. The image features are classified based on the features in the convolution network using the classification as formations of the gradient vector in the direction in the subsequent formation in the setup. The pixel value in the binary image is calculated with the parametric values in the $px(X, Y)$ based on equations (2), (3) & (4). The power spectral density is estimated for the signal measured within the computing environment and the spectral density is depicted as in Figure 6.

The processing time for fall detection for the proposed system of Deep CNN with the related methods of ANN and SVM and the performance result shows that the proposed technique has minimized processing time in Figure 7.

Figure 8 demonstrates the comparison results for accuracy, precision and recall according to the features in the proposed Deep CNN model with the related methods of SVM and ANN. The simulation result proves that the proposed technique has the highest amount of performances compared to the related techniques.

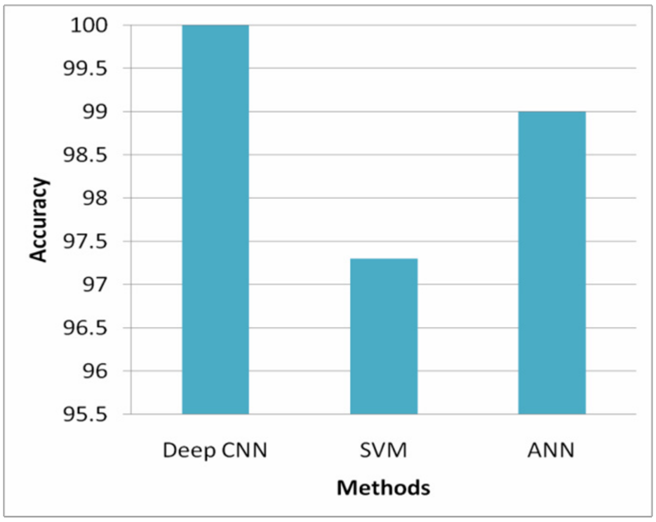

Figure 5. Accuracy Prediction using CNN using hybrid data

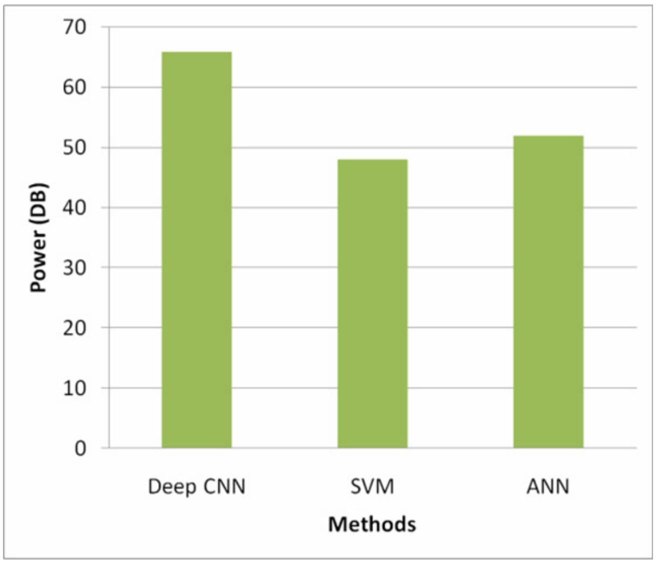

Figure 6. Power spectral density in the proposed method

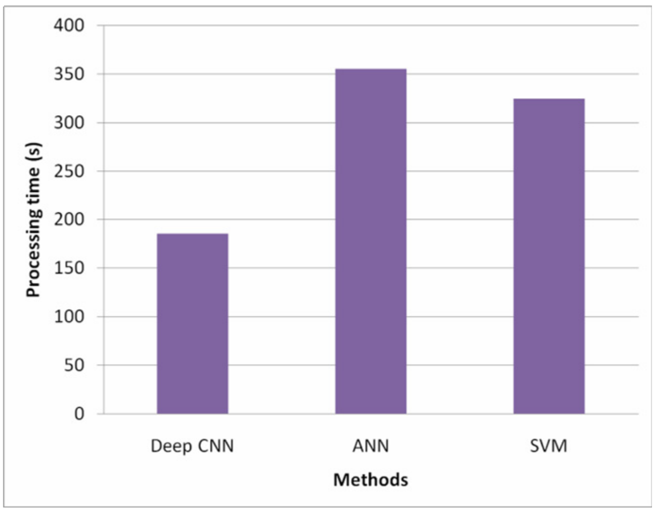

Figure 7. processing time

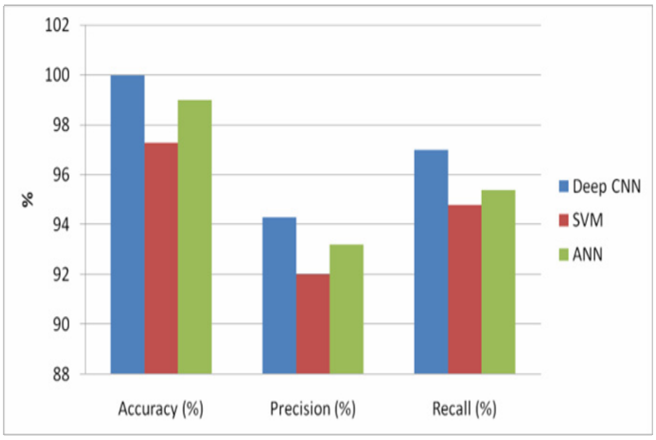

Figure 8. Performance parameters comparison

Figure 9 demonstrates the classification cost from the dataset for the proposed technique compared to the related techniques and the result proves that the proposed technique has the reduced amount of classification cost than other methods.

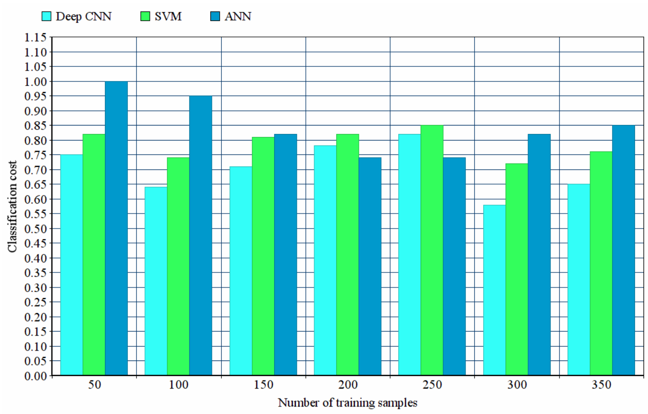

Figure 9. Classification cost

5 Conclusion

A fall detection method is proposed in this paper with higher accuracy level ensured with the support of three levels - convolution layer, pooled layer and the overall layer- to assemble the data processing for predicting the fall detection with feature detection. The experimental result proves a 98% accuracy for the vision based estimation. The study involves different images in a data set for estimating the fall detection accuracy and estimation through SVM & ANN. The IoT sensor data and the data storage through the fog based retrieval enhance the classification and detection accuracy using the CNN algorithm. The coverage of wifi using LoRA covers the detection accuracy in rural areas too. The data analysis has been done in the edge gateway to enhance the transmitted data and hence the system performance in prediction is gradually improved. The notification of the fall detection is reported for clinical observation using the raw data information collected from the analysis of online data sequencing.

Conflict of interest

Declaration of Interest Statement: The authors declare that they do not have any conflict of interests. This research does not involve any human or animal participation. All authors have checked and agreed the submission.

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Biographies

S. Vimal is working in Department of Information Technology, National Engineering College, Kovilpatti, Tamilnadu, India. He has around Thirteen years of teaching experience, EMC certified Data science Associate and CCNA certified professional too. He holds a Ph.D in Information and Communication Engineering from Anna University Chennai.

Y. Harold Robinson is currently working in School of Information Technology and Engineering, Vellore Institute of Technology, Vellore, India. He has received Ph.D degree in Information and Communication Engineering from Anna University, Chennai in the year 2016. He is having more than15 years of experience in teaching.

Seifedine Kadry received the bachelor's degree in applied mathematics from Lebanese University, in 1999, the M.S. degree in computation from Reims University, France, and EPFL, Lausanne, in 2002, the Ph.D. degree in applied statistics from Blaise Pascal University, France, in 2007, and the HDR degree from Rouen University, in 2017. He is currently an Associate Professor with the Department of Mathematics and Computer Science, Beirut Arab University, and also an ABET Program Evaluator. His research interests include education using technology, system prognostics, stochastic systems, and probability and reliability analyses.

Hoang Viet Long is in the Division of Computational Mathematics and Engineering, Institute for Computational Science, Ton Duc Thang University, Ho Chi Minh City, Vietnam. He obtained a Ph.D. diploma in Computer Science at Hanoi University of Science and Technology in 2011.

Yunyoung Nam received the B.S., M.S., and Ph.D. degrees in computer engineering from Ajou University, Korea in 2001, 2003, and 2007 respectively. He was a Senior Researcher with the Center of Excellence in Ubiquitous System, Stony Brook University, Stony Brook, NY, USA, from 2007 to 2013. He was a Postdoctoral Fellow with the Worcester Polytechnic Institute, Worcester, MA, USA, from 2013 to 2014.