IoT-Based Vibration Sensor Data Collection and Emergency Detection Classification using Long Short Term Memory (LSTM)

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2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC) | 978-1-7281-7638-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICAIIC51459.2021.9415228

***Abstract*—In this paper, we used a vibration sensor known as G-Link 200 to collect real time vibration data. The sensor is connected through the internet gateway and Long Short Term Memory (LSTM) used for the classification of sensor data. The classification allows for detecting normal and anomaly activity situation which allows for triggering emergency situation. This is implemented in smart homes where privacy is an issue of concern. Example of such places are toilets, bedrooms and dressing rooms. It can also be applied to smart factory where detecting excessive or abnormal vibration is of critical importance to factory operation. The system eliminates the discomfort for video surveillance to the user. The data collected is also useful for the research community in similar research areas of sensor data enhancement. MATLAB R2019b was used to develop the LSTM. The result showed that the accuracy of the LSTM is 97.39% which outperformed other machine learning algorithm and is reliable for emergency classification.**

***Index Terms*—Classification, Emergency detection, IoT, LSTM**

I. Introduction

The Internet of Things (IoT) has become pervasive and finds ready application in so many fields including smart homes, smart factories, smart farms, water quality monitoring systems and for various uses such as metering, data collection, body area networking and activity recognition systems. One of the critical purpose of IoT or IIoT is the data gathering abilities [1]–[4]. In this paper, we deployed IoT in form of a wireless vibration sensor for the purpose of collecting vibration signals in a smart home or indoor scenario. The vibration sensor data is sent through the internet via a gateway to a computer domiciled in the building and can also be sent via the cloud to agencies such as community security service or police or emergency response units in case of emergency. Using the vibration sensor allows for the detection of abnormal vibrations such as made possible where someone indoor experiences either an attack, or any form of situation that can make the house or walking steps or falling situations calls for emergency attention.

This system builds a database of vibration data and uses Long Short Term Memory (LSTM) neural network algorithm to improve the accuracy of emergency classification. LSTM algorithm is widely used in activity recognition where data is time series. LSTM as a recurrent neural network (RNN) found usefulness in the fact that not only does it have the capability of processing single data points, it has the advantage of also processing sequence of data which is useful for anomaly detection. They are useful and well suited to classifying, processing and making predictions based on time series data due to the following reasons:

- LSTM can effectively handle problems of vanishing and exploding gradient as common in traditional RNNs.
- LSTM has relative insensitivity to gap length in between time series data and this is an advantage over traditional RNNs
- Effective handling of long term memories due to its Gating mechanism.

The aim is to detect vibration without using any form of inconvenience to the residence such as the case of noisy sensors or use of camera which is usually associated with privacy violations.

Principally, the major contributions of this paper are:

1) Design and implementation of an emergency detection system which incorporated vibration sensor, IoT gateway and use of LSTM for classification of data collected for the monitoring of emergency.
2) Compiled a vibration sensor dataset useful to the research community who may be interested in vibration sensor data for indoor environment.
3) LSTM algorithm development for the classification of vibration sensor dataset and effective classification of emergency and non emergency detection.

The rest of the paper is arranged as: following this Section I is Section II, where we reviewed relevant related works to serve as state of the art background information on the subject matter. In Section III, a block diagram description of the proposed systems requirements. This is followed by Section IV where the prototype is presented. Results and discussion of the findings are presented in Section V while paper is concluded in Section VI.

Fig. 1. System model showing the placement of the G-Link sensor at strategic location of the bedroom and toilet scnearios. The sensor connect software helps in the visulation and data collection while the gateway serves as the link for sending the data within 10 meter range of the sensor and host computer.

II. Related Works

1) Emergency Detection Systems: Several systems exist which are targeted at addressing various emergency situations. For instance, fire detection and alarm systems are designed to detect cases of fire and provide proactive response. Breach of security can also account for the need of emergency detection by way of intrusion detection and alert systems. In homes especially to take care of elderly, there exists wearable devices, sensors and actuators used to serve as health or care emergency needs which can then be transmitted to care givers of health facilities. The goal of all emergency detection systems is to provide early warning, accurate classification of emergency and proactive alert to relevant source of solution to avoid more damages [5].

In [6], authors built up a responsive disaster alert (IoT)-based framework for the elderly (DASE), that calls for help in defensive environment crises, for example, floods, quakes, home fires, volcanic emissions, and tempests. Various routine information is gathered through three sources: fridge entryway, washroom gateway, and primary entry. After putting away data and choosing if there should be an occurrence of a notice, cautions are sent to the catastrophe help specialists and different parental figures too. However, the difficult issue is taking a shot at the capacity to catch everyday schedule changes of an older person accurately to understand shortly that is the reason, some crisis identification can be missed.

2) Sensor Based Approach to Detection Systems: Sensors and wide range of wearable devices have provided the opportunity for the growth of emergency and monitoring systems. The sensors serve the purpose of data collection, processing, analysis and transfer of relevant data to desire response providers such as health care center. These found ready application in automated emergency call systems, vital signs monitoring systems [7], automated activity and fall detection systems [8], reminding systems, automated health assessment for the elderly [9].

3) IoT and Emergency Detection Systems: IoT has made the collection, measurement and analysis of data very possible more than ever possible before now. This is because, the pervasive growth of IoT has resulted in compact, intelligent end nodes and cheap implementation of IoT based systems [10]. Potential IoT applications include but not limited to the following: Smart home, Healthcare [11], Transportation, energy, manufacturing [12] and environmental monitoring [13].

4) Machine Learning adoption to Emergency Detection Systems: To enhance the ability of emergency detection systems and ensure a reduction in false alarm rate, several machine learning approaches have been adopted depending on several variables such as type of data, need for real time response, time complexity and nature of data collection. For instance, in [8], authors relied on floor vibration as their recognition source. In their work, they adopted a robust approach to fall detection system that relied on sensor data collection and classification using one-class-support vector machine.

Similarly, in [14], a novel indoor stride localization strategy called angle time contrast of appearances depending on both edge and appearance data of the stride vibration information from seismometer units was proposed. Relying on footstep-induced vibration, they extracted features relating to gait patterns and identical strolling of the indoor individuals walking action. Social association and individual movement pattern can be observed using a machine learning clustering model.

In [13], authors designed a fire detection system to solve the challenges in uncertain surveillance environment using Convolutional Neural Networks (CNN). CNN was used to help in classifying videos captured in uncertain surveillance environment. In [15], authors developed a testbed for intelligent smart gardening system. The system was based on LSTM used in predicting the future values of sensor from the collected data and previous record using the LSTM neural network.

III. System Model

1) Overall System Model of the Detection System: AS described in Fig. 1, the vibration sensor is placed at the floor of the bedroom and toilet to detect human activity in terms of vibration of the floor under three scenarios: falling human, falling object and normal situation devoid of the need for emergency. The goal is to avoid camera based schemes due to privacy concerns of residence of the room. The sensor is then connected via the gateway connected to the computer serving as the host computer. LSTM is applicable to the data collected and classification can be offloaded on the cloud from which various options are available to either have the emergency alert on phone, community watch , police or any desired emergency response unit of government.

2) LSTM Architecture and Description: As shown in Fig. 2, LSTMs are made off memory cells, cell state vector (or explicit memory) and gating mechanisms. The gating systems serve to control the flow of information into and out of the memory. The first gate is called **forget gate** which is set to 1 whenever the old memory is needed to go through. Following this is the second gate known as **input gate** which regulates the extent to which new memory influences the old memory. It simply determines how much new input should come in. Next is the **+ operator** used to merge the current input and the old memory based on the operation. The last is the **output gate** which serves the purpose of controlling how much new memory should output to the next LSTM unit [15].

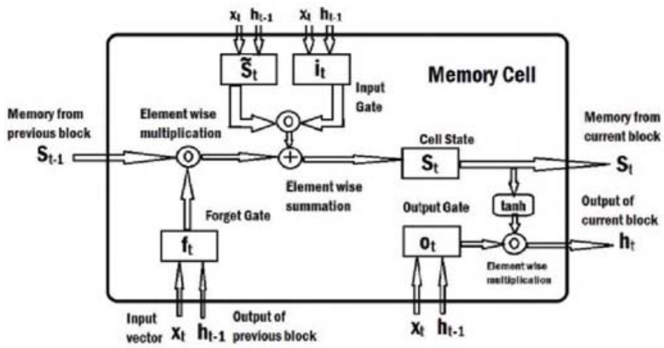

Fig. 2. Basic Building Block of LSTM showing the various memory and gating mechanism making LSTM useful for long term memory dependent scenario.

3) LSTM Justification for Emergency Detection: LSTM is arguably one of the most powerful and well known Recurrent neural networks. The use of LSTM in this project is justified since the vibration sensor data are sequential time series type and the desire to carry out classification is the goal of this project. Several researchers working with sensors or have the need for sequential data classification in recent times have found LSTM useful [15]–[17]. In [18], authors leveraged on the power of LSTM for the prediction of power grid frequency. Their work shows an extensive explanation of the LSTM and how it is best suited for prediction with historical data. Authors in [19] also developed an LSTM model for the detection and classification of possible disaster situation using human action activity such as running, walking, stopping and running for safety. They achieved an accuracy of 97.12%. Furthermore, the authors in = [20] monitored and detected emergency for single-person households based on sound recognition which is used to determine the occupant behaviour. In this work, LSTM was used with an average precision and recall rates of 78.0% and 90.8% respectively.

IV. Experiment and Design Set up

In this section, we describe the steps adopted in data collection, analysis and training of LSTM. We used vibration sensor G-Link 200 to gather real data as shown in Fig. 1. The steps followed are :

1) Assemble the G-Link 200 Sensor and place on a strategic part of the smart home
2) Connect the Gateway which comes in form of Universal Serial Bus (USB) to the computer system
3) Install the Sensor Connect Desktop sensing software or any other chosen compatible dashboard
4) Follow the instructions as prompted until a connection is set up between the G-Link 200 sesnor and the sensor connect software.
5) Collect, record and visualize data as sensor works
6) Save as CSV file or any acceptable format and export
7) Use the exported CSV file as dataset for the chosen machine learning optimization. In our case, we used LSTM
8) In our case, we used MATLAB deep learning designer to set up LSTM used for the training, testing and validation of data (see Fig. 3).
9) Carry out data classification
10) Visualization and Decision (see Fig. 4).

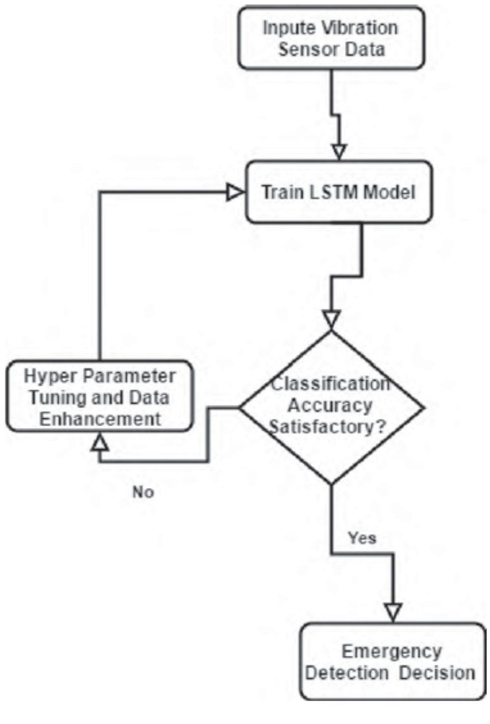

Fig. 3. Flow chart description of LSTM Model for Vibration Data Classification

Fig. 4 is the dashboard showing the variation of the behaviour of vibration data. When there is no vibration or within -0.005 to +0.005, the situation is considered normal.

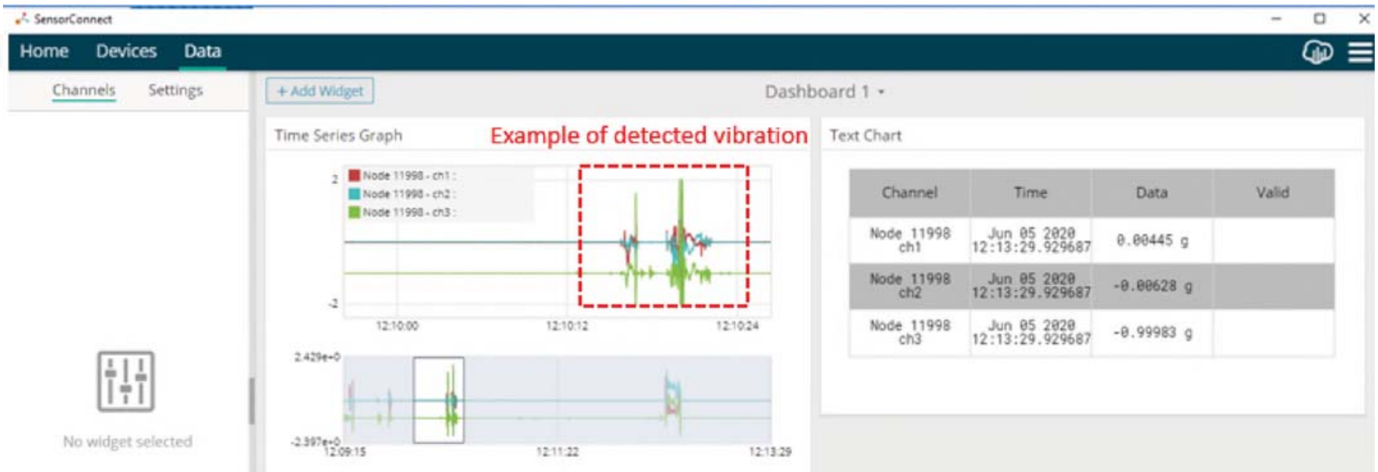

Fig. 4. Typical Dashboard display of anomaly detected in the vibration from sensor data using Sensor Connect

However, higher values indicate an abnormal impact by virtue of falling or serious vibration occasioned by falling objects and or unusual footsteps which calls for emergency situation. The raw data is available for the research community.

V. Performance Evaluation

Fig. 5 shows the classification of the data into detection and non detection of emergency based on the vibration figure as already explained. MATLAB deep learning network designer toolbox was used.

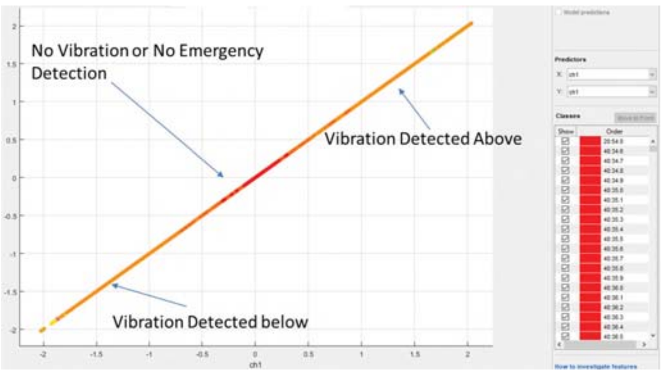

Fig. 5. Classification of vibration Data using LSTM. This is classified into normal, abnormal above zero and abnormal below zero as indicated. Emergency is detected when signal varied away from +0.005 to -0.005.

TABLE I
RMSE Comparison of LSTM Parameters

Epoch Size	Batch Size	LSTM Cells	Time(secs)	RMSE(%)
50	3	5	97	4.20
250	3	5	223	3.56
250	15	5	180	3.89
50	15	5	78	3.77
250	30	5	154	3.05
50	30	5	36	0.086

A. Accuracy of training and validation

According to [15], LSTM accuracy depends on the number of hidden layers in the network. In this work, data were divided into training and test data ratio of 80:20. Several variations of learning rate, epoch size, batches were implemented in various iterations. Table I shows that the LSTM with 5 hidden layers with epoch size 50 and batch size of 30 gave the best performance.

B. Evaluation Metrics

The performance of the LSTM model was compared based on accuracy, loss function, false positive rate (FPR), true positive rate (TPR), and area under Receiver Operating Characteristics (ROC) curve or area under curve (AUC). The objective is to have high accuracy while keeping loss to the minimum. The accuracy is calculated by equations (1), (2) , (3) respectively.

$$F1 = \frac{2Precision \times Recall}{Precision + Recall}, \tag{1}$$

$$Precision = \mathrm{TP}/(\mathrm{TP}+\mathrm{FP}), \tag{2}$$

$$Recall = \mathrm{TP}/(\mathrm{TP}+\mathrm{FN}), \tag{3}$$

where TP, FP and FN represent true positive, false positive and false negative, respectively.

To check the ability of the model, there is need to confirm the prediction, testing and training accuracy which is a ratio of how the model can detect the intrusion. This is given by the equation (4)

$$Accuracy = \mathrm{TP}+\mathrm{TN}/(\mathrm{TP}+\mathrm{FN}+\mathrm{FP}+\mathrm{TN}), \tag{4}$$

Another important metrics used in evaluation is the AUC-ROC. The AUC-ROC is needed to know how much or to what extent a machine learning model is capable of detecting or classifying various categories of scenarios. The AUC-ROC is plotted with TPR on the vertical axis (y-axis) against the FPR on the horizontal axis (x-axis). The implication of this is that the higher the AUC, the better the model ability to classify. In addition, the z-score can be computed on the predicted data, output from LSTM. The z-score is given as (5)

$$z = \frac{(\beta - \varphi)}{\alpha}, \tag{5}$$

where β is the raw score, φ is the population mean, and α is the population standard deviation. As the formula shows, the z-score is simply the raw score minus the population mean, divided by the population standard deviation

C. Performance Evaluation

The performance evaluation criteria used was Root Mean Square Error (RMSE). This is widely used to judge the accuracy of machine learning algorithms. Our proposed LSTM had accuracy of 97.39% , loss of 0.086 and ROC of 0.98 as shown in Fig. 6, Fig. 7 and Fig. 8 respectively.

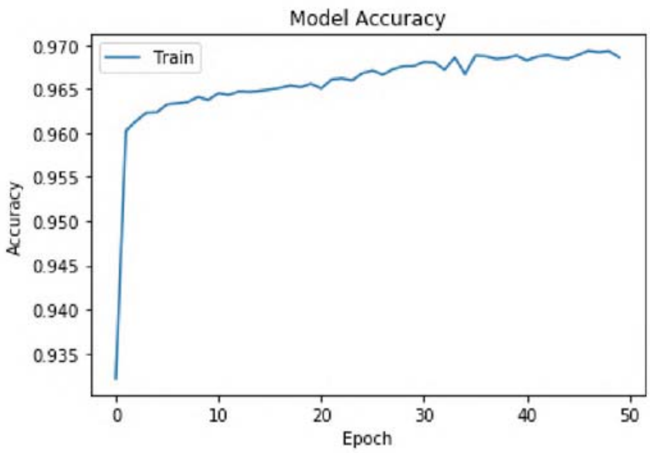

Fig. 6. Model Accuracy Performance Evaluation.

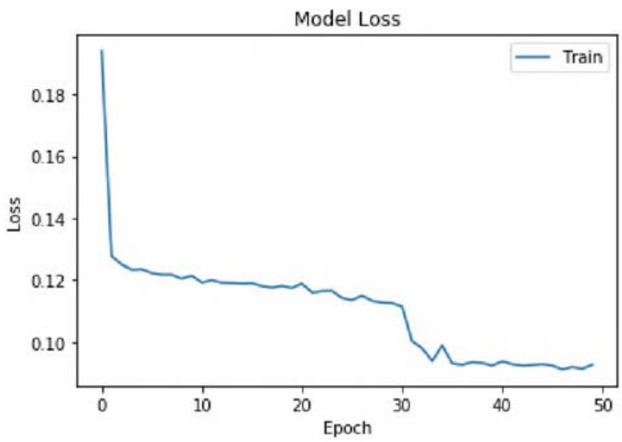

Fig. 7. Model Loss Performance Evaluation.

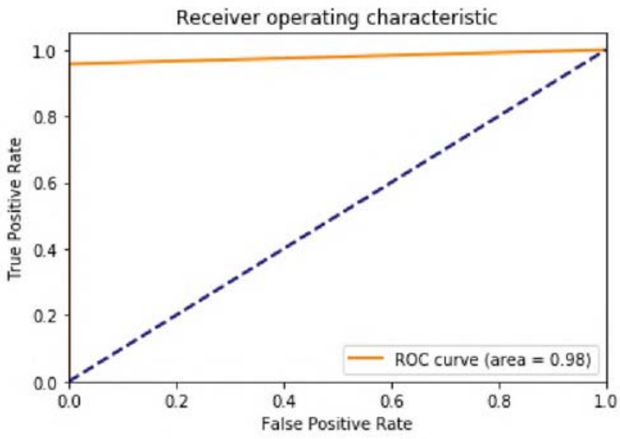

Fig. 8. ROC Performance Evaluation.

D. Dataset Description

The dataset is based on three scenarios such as falling, jumping and falling object data. A total of 10,961 data was collected and saved as csv. The emergency situation here is where the vibration of the room exceeds acceptable threshold. The entire range of the raw data was not conducive for training and convergence of LSTM. Thus, z-score was used for the standardization of the raw data after which data was spilt as 75% and 25% for training and testing respectively.

E. Result Comparison with other Machine Learning Algorithms

Table II summarises the superior performance of the proposed LSTM over other traditional algorithms.

TABLE II
COMPARING THE LSTM WITH VARIOUS ALGORITHMS

Algorithm	Accuracy (%)
Proposed LSTM	**97.39**
Fine Tree	66.9
Medium Tree	67.7
Coarse Tree	67.8
Quadratic Discriminant	46.7
Linear Discriminant	53.3
Logistic Regression	46.7
Gaussian Naïve Bayes	53.3
Kernel Naïve bayes	67.4
Quadratic SVM	48.6
Cubic SVM	49.5
Fine Gaussian SVM	61.2
Coarse Gaussian SVM	51.3
Fine Gaussian SVM	61.2
Medium Gaussian SVM	55.0
Fine KNN	56.9
Medium KNN	64.0
Coarse KNN	67.3
Cosine KNN	50.0
Cubic KNN	64.0
Weighted KNN	58.3
Boosted Trees	67.6
Bagged Trees	57.3
Ensembled Subspace Discriminant	46.7
Ensembled Subspace KNN	56.9
RUSBoosted Trees	67.6

F. Result Comparison with related works

This section describes the performance comparison of the proposed LSTM with related works such as [19], [20]. Table III shows that the proposed LSTM had accuracy of 97.39% which is an improvement to the works of [19] (97.12%) and [20] (90.8%).

TABLE III
COMPARING THE PROPOSED LSTM WITH RELATED LSTM ALGORITHMS FOR EMERGENCY DETECTION

Algorithm	Accuracy (%)
Proposed LSTM	**97.39**
[19]	97.12
[20]	90.80

VI. CONCLUSION

This work demonstrated using a test-bed, an IoT-Based emergency detection system. The sensor collects vibration data which assist in monitoring, visualization and predicting emergency scenario. Also, in this work, vibration dataset using the G-link 200 sensor was developed. This dataset is available upon request to assist the research community in vibration signal processing for smart factories or smart homes. An LSTM algorithm was implemented to help in the prediction. Results showed an accuracy of 97.39% which is considered reliable for the scenario targeted. It is a future research direction to expand the scope of this work to introduce more complexities like a combination of vibration sensor. It is also desired to introduce better intelligence to take care of challenges of false alarm.

ACKNOWLEDGMENT

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the Grand Information Technology Research Center support program(IITP-2020-2020-0-01612) supervised by the IITP(Institute for Information & communications Technology Planning & Evaluation) and Priority Research Centers Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2018R1A6A1A03024003). It is also supported by National Research Foundation of Korea (NRF) grant funded by Korea government (MSIT)(2019R1F1A1064055)

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