Heterogeneous IoT Sensor Data Classification for Emergency Detection using Machine Learning

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***Abstract*—Inertial Measurement Unit (IMU) and Ultra Wide Band (UWB) sensors were integrated to collect heterogeneous data in a smart factory scenario. In this paper, various machine learning algorithms were used to classify the data with a view to detect normal and anomaly situations based on threshold values of the sensor data. System was simulated using keras with GPU 1xTesla K80, 2496 CUDA cores and 12GB GDDR5 VRAM on top of Google colaboratory. Training and testing data were split into 75% and 25% respectively. Classification of the vibration data from the IMU gave Logistic regression (75.9%), KNN1 (73.37%) and KNN2 (78.4%). In the case of the UWB sensor, KNN1 (100% for movement and respiration), KNN2 (98.60% for movement and 100% for respiration) and Logistic regression gave 100% accuracy both for movement and respiration data. Therefore, it is recommended that based on trade-off, KNN-2 outperformed other machine learning algorithms.**

***Index Terms*—Artificial Intelligence, IoT, sensor data, smart factories, trade off.**

I. INTRODUCTION

THERE exist plethora sensor based technologies for smart factory monitoring. These are made possible in recent time due to growth in Internet of Things (IoT) and possible integration of sensors for data gathering and evaluation [1]. Inertial Measurement Unit (IMU) and Ultra Wide Band (UWB) sensors are ready examples of such enabling technologies as seen in recent research works [2]. However, handling of heterogeneous data collected by integrating multiple sensors is now attracting research attention due to the rising need for smart factory and challenges of interoperability [3], [4].

The major contribution of this paper is the proposal of an integrated sensor arrangement for data capturing in smart factory combining IMU and UWB sensors to collect movement, breathing and vibration data. Secondly, various machine learning algorithms were implemented on the collected data and accuracy of the classification used to carry out a trade-off analysis. Trade-off analysis is a means of choosing or selecting a scheme from several schemes by considering all gain and loss of a system [5] . Following this section I, is the section II where the overall system model is presented. In section III, paper presented the visualization and data gathering features of the sensors. Performance evaluation was done in section IV while paper was concluded in section V.

II. SYSTEM MODEL

The test bed comprises the IMU vibration sensor G-Link 200 connected to the host computer using a customized Universal Serial Bus (USB) gateway as shown in Fig. 1. The UWB sensor is integrated into the same host computer using Universal Asynchronous Receiver Transmitter (UART) connector. The data visualization is made possible by RealTerm software.

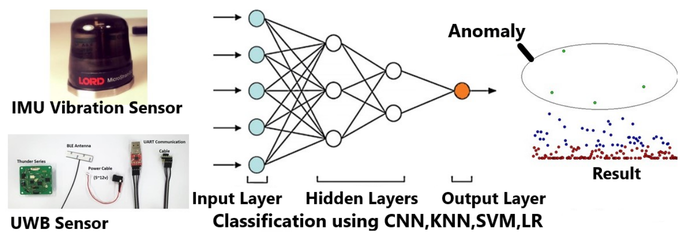

Fig. 1. The overall System Model Showing the connection or the UWB and IMU Sensor for data Collection and Storage on the Host computer. We also show the machine learning classification candidates where the best is selected

III. IMU-UWB DATA COLLECTION AND VISUALIZATION

The G-Link 200 (IMU) vibration sensor displays data under three channels as indicated in Fig. 2 with three colours. The channels are named Channel 1(CH 1 Green), Channel 2 (CH 2 Red)and Channel 3 (CH 3 Blue) respectively. Normal scenario indicates the absence or near absence of vibration at the smart factory while abnormal scenarios were created by causing changes in variations such as falling objects, Human falling and jumping or activities considered not desirable in the factory (see Fig. 2). The data collected over a period of time were saved as csv and processed for machine learning classification.

In similar vein, the UWB sensor is connected to the host computer using the UART communication port but data capture is done suing RealTerm Serial Capture Program 2.0.0.70 version as shown in Fig. 3. The data comprises human movement as well as breathing signal detected within the smart factory. This is important to monitor both human intrusion and or case of emergency need should the section of the smart factory be such that no movement is allowed or human is allowed.

IV. PERFORMANCE EVALUATION

As explained earlier, four machine learning algorithms were used to implement the classification. Tables I and II respectively shows the performance of all algorithms.

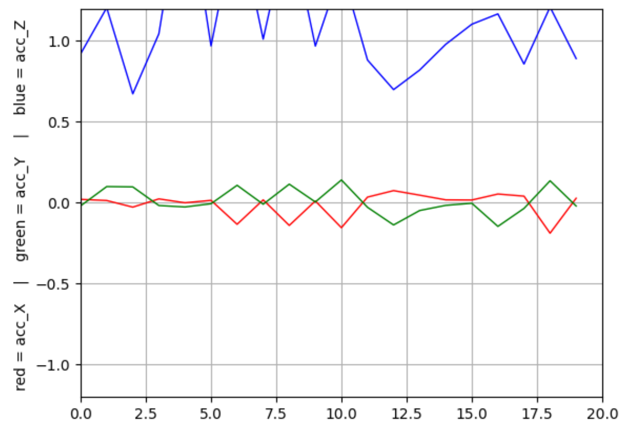

Fig. 2. Response of G-Link Vibration sensor to Vibration as shown in the movement of the plot indicated by colours representing all channels

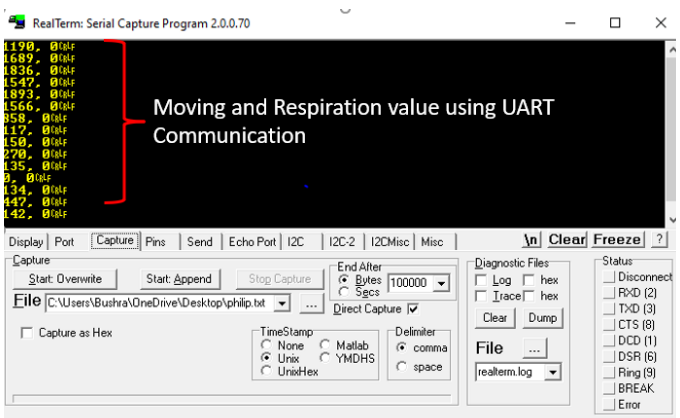

Fig. 3. Movement and Respiratory Data Collection and Visualization using UWB Sensor and RealTerm Serial Capture Program 2.0.0.70

TABLE I
SUMMARY OF VARIOUS MACHINE LEARNING CLASSIFICATIONS IMPLEMENTED ON THE DATA COLLECTED USING IMU SENSOR

IMU Channel	CNN	SVM	LR	KNN-1	KNN-2
CH 1	75.90%		75.90%	65.00%	76.00%
CH 2	75.90%		75.90%	63.50%	76.00%
CH 3	75.90%		75.90%	73.37%	78.40%

TABLE II
SUMMARY OF VARIOUS MACHINE LEARNING CLASSIFICATIONS IMPLEMENTED ON THE DATA COLLECTED USING UWB SENSOR

UWB DATA	CNN	SVM	LR	KNN-1	KNN-2
Movement	97.78%	100.00%	100.00%	100.00%	98.60%
Respiration	100.00%	100.00%	100.00%	100.00%	100.00%

Having chosen KNN based on the need to reduce complexity of multiple machine learning algortihm, Fig. 4 shows the vibration visualization using KNN over time.

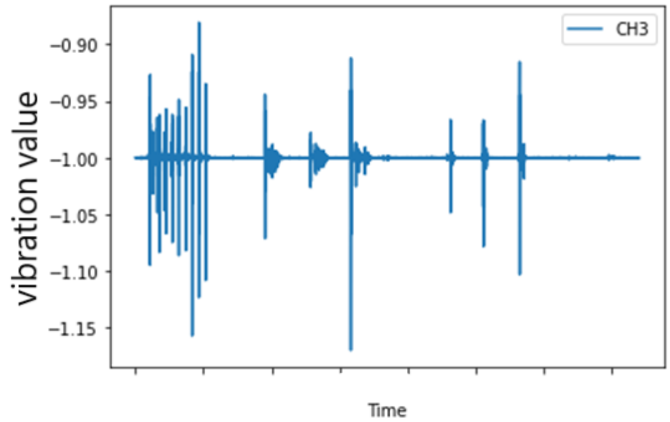

Fig. 4. KNN result for classification of the vibration data. Note that KNN was selected based on tradeoff in terms of accuracy in vibration data, breathing and movement data

V. CONCLUSION

To monitor anomaly in smart factory, this paper set up two sensors for capturing movement, respiration and vibration signals. These heterogeneous data were classified using machine learning algorithms. In terms of trade off, KNN-2 was selected since it gave a comparatively good accuracy on all data types. It is a future research direction to include LiDAR data to enhance the robustness of the data as well increase monitoring possibilities.

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