Thermal Sensor-Based Activity Detection in Smart Spaces using GentleBoost Optimized Classifier

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***Abstract*—On the smart factory shop floor, the safety of persons can be enhanced with an effective human activity detection system. This system should have the ability to monitor issues like fall detection which is a common work-related accident. In this work, we have used a public dataset that is based on a thermal array (ambient) sensor for the detection and classification of falls on the smart factory shop floor. The performance of the proposed optimized ensemble learning in MATLAB R2019b shows an accuracy of 100%, and a loss value of 0.00015642 using the minimum classification error plot.**

***Index Terms*—Fall Detection, Ensemble Learning, CNN, Smart spaces,**

I. Introduction

The fifth generation (5G) and beyond 5G (B5G) with its improved connectivity, extremely low-latency, increased in number of connected devices and large bandwidth has impacted on smart spaces such as smart factory shop floor especially when artificial intelligence is used as an enabler [1]. Recently, the authors of [2] comprehensively showed the drawbacks of various approaches to human activity detection. In the end, they posited that thermal array sensors (or ambient sensors) find ready usage due to the privacy preservation and no discomfort issues as experienced in multimedia or wearable devices respectively.

In [3], the authors used a low resolution and cost effective ambient sensor to classify falls and triggering the need for medical attention for the elderly. In the works of [4], authors developed a simple testbed wherein they collected datasets for smart factory for emergency response based on the classification of abnormal human activities detected. However, all these works still gave possible room for further research in search for better accuracy and time efficient system. Inspired by the work of [2], this work makes the following contributions:

1) Leveraging on the “Omron thermal sensor dataset” [5], we processed the thermal array sensor dataset for fall detection by removing redundant data thus, providing clean data fall detection in smart spaces.
2) In addition, a comparison of the performance of the proposed scheme with state-of-the-art algorithms was presented.

The organization of this work is: following section I is section II where we described the system model, sensor parameters, and the dataset. Section III presents the performance evaluation of the CNN as compared to other algorithms. The paper was concluded in section IV.

II. Dataset Description and System Model

1) Dataset: The dataset used is known as an Infrared Thermal sensor dataset for automatic fall detection research [5]. This dataset was collected using a low-cost ambient sensor Omron D6T-8L-06 infrared thermal sensor. In all, it comprised 32 predictors (sensor readings of human activity) and one binary label (fall(0) or no fall(1)) The dataset contains 313,279 observations. The temperature data from the sensor as shown in Fig. 1 depicts a normal activity (series 1 and 2), as well as fallen activity (series 3 and 4) as seen in the spike in the temperature value.

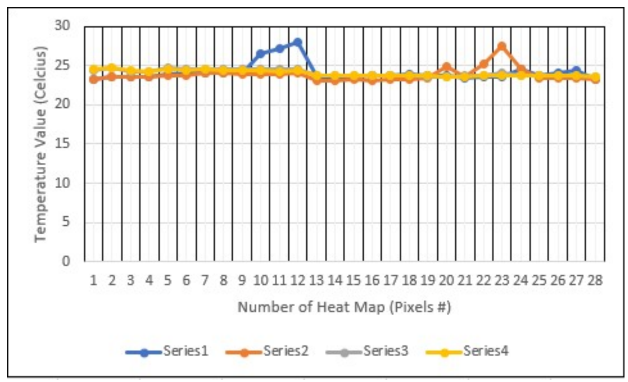

Fig. 1. Thermal array sensor spread for normal activity (straight lines, series 3 and 4) and falling activity (spikes in line for example the blue (series 1) and orange (series 2) lines.)

2) GentleBoost Optimized Classifier (GBC): The ensemble learning used is the GBC. Using MATLAB R2019b, the simulation parameters as shown in Table I.

TABLE I
Ensemble GentleBoost Network Parameters

Parameters	**Settings**
Ensemble method,	**Optimizable Ensemble**
Learning rate,	**0.69331**
Learner type	**Decision tree**
Optimizer,	**Bayesian optimization**
Iterations (epochs)	**30**

III. Performance Evaluation

A. Performance Metrics

1) Minimum Classification Error (MCE): Minimum classification error (MCE) is designed to aid the optimization of neural networks. The MCE is given as (1)

$$\frac{1}{R}\sum_{j=1}^{C}\sum_{r=1}^{R_j}\frac{1}{1+exp(-D_{r,j}(x_r;\Lambda)/H_r} \tag{1}$$

Where C denotes the classification problem class, x is represents the observations to be classified, r is the risk function or cost of classifying a class j observation into class i, Λ denotes the classifier parameters, R is the number of training samples for class j, D is the misclassification score associated with the training samples for class j and H_r is the bandwidth of the one-dimensional kernel function [6].

B. GentleBoost Ensemble Classifier Performance

At the end of the simulation, the ensemble method with the least minimum classification error of 0.00015642 (see Fig. 2) is the '**GentleBoost** with the an accuracy of 100%, 49 misclassifcation cost, at a learning rate of 0.69331. The minimum classification error plot and confusion matrix is shown in Fig. 2 and Fig. 3 respectively. The concept of 'Boosting' is aimed at producing a "stronger" classification from the combination of several "weak" ones. GBC performed better than CNN, Long Short Term Memory (LSTM), Gated Recurrent Units (GRU), Bi-LSTM, Naive Bayes (NB) and simple Feed-forward Neural Network (FNN) from related works [2], [3] as shown in Table II. Results show that **GBC** has an accuracy of **100%** while CNN 99.50%, Bi-LSTM 93%, FNN 91.64%, LSTM 91%, and GRU 87.5% being the least performed.

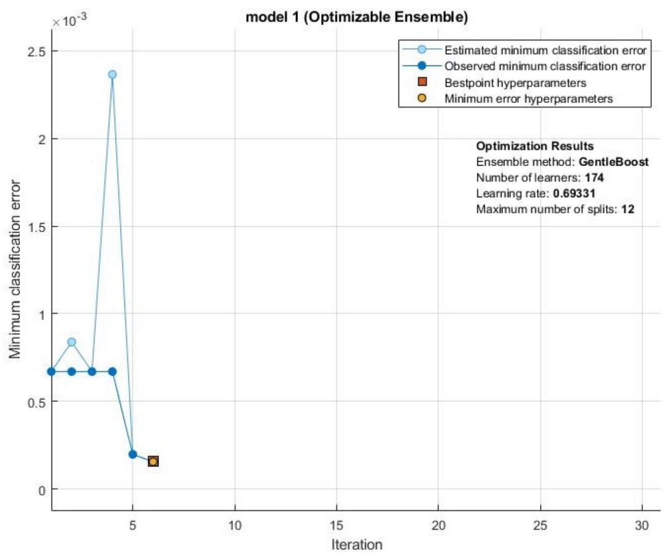

Fig. 2. Minimum Classification Error Plot of the Ensemble GentleBoost Classifier. Notice that the best results was achieved at the 6th iteration (Epoch) unlike in other schemes that requires more iterations.

IV. Conclusion

This work presented the use of ambient sensor (thermal array sensor) for activity detection in smart spaces. In particular, the work demonstrated the superior performance of Ensemble GentleBoost Classifier for data classification of fall types using a public dataset. The result shows an accuracy of 100% which is higer than the use of CNN (99.5%).

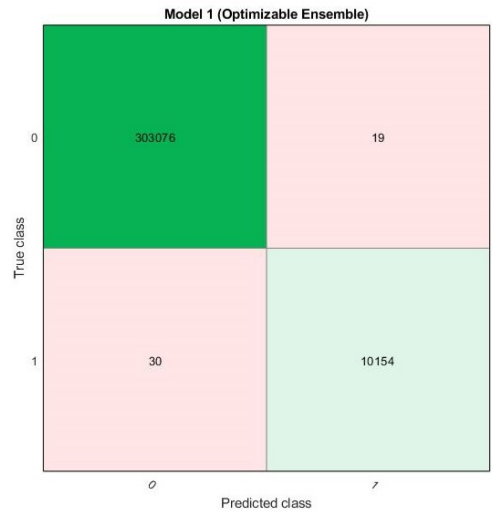

Fig. 3. Confusion Matrix Of the GentleBoost Ensemble Classifier

TABLE II
Performance evaluation of the proposed Classifier

Algorithms Compared	GBC	CNN	Bi-LSTM	FNN	LSTM
Accuracy (%)	**100**	99.5	93	91.64	91

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