

# Breathing Pattern Forecasting using Deep Learning in Smart Factory Environment

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**Abstract**—This paper provides a Deep Learning (DL) based design framework for forecasting respiratory behaviors of factory floor workers in a smart factory environment (or Industrial Internet of Things (IIoT)). A continuous 30 min breathing responses were collected through Ultra-Wide Band (UWB) sensor and then applying Artificial Neural Network (ANN) models to acquire the highest prediction accuracy. Eight ANN models with different input, hidden, and output nodes were compared with the proposed scheme code-named ANN-5. The result shows that the proposed ANN-5 outperformed other algorithms with 87.43% precision.

**Index Terms**—Machine Learning (ML), Industrial Internet of Things (IIoT), R Programming, Artificial Neural Network (ANN)

## I. INTRODUCTION

The Industrial Internet of Things (IIoT) guarantees broad appropriateness and economic progression to dependability, flexibility, and interoperability [1]. Smart factories scenarios often can be threatened life dangers and terrible occurrences by experiencing with hardware instruments, and harmful materials capable of influencing workers health [2]. For example, on January 28, 2021, the Georgia poultry plant suffered an industrial disaster with six killed and ten injured caused by a liquid nitrogen leak in Georgia, United States [3].

Nowadays, The Ultra-Wide Band (UWB) innovation has enabled solutions for capturing breathing signs by offering remote supervision of respiratory patterns, without requiring any electronic gadget, guaranteeing security, adaptable to temperature and light conditions [4], [5].

In an emergency related to human respiratory in the smart factory floor, the breathing patterns of workers are collected using UWB sensors, connected through Bluetooth Low Energy (BLE) or UART interfaces and specified software in any host computer working as a fog node. By analyzing patterns with the help of Deep Learning (DL) approaches, detecting emergencies, and confirming, DL analyzed results are transmitted to edge cloud and then dispatch information to the factory control unit instantly so that they can take precaution before it takes place.

In this paper, the "UMAIN" Thunder series UWB sensor of frequency (7GHz-9GHz) was used in smart industry scenarios to recognize the presence of an individual. After collecting a piece of continuous breathing information, and adopting Artificial Neural Network (ANN) models to predict

respiratory signs, and investigated model performances for higher accuracy. The significant contributions of this paper are summarized as follow:

- 1) A UWB breathing sensor is employed to capture 30 minutes of vital signs in smart factory environment.
- 2) A comprehensive dataset is collected by UWB sensor and then trained by eight types of ANN models for forecasting breathing patterns.
- 3) Select the best ANN model based on accuracy and nodes of the models.

The rest of the paper is detailed as: following this Section I, an experimental setup is described in Section II, where we have focused on data collection and employed ANN models. Performance evaluation of models are presented Section III and paper is concluded in Section IV.

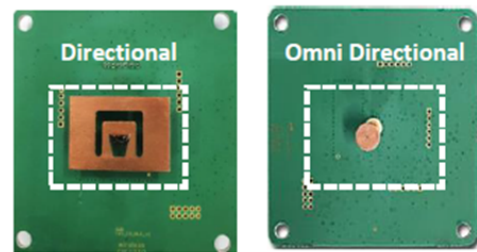


Fig. 1. The omni directional and directional UWB sensors.

## II. EXPERIMENTAL SETUP

The two types of UWB sensors used are shown in Fig. 1. These are the directional and omnidirectional with 4.5m and 7m of respiration detection and 5m and 10m of movement detection, respectively. The sensor first captures the moving activity of the person and when there is no moving, it then captures the breathing values. In the experiment, a directional UWB sensor was mounted for experimental purposes, 2m higher from the floor to cover a medium-sized room. After installing the sensor vertically and connecting to UART cable, it is then connected to a system where Realterm software is installed to visualize the moving and breathing values of the sensor.

The sensor displays the moving values of persons in the Smart factory if well installed and set up. With this, the breathing values of fallen persons but not moving are

collected. The experiment stopped after 30 minutes to allow for data gathering. Data collected includes only breathing values, and save as CSV. files.

TABLE I

THE APPLIED ANN MODELS FOR ANALYZING BREATHING PATTERNS.

ANN Models	Input Node	Hidden Node	Output Node
ANN1	5	15	5
ANN2	5	10	10
ANN3	5	15	15
ANN5	10	25	20
ANN6	15	25	5
ANN7	20	25	5
ANN8	20	25	10

### III. PERFORMANCE EVALUATION

A total of 648 raw breathing samples were collected. These data served as an input to various ANN algorithms compared with the proposed scheme. ANN consists of three layers known as input, hidden, and output layer. The hidden layer employs the activation with the given weights from input and output nodes and extracts the samples are provided to train the models. We focused on eight ANN models with different parameters, shown in table I.

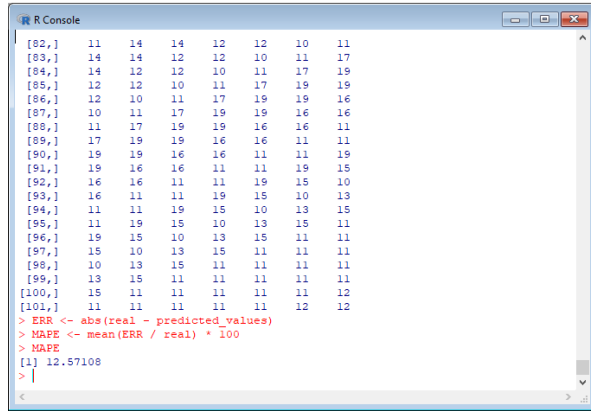


Fig. 2. The MAPE value of breathing dataset for ANN5 model.

We have developed these ANN models in R programming environments. While training the ANN algorithms, we have found out the results are affected by the number of input, hidden and output layers. We utilized the Mean Absolute Percentage Error (MAPE), ratio of predicting accuracy of samples to observe forecasting accuracy. It is defined as:

$$MAPE = \frac{1}{m} \sum_{i=1}^m \frac{|Real_i - Predict_i|}{Real_i} * 100\% \quad (1)$$

Where,  $Real_i$  the actual value and  $Predict_i$  is the forecast value.

The accuracy from MAPE is:

$$Accuracy = \max(0, 1 - MAPE) \quad (2)$$

The results of the ANN models are shown in Fig. 3 where ANN5 has achieved the lower MAPE 12.57 with higher

accuracy 87.43%. ANN2 and ANN3 also performed well by providing accuracy of 87.11% and 87.22%, respectively.

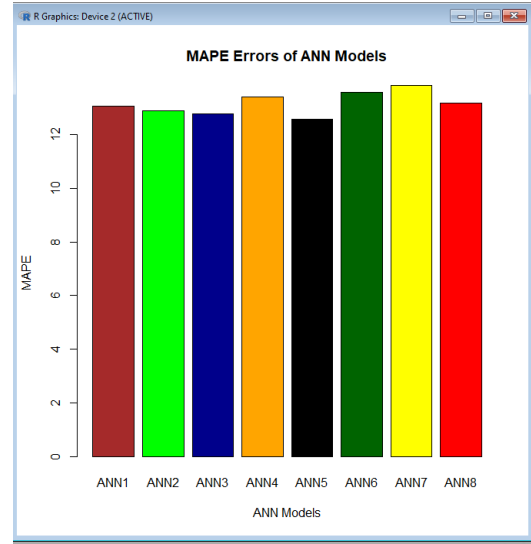


Fig. 3. The Comparison of MAPE errors of eight ANN Models.

### IV. CONCLUSIONS

In this paper, breathing pattern monitoring and vital sign data was collected. The sensor as mounted at a fair position from floor to provide the maximum range. In all, about 648 raw data samples was collected, and trained utilizing eight ANN models to observe the forecasting accuracy of patterns. The result indicated the ANN-5 outperformed the others by showing 87.43% with 10 input, 25 hidden and 20 output layers. In the future work, it is desired to expand the quantity of dataset as well as see the option of exploring the possibilities of using transfer learning to ensure maximise the efficiency.

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